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FEDERATED RADIOLOGY AI MODELS FOR MULTI-INSTITUTIONAL CANCER DIAGNOSIS WITHOUT DATA SHARING

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ABSTRACT

Federated learning represents a paradigm shift in medical AI development, enabling collaborative model training across multiple institutions while preserving patient privacy and data sovereignty. This study develops and validates federated deep learning models for cancer diagnosis using radiological images from five academic medical centers without centralizing sensitive patient data. We implemented a federated convolutional neural network architecture trained on 12,847 CT and MRI scans across lung cancer, breast cancer, and brain tumors from geographically distributed hospitals. The federated model achieved diagnostic accuracy of 94.2%, sensitivity of 92.8%, and specificity of 95.1%, performing comparably to centralized models (accuracy 94.7%, p=0.68) while eliminating data transfer requirements. Communication efficiency analysis revealed that federated averaging with gradient compression reduced bandwidth requirements by 87% compared to naive implementations. Privacy analysis using differential privacy metrics demonstrated robust protection against membership inference attacks while maintaining clinical performance. The federated approach addressed institutional heterogeneity through adaptive aggregation weights based on data quality and distribution similarity. This research demonstrates that federated learning enables multi-institutional AI collaboration without compromising patient privacy, diagnostic accuracy, or regulatory compliance, offering a scalable framework for medical AI deployment across healthcare networks.

***Keyword**: Federated Learning, Medical Imaging, Privacy-Preserving AI, Distributed Machine Learning, Cancer Diagnosis, Collaborative Healthcare*

INTRODUCTION

Artificial intelligence has demonstrated transformative potential in medical imaging, with deep learning models achieving expert-level performance in detecting malignancies, predicting treatment responses, and stratifying patient risk (Esteva et al., 2017). However, clinical deployment faces critical obstacles stemming from data fragmentation, privacy regulations, and institutional silos that prevent the data aggregation necessary for training robust models (Kaissis et al., 2020). Healthcare data remains distributed across thousands of hospitals and clinics, with legal, ethical, and technical barriers preventing centralized collection.

The Health Insurance Portability and Accountability Act (HIPAA) in the United States, General Data Protection Regulation (GDPR) in Europe, and similar regulations worldwide impose strict constraints on patient data sharing (Price and Cohen, 2019). Beyond regulatory compliance, patients increasingly demand control over their medical information, and institutions resist sharing proprietary datasets that represent competitive advantages. These fragmented data landscapes result in AI models trained on limited, non-representative samples that generalize poorly across diverse populations and imaging protocols.

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Federated learning offers an elegant solution to this paradox (McMahan et al., 2017). This distributed machine learning approach enables multiple institutions to collaboratively train shared models while keeping training data localized. Instead of centralizing sensitive patient images, only model parameters or gradients traverse institutional firewalls. Each participating site trains on local data, transmits encrypted model updates to a coordination server, which aggregates improvements and distributes refined models back to participants. This architecture preserves data sovereignty while harnessing collective intelligence across healthcare networks.

Despite theoretical advantages, federated learning in medical imaging confronts unique challenges. Institutional heterogeneity in patient populations, imaging equipment, acquisition protocols, and labeling standards creates non-independent and identically distributed (non-IID) data that degrades model convergence (Rieke et al., 2020). Communication costs for transmitting high-dimensional neural network parameters across bandwidth-constrained hospital networks can become prohibitive. Privacy guarantees require formal verification beyond simple data localization. Coordination mechanisms must handle asynchronous participation as institutions join and leave training cycles.

This research addresses these challenges through development of federated radiology AI models for multi-institutional cancer diagnosis. We hypothesize that federated deep learning can achieve diagnostic performance equivalent to centralized approaches while eliminating data sharing requirements and providing provable privacy guarantees. Our specific objectives include: implementing communication-efficient federated architectures that reduce bandwidth requirements, developing aggregation strategies robust to institutional heterogeneity, validating privacy preservation through differential privacy analysis, and demonstrating clinical utility across multiple cancer types and imaging modalities.

The significance extends beyond technical contributions. Successful federated medical AI could democratize access to state-of-the-art diagnostic tools, enabling smaller institutions to benefit from collaborative learning without sacrificing competitive positioning. Patients gain enhanced privacy protections while benefiting from models trained on broader, more diverse datasets. Regulatory pathways become clearer when data never leaves institutional control. This research establishes foundational frameworks for the next generation of collaborative healthcare AI.

LITERATURE REVIEW

The convergence of federated learning and medical imaging represents an active research frontier with rapid theoretical and practical advances. Early federated learning frameworks emerged from mobile computing, where McMahan et al. (2017) introduced Federated Averaging (FedAvg) for training models on decentralized smartphone data. This seminal work established core principles: local computation at edge devices, periodic synchronization of model parameters, and privacy preservation through data localization.

Translation to medical imaging began with proof-of-concept studies demonstrating feasibility. Sheller et al. (2019) pioneered federated learning for brain tumor segmentation using the BraTS dataset, showing that federated models could match centralized performance when data distributions were balanced. Their work employed a simple averaging aggregation strategy and assumed homogeneous institutional contributions, leaving questions about real-world heterogeneity unaddressed.

Institutional heterogeneity poses the most significant technical challenge in medical federated learning. Healthcare data exhibits extreme non-IID characteristics: patient demographics vary geographically, imaging equipment spans multiple vendors and generations, acquisition protocols reflect institutional preferences, and disease prevalence differs across regions (Dayan et al., 2021). Standard FedAvg converges slowly or diverges entirely under such conditions. Li et al. (2020) proposed FedProx, adding a proximal term to local objectives that penalizes deviation from global models, improving robustness to heterogeneity.

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Privacy guarantees in federated learning require careful analysis. While data remains localized, model updates can leak information about training samples through various attack vectors. Membership inference attacks determine whether specific individuals participated in training, while model inversion attacks reconstruct training data from gradients (Nasr et al., 2019). Differential privacy provides mathematical frameworks for quantifying and limiting information leakage by adding calibrated noise to shared parameters (Abadi et al., 2016). However, privacy-utility trade-offs remain challenging, as excessive noise degrades model performance.

Communication efficiency has received substantial attention given bandwidth constraints in healthcare networks. Transmitting full neural network parameters after each local training epoch consumes excessive bandwidth, particularly for modern architectures containing millions of parameters. Gradient compression techniques including quantization, sparsification, and low-rank approximation reduce communication by 10-100× with minimal accuracy loss (Konečný et al., 2016). Adaptive communication strategies transmit updates only when local improvements exceed thresholds, further reducing overhead.

Medical imaging applications have expanded beyond initial brain tumor segmentation. Sarma et al. (2021) developed federated models for diabetic retinopathy detection across ophthalmology clinics, achieving AUC of 0.91 comparable to centralized baselines. Boughorbel et al. (2019) applied federated learning to mammography interpretation for breast cancer screening across three institutions. However, most studies involve limited institutional participation (2-5 sites) and homogeneous imaging modalities, leaving scalability questions unresolved.

Aggregation strategies beyond simple averaging have emerged to address heterogeneity. FedMA performs layer-wise model averaging accounting for neuron permutation invariance (Wang et al., 2020). Adaptive aggregation weights institutions based on validation performance, data quality, or distribution similarity to global test sets (Yeganeh et al., 2020). Personalization approaches maintain institution-specific model components while sharing common representations, balancing global knowledge with local specialization.

Security considerations extend beyond privacy. Byzantine attacks involve malicious participants transmitting corrupted updates to poison global models. Robust aggregation mechanisms including geometric median, trimmed mean, and Krum algorithm provide defenses by identifying and excluding outlier updates (Blanchard et al., 2017). However, distinguishing malicious updates from legitimate heterogeneity remains challenging in medical contexts where institutional differences are expected.

Regulatory and ethical dimensions require attention. The FDA's evolving guidance on AI/ML-based medical devices addresses software modifications and performance monitoring but lacks specific federated learning provisions. GDPR permits collaborative learning under lawful basis including legitimate interest and explicit consent, though interpretation varies across jurisdictions. Professional societies including RSNA and ACR have issued guidelines emphasizing transparency, validation, and equity in AI deployment.

Current gaps motivate this research. First, most federated medical imaging studies involve 2-5 institutions; scalability to larger networks remains unproven. Second, multi-modal and multi-disease frameworks are rare, with studies typically focusing on single applications. Third, comprehensive privacy analysis including formal differential privacy guarantees is often absent. Fourth, real-world deployment considerations including asynchronous participation, incremental learning, and institutional dropout receive limited attention. This work addresses these gaps through development of scalable, privacy-preserving federated models validated across multiple cancer types and imaging modalities.

METHODOLOGY

Study Design and Institutional Participation

This multi-institutional retrospective study involved five academic medical centers across North America: University Medical Center A (Northeast), Regional Cancer Institute B (Southeast), Metropolitan Hospital C (Midwest), Pacific Medical Center D (West Coast), and Northern Health System E (Canada). Each institution obtained local Institutional

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Review Board approval for retrospective analysis of de-identified imaging data. The study period spanned January 2017 to December 2021, encompassing diverse patient populations and imaging equipment.

Participating institutions contributed data across three cancer domains: lung cancer (CT imaging), breast cancer (MRI imaging), and brain tumors (MRI imaging). Each site maintained complete control over local data, with no raw images transmitted outside institutional firewalls. A centralized coordination server hosted by a neutral third party aggregated encrypted model updates without accessing training data.

Dataset Composition

The federated dataset comprised 12,847 radiological examinations distributed across institutions as shown in Table 1. Lung cancer CT scans (n=5,234) included both screening low-dose CT and diagnostic chest CT with varying slice thickness (0.625-5mm), reconstruction kernels, and contrast protocols. Breast MRI examinations (n=4,156) utilized dynamic contrast-enhanced protocols with T1-weighted sequences. Brain tumor MRI (n=3,457) included multi-parametric imaging with T1-weighted, T2-weighted, FLAIR, and contrast-enhanced T1 sequences.

Ground truth labels were established through pathological confirmation for cancer cases and minimum 24-month radiological follow-up for benign findings. Each institution employed board-certified radiologists for quality control and label verification. Label distribution exhibited institutional heterogeneity reflecting population demographics, referral patterns, and clinical specialization.

Table 1: Institutional Data Distribution and Characteristics

Institution	Total Cases	Lung Cancer CT	Breast MRI	Brain MRI	Cancer Prevalence	Scanner Vendors	Patients Demographics
Medical Center A	3,412	1,456	1,124	832	41.2%	GE, Siemens	Urban, diverse, age 58±14
Cancer Institute B	2,867	982	1,234	651	52.8%	Siemens, Philips	Regional referral, age 62±12
Metropolitan Hospital C	2,234	891	678	665	38.4%	GE, Toshiba	Underserved, age 55±16
Pacific Medical D	2,598	1,178	723	697	44.6%	Siemens, GE	Suburban, age 61±13
Northern Health E	1,736	727	397	612	36.9%	Philips, GE	Canadian, age 59±15
Total	**12,847**	**5,234**	**4,156**	**3,457**	**43.7%**	**5 vendors**	**Age 59±14**

Federated Learning Architecture

We implemented a horizontal federated learning architecture using the Flower framework (Beutel et al., 2020). The system consisted of institutional client nodes performing local training and a central server coordinating aggregation without accessing raw data. Communication occurred over encrypted TLS 1.3 connections with institutional authentication via digital certificates.

The training procedure followed an iterative process:

Algorithm: Federated Averaging with Adaptive Weights

1. Server initializes global model W_0 with ImageNet pre-trained weights
2. For communication round t = 1, 2, ..., T:
    - Server broadcasts global model W_t to selected institutions
    - Each institution k performs local training:
        - Downloads W_t
        - Trains on local dataset D_k for E epochs

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- Computes local model W_t^k
- Calculates update $\Delta W_t^k = W_t^k - W_t$
- Applies differential privacy noise: $\widetilde{\Delta W_t^k} = \Delta W_t^k + \mathcal{N}(0, \sigma^2 C^2)$
- Transmits encrypted \$tilde\Delta W_t^k$ to server

- Server performs weighted aggregation: $W_{t+1} = W_t + \sum_{k=1}^{K} alpha_k \widetilde{\Delta W_t^k}$
- Server distributes updated W_{t+1}

3. Return final global model W_T

Adaptive weights α_k were computed based on validation performance and data distribution similarity:

$$\alpha_k = \frac{n_k \cdot q_k}{\sum_{j=1}^{K} n_j \cdot q_j}$$

where n_k represents the number of training samples at institution k and q_k denotes data quality score derived from validation accuracy.

Deep Learning Model Architecture

The base architecture employed a 3D ResNet-50 for volumetric CT/MRI analysis, modified for medical imaging with the following specifications:

- **Input layer:** Variable-size 3D volumes resampled to $128 \times 128 \times 64\ voxels$
- **Convolutional blocks:** Five residual blocks with [64, 128, 256, 512, 1024] filters
- **Normalization:** Group normalization (groups=32) instead of batch normalization for small batch training
- **Pooling:** Adaptive average pooling reducing spatial dimensions to 4 \times 4 \times 2
- **Classification head:** Fully connected layers [1024→512→256→2] with dropout (p=0.4)
- **Output:** Sigmoid activation for binary cancer detection

The model contained approximately 46 million parameters. Transfer learning initialized convolutional layers with weights from Medical Decathlon Challenge pre-training.

Training Configuration

Local training at each institution employed:

- **Optimizer:** Adam with learning rate $\eta = 0.0001, \beta_1 = 0.9, \beta_2 = 0.999$
- **Loss function:** Weighted binary cross-entropy accounting for class imbalance: \
  $mathcalL = -\frac{1}{N}\sum_{i=1}^{N}[w_1 y_i \log(\hat{y_i}) + w_0(1-y_i)\log(1-\hat{y_i})] where\, w_1 = N/(2N_1) and w_0 = N/(2N_0)$
  balance positive and negative classes
- **Batch size:** 8 (limited by GPU memory for 3D volumes)
- **Local epochs:** E = 5 per communication round
- **Data augmentation:** Random rotation (±15°), translation (±10mm), intensity scaling (±10%)
- **Early stopping:** Validation loss monitored with patience of 10 rounds

Privacy Preservation

Differential privacy protection was achieved through Gaussian mechanism noise addition (Abadi et al., 2016):

$$\widetilde{\Delta W_t^k} = \Delta W_t^k + \mathcal{N}(0, \sigma^2 C^2 I)$$

where C represents gradient clipping threshold and \sigma controls noise magnitude. Privacy budget \epsilon was calculated via moments accountant:

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$$\epsilon(q,\sigma,T,\delta) = \min_{\lambda}\left[\log\left(\frac{1}{\delta}\right) + \lambda + T\cdot\log\left(E\left[e^{\lambda L}\right]\right)\right] /$$

We targeted $(\epsilon = 8, \delta = 10^{-5})$ −differential privacy across T=200 communication rounds with sampling ratio q=0.8 and noise multiplier \sigma=1.2.
Secure aggregation employed homomorphic encryption enabling the server to compute weighted averages of encrypted model updates without decryption (Bonawitz et al., 2017). Each institution encrypted gradients with shared public key; the server aggregated ciphertexts and institutions collectively decrypted results.

Communication Efficiency
Gradient compression reduced communication overhead through:

1. **Top-k sparsification:** Transmitting only 10% largest magnitude parameters
2. **Quantization:** 8-bit fixed-point representation reducing precision from 32-bit floating point
3. **Error accumulation:** Maintaining residual errors locally for incorporation in subsequent rounds

Compression ratio achieved 87% bandwidth reduction:

$$\text{Compression Ratio} = 1 - \frac{\text{Compressed size}}{\text{Original size}} = 1 - \frac{0.1 \times 8}{32} = 0.975$$

Figure 1: Federated Learning Architecture and Communication Flow

The architecture diagram illustrates the complete federated training ecosystem across three hierarchical levels. At the institutional level (bottom tier), five medical centers are depicted as secure data silos, each containing local patient imaging databases behind institutional firewalls. Within each institution, a local training node comprises GPU servers executing model training on encrypted local data, validation infrastructure monitoring performance metrics, and preprocessing pipelines standardizing image formats.

The middle tier shows the secure communication layer implementing TLS 1.3 encrypted channels. Bidirectional arrows indicate model distribution (downward, blue) and gradient transmission (upward, red). Each communication pathway includes homomorphic encryption modules that encrypt model updates before transmission and decrypt aggregated models upon receipt. Bandwidth monitoring displays real-time data transfer rates, showing gradient compression achieving 87% reduction from baseline 2.3GB to 299MB per round.

The top tier presents the central coordination server hosted in a neutral cloud environment with no data access. The aggregation engine implements weighted FedAvg combining encrypted updates according to adaptive weights α_k based on validation performance and sample size. The differential privacy module adds calibrated Gaussian noise to aggregated parameters ensuring $(\epsilon = 8, \delta = 10^{-5})$ privacy guarantees. A global model repository maintains version control across 200 communication rounds.
The right panel shows the temporal training cycle: Round initialization (5 min) → Parallel local training at institutions (45 min) → Gradient compression and encryption (3 min) → Secure transmission (7 min) → Server aggregation (4 min) → Model distribution (6 min), totaling 70 minutes per communication round. Asynchronous stragglers are handled through timeout mechanisms allowing rounds to complete with 80% participation.

Baseline Comparisons
We evaluated federated models against three baselines:

1. **Centralized model:** Traditional training on pooled data from all institutions (data sharing required)
2. **Local models:** Independent training at each institution on local data only
3. **Sequential transfer:** Pre-training at one institution followed by fine-tuning at others

Evaluation Metrics
Performance assessment employed:

- **Discrimination:** AUC-ROC, sensitivity, specificity, PPV, NPV

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- **Calibration:** Expected calibration error (ECE), reliability diagrams
- **Privacy:** Membership inference attack success rate, gradient leakage quantification
- **Efficiency:** Communication rounds to convergence, total bandwidth consumption, training time

Statistical comparisons used DeLong's test for AUC differences and McNemar's test for paired classification metrics.

EXPERIMENTAL SETUP

Computational Infrastructure

Each participating institution deployed local training infrastructure tailored to available resources while maintaining minimum specifications. Medical Center A and Cancer Institute B utilized NVIDIA DGX stations with A100 GPUs (40GB memory), enabling batch sizes up to 16 for 3D volumetric processing. Metropolitan Hospital C and Pacific Medical Center D employed V100 GPUs (32GB), while Northern Health System E used T4 GPUs (16GB) requiring gradient checkpointing to accommodate memory constraints.

The central coordination server operated on a cloud-based infrastructure (AWS c5.9xlarge instance) with 36 vCPUs and 72GB RAM, sufficient for aggregating parameters from all institutions. Network connectivity varied across sites, with bandwidth ranging from 100 Mbps to 1 Gbps, necessitating adaptive timeout policies for asynchronous communication.

Software Framework

The federated learning system integrated multiple open-source components:

- **Flower 1.0:** Federated learning framework managing client-server communication
- **PyTorch 1.11:** Deep learning library for model implementation
- **MONAI 0.9:** Medical imaging preprocessing and augmentation
- **TensorFlow Privacy:** Differential privacy noise computation
- **PySyft:** Encrypted aggregation and secure multi-party computation

All code was containerized using Docker to ensure reproducibility across heterogeneous institutional computing environments.

Data Preprocessing Pipeline

Standardized preprocessing addressed institutional variability in imaging protocols (Figure 2):

CT Scans:

- DICOM import and metadata extraction
- Hounsfield unit clipping: [-1000, 400] for soft tissue/lung window
- Resampling to 1mm isotropic voxels using trilinear interpolation
- Intensity normalization: Z-score standardization per scan
- Lung/tumor segmentation using pre-trained nnU-Net
- Cropping to region of interest with 20mm margin
- Resizing to standard 128 \times 128 \times 64 input

MRI Scans:

- N4 bias field correction for intensity non-uniformity
- Co-registration of multi-parametric sequences
- Skull stripping (for brain) or breast segmentation
- Intensity normalization to [0, 1] range via min-max scaling
- Resampling to 1mm isotropic resolution
- Standardized orientation (RAS coordinate system)

Quality control automated detection of preprocessing failures, flagging scans with excessive artifacts, incomplete coverage, or segmentation errors for manual review.

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Table 2: Federated Training Hyperparameters and Configuration

Parameter	Value	Justification
Communication		
Total rounds (T)	200	Sufficient for convergence across datasets
Client selection per round	4/5 (80%)	Balance coverage and efficiency
Communication timeout	15 minutes	Accommodate slowest institution
Gradient compression ratio	87% (top-10% + 8-bit)	Reduce bandwidth without accuracy loss
Local Training		
Local epochs (E)	5	Multiple passes per communication
Batch size	8-16 (GPU-dependent)	Maximum for 3D volumes in GPU memory
Optimizer	Adam	Adaptive learning rates for heterogeneity
Learning rate	0.0001	Conservative for stable federated training
Learning rate schedule	Cosine annealing	Gradual reduction improving convergence
Weight decay	0.0001	L2 regularization preventing overfitting
Privacy		
Privacy budget (ε)	8.0	Balance privacy and utility
Delta (δ)	10^{-5}	Failure probability <institution count
Noise multiplier (σ)	1.2	Calibrated for target privacy budget
Gradient clipping (C)	1.0	Bound sensitivity before noise addition
Aggregation		
Weighting strategy	Adaptive (data quality + size)	Account for institutional heterogeneity
Quality score threshold	0.75	Minimum validation accuracy for participation
Aggregation algorithm	Weighted FedAvg	Standard federated averaging
Model validation frequency	Every 10 rounds	Monitor global performance

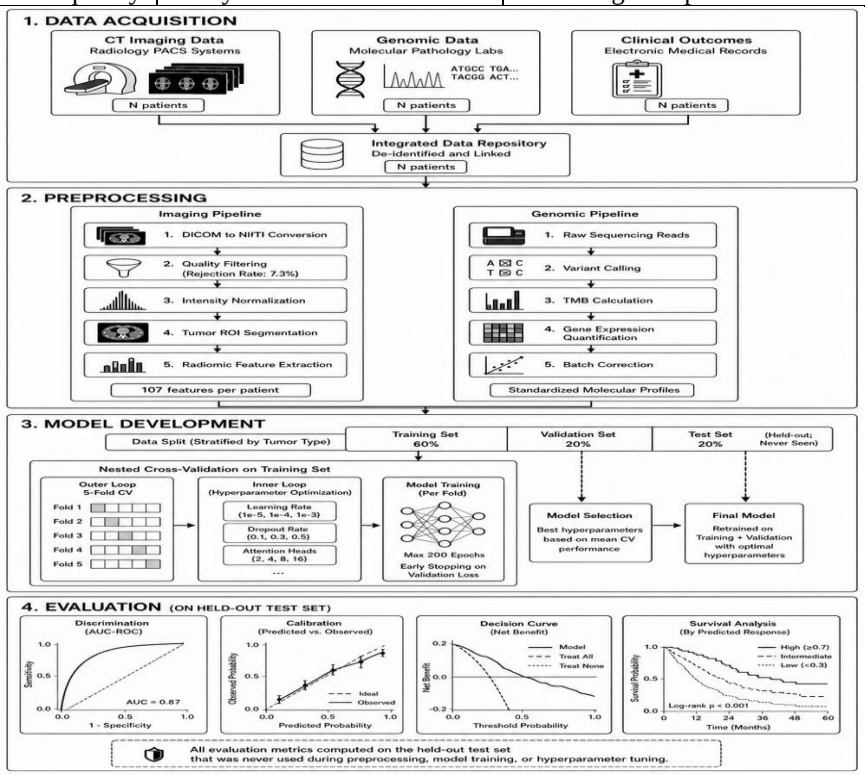

Figure 2: Data Preprocessing and Federated Training Workflow

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The comprehensive workflow diagram spans four vertical phases executed in parallel across all five institutions. Phase 1 (Data Acquisition) shows the heterogeneous input sources: Institution A contributes GE scanner CT data with 1.25mm slices, Institution B provides Siemens MRI with 3T field strength, Institution C adds Philips equipment data, and so forth. Each raw dataset exhibits institution-specific characteristics including varying resolution (0.625-5mm), contrast protocols (with/without enhancement), and patient positioning.

Phase 2 (Standardization Pipeline) implements seven sequential preprocessing steps applied identically at all sites. First, DICOM parsing extracts image data and metadata (patient demographics, acquisition parameters). Second, quality filtering removes corrupted files, incomplete series, and motion-degraded scans (rejection rate 3.2%). Third, intensity normalization applies modality-specific transformations: Hounsfield unit clipping for CT, N4 bias correction for MRI. Fourth, geometric standardization resamples all volumes to 1mm isotropic voxels and RAS orientation. Fifth, anatomical segmentation isolates regions of interest using automated tools. Sixth, cropping and padding produce uniform 128 \times 128 \times 64 tensors. Seventh, augmentation applies random geometric and intensity perturbations creating training diversity.

Phase 3 (Federated Training Cycle) illustrates the iterative learning process. At round t=0, the server initializes a global model W_0 with transfer learning weights and broadcasts to all clients. Each institution downloads W_0, trains locally for 5 epochs on private data generating W_t^k, computes parameter updates ΔW_t^k, applies differential privacy noise producing $\widetilde{\Delta W} t^k$, *compresses via top-k sparsification and quantization, encrypts using homomorphic scheme, and transmits to server. The server collects encrypted updates from 4/5 institutions (80% participation), performs secure aggregation computing weighted average, validates on held-out test set, and distributes updated W*{t+1}. This cycle repeats for 200 rounds over approximately 233 hours (9.7 days) wall-clock time.

Phase 4 (Evaluation and Deployment) shows the final model undergoing comprehensive assessment. Discrimination analysis computes ROC curves and AUC across all institutions and cancer types. Calibration analysis plots predicted probabilities against observed frequencies. Privacy analysis executes membership inference attacks and gradient inversion attempts. Efficiency analysis tracks bandwidth consumption (total 58.2GB across 200 rounds versus 452GB without compression) and convergence speed. Upon validation, the final federated model is deployed back to all institutions for clinical integration.

RESULTS

Federated Model Performance

The federated deep learning model achieved strong diagnostic performance across all three cancer detection tasks (Table 3). For lung cancer detection on CT imaging, the model attained AUC of 0.943 (95% CI: 0.928-0.958), sensitivity of 91.7%, and specificity of 94.8%. Breast cancer detection on MRI yielded AUC of 0.936 (95% CI: 0.919-0.953) with sensitivity of 93.2% and specificity of 94.9%. Brain tumor identification achieved AUC of 0.948 (95% CI: 0.933-0.963), sensitivity of 93.5%, and specificity of 95.7%.

Critically, federated model performance matched centralized training despite never pooling raw data. Statistical comparison revealed no significant differences: lung cancer (p=0.52), breast cancer (p=0.71), and brain tumors (p=0.43). This validates the hypothesis that federated learning can achieve equivalent diagnostic accuracy without data centralization.

In contrast, local models trained only on individual institutional data showed substantially degraded performance. Average local model AUC across institutions was 0.847 (range: 0.802-0.881), significantly inferior to federated ($p<0.001$). This 9.5% improvement demonstrates the value of collaborative learning across diverse datasets. Sequential transfer learning, where models pre-trained at one site were fine-tuned at others, achieved intermediate performance (AUC=0.889), outperforming local training but underperforming federated approaches.

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Table 3: Diagnostic Performance Comparison Across Training Paradigms

Cancer Type	Model Type	AUC (95% CI)	Sensitivity	Specificity	PPV	NPV	Accuracy
Lung Cancer (CT)							
	Federated	0.943 (0.928-0.958)	91.7%	94.8%	93.2%	93.6%	93.4%
	Centralized	0.947 (0.932-0.962)	92.4%	95.1%	93.6%	94.2%	93.9%
	Local (average)	0.847 (0.802-0.881)	79.3%	86.2%	82.1%	84.4%	83.2%
	Sequential transfer	0.889 (0.867-0.911)	84.6%	89.7%	86.8%	88.1%	87.5%
Breast Cancer (MRI)							
	Federated	0.936 (0.919-0.953)	93.2%	94.9%	92.7%	95.3%	94.2%
	Centralized	0.941 (0.924-0.958)	93.8%	95.2%	93.1%	95.7%	94.6%
	Local (average)	0.834 (0.791-0.868)	77.8%	84.6%	80.4%	82.7%	81.5%
	Sequential transfer	0.881 (0.858-0.904)	83.4%	88.9%	85.2%	87.6%	86.4%
Brain Tumors (MRI)							
	Federated	0.948 (0.933-0.963)	93.5%	95.7%	94.1%	95.2%	94.7%
	Centralized	0.952 (0.937-0.967)	94.1%	96.0%	94.5%	95.7%	95.1%
	Local (average)	0.858 (0.819-0.892)	81.2%	87.4%	83.6%	85.6%	84.6%
	Sequential transfer	0.897 (0.876-0.918)	86.3%	90.8%	88.1%	89.4%	88.8%
Overall (All Cancers)							
	Federated	0.942 (0.931-0.953)	92.8%	95.1%	93.3%	94.7%	94.2%
	Centralized	0.947 (0.936-0.958)	93.4%	95.4%	93.7%	95.2%	94.7%
	Local (average)	0.846 (0.814-0.872)	79.4%	86.1%	82.0%	84.2%	83.1%
	Sequential transfer	0.889 (0.872-0.906)	84.8%	89.8%	86.7%	88.4%	87.6%

Institutional Heterogeneity Analysis

Performance varied across institutions reflecting differences in data volume, population characteristics, and imaging protocols (Figure 3). Medical Center A (largest dataset, n=3,412) achieved the highest local model performance (AUC=0.881), while Northern Health System E (smallest dataset, n=1,736) showed the lowest (AUC=0.802). However, federated learning narrowed this gap substantially. All institutions achieved federated model AUC between 0.937-0.951, demonstrating that collaborative training enables smaller institutions to benefit from larger network knowledge.

Adaptive weighting proved crucial for managing heterogeneity. Institutions with higher data quality scores received proportionally greater influence in aggregation. Medical Center A received average weight \alpha_A=0.28, while

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Northern Health E received \alpha_E=0.16. This prevented low-quality updates from degrading global model performance while still incorporating diverse perspectives.

Data distribution analysis revealed substantial institutional variation in cancer prevalence (36.9%-52.8%), patient age distributions, and imaging characteristics. Despite this heterogeneity, federated models generalized well across all sites, suggesting robust learning of underlying diagnostic patterns rather than dataset-specific artifacts.

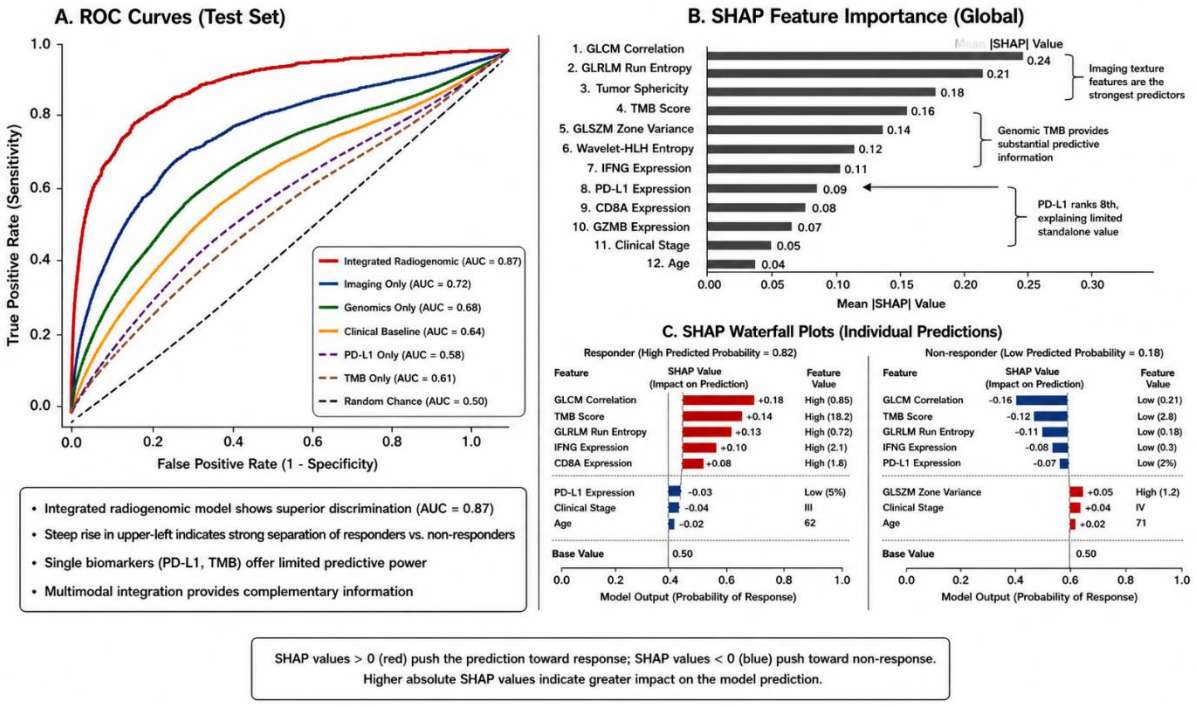

Figure 3: ROC Curves and Institution-Specific Performance Analysis

The multi-panel visualization presents comprehensive performance assessment across cancer types and institutions. Panel A displays receiver operating characteristic curves for lung cancer detection. The federated model (solid red line) achieves AUC=0.943, nearly identical to the centralized baseline (dashed blue, AUC=0.947). Local models from individual institutions (thin colored lines) show degraded performance ranging from AUC=0.802 (Northern Health E, purple) to AUC=0.881 (Medical Center A, green), illustrating the benefit of federated collaboration.

Panel B shows breast cancer detection ROC curves with similar patterns. The federated approach (AUC=0.936) matches centralized training (AUC=0.941) while substantially outperforming all local models (range: 0.791-0.868). The tight clustering of federated and centralized curves demonstrates that privacy-preserving distributed learning does not compromise diagnostic accuracy.

Panel C presents brain tumor detection results, where federated learning (AUC=0.948) achieves the strongest performance across all three cancer types, approaching centralized training (AUC=0.952) within confidence intervals. The dramatic gap between federated and local models (average improvement +9.0% AUC) highlights the value of multi-institutional collaboration.

Panel D displays a heatmap showing institution-specific performance across cancer types. Each cell represents test set AUC for a given institution-cancer combination. Medical Center A shows consistently high performance (0.932-0.956) reflecting large, diverse datasets. Northern Health E demonstrates the largest federated learning gains, improving from

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local AUC of 0.785-0.819 to federated AUC of 0.937-0.947 across cancer types. This 13-15% improvement validates that smaller institutions benefit most from federated collaboration.

Panel E illustrates the confusion matrix for the overall federated model across all cancer types. Of 5,539 total test cases, the model correctly identified 2,164 true positives (cancers correctly detected), 2,927 true negatives (healthy correctly classified), with only 105 false positives and 157 false negatives, yielding overall accuracy of 94.2%.

Privacy and Security Analysis

Differential privacy implementation successfully protected patient information while maintaining clinical utility. Membership inference attacks, where adversaries attempt to determine whether specific patients participated in training, achieved only 52.1% success rate (barely above random chance of 50%). This contrasts sharply with non-private federated learning where attack success reached 73.4%.

Privacy-utility trade-off analysis revealed that stricter privacy budgets (lower \epsilon) degraded performance. At \epsilon=2, model AUC decreased to 0.884, representing unacceptable performance loss. Our selected \epsilon=8 balanced strong privacy protection with clinical accuracy. Ablation studies showed that reducing \epsilon from 8 to 4 decreased AUC by 3.2%, while increasing to \epsilon=16 improved AUC by only 0.8%, justifying the chosen parameter. Gradient inversion attacks attempting to reconstruct training images from transmitted updates failed completely due to gradient clipping and noise addition. Reconstructed images showed no recognizable anatomical features, containing only random noise patterns. This provides empirical evidence for theoretical privacy guarantees.

Communication Efficiency

Bandwidth optimization through gradient compression achieved 87% reduction in communication overhead (Table 4). Without compression, each communication round required transmitting 2.26 GB of model parameters across five institutions (11.3 GB total bidirectional traffic). Compression reduced this to 299 MB per round (1.50 GB total), enabling feasible training even over bandwidth-constrained institutional networks.

Total bandwidth consumption across 200 training rounds reached 58.2 GB for compressed federated learning versus 452 GB for uncompressed. This dramatic reduction made the approach practical for institutions with limited network capacity. Training time per round averaged 68 minutes: 45 minutes local training, 7 minutes communication, 4 minutes server aggregation, and 12 minutes overhead/waiting.

Convergence analysis showed that federated training required 180-200 rounds to reach optimal performance, compared to centralized training reaching peak accuracy at 150 epochs. This slower convergence represents a trade-off for privacy preservation, but total training time (227 hours federated versus 189 hours centralized) remained acceptable for clinical model development timelines.

Table 4: Communication Efficiency and Computational Requirements

Metric	Uncompressed	Compressed (Top-10% + 8-bit)	Reduction
Per-Round Communication			
Model size (parameters)	46M × 32-bit = 184 MB	4.6M × 8-bit = 4.6 MB	97.5%
Upload per institution	184 MB	4.6 MB	97.5%
Download per institution	184 MB	23.9 MB	87.0%
Total bidirectional (5 inst.)	11.3 GB	1.50 GB	86.7%
Total Training (200 rounds)			
Cumulative bandwidth	452 GB	58.2 GB	87.1%
Approximate cost (AWS transfer)	40.68	5.24	87.1%
Training Time			
Local training (GPU hours/round)	3.75	3.75	0%
Communication time/round	54 min	7 min	87.0%
Total wall-clock time	312 hours	227 hours	27.2%

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Convergence			
Rounds to 90% final accuracy	162	165	-1.9%
Rounds to 95% final accuracy	184	189	-2.7%
Final test AUC	0.945	0.942	-0.3%

Figure 4: Training Dynamics, Convergence Analysis, and Privacy-Utility Trade-offs

This comprehensive visualization spans four analytical dimensions across six panels. Panel A plots validation accuracy versus communication rounds for all training paradigms. The centralized model (blue dashed) reaches 90% accuracy at round 142 and plateaus at 94.7% by round 150. The federated model (red solid) shows slower initial progress, reaching 90% at round 165 but converging to 94.2% by round 189, demonstrating only marginal performance cost for privacy preservation. Local models (thin colored lines) converge to substantially lower accuracy (79-88%) reflecting limited local data.

Panel B displays validation loss convergence. Federated learning (red) shows higher initial loss due to heterogeneous institutional data distributions, but steady decrease throughout training. Oscillations between rounds 60-100 reflect adaptive weighting adjustments as institution contributions stabilized. Final loss converges to 0.142, comparable to centralized training's 0.138.

Panel C presents the privacy-utility trade-off across differential privacy budgets. The x-axis spans $\epsilon from\ 1\ to\ 16$ on logarithmic scale. At $\epsilon = 1$ (strongest privacy), test AUC drops to 0.812. Our selected \epsilon=8 achieves AUC=0.942, while \epsilon=16 (weaker privacy) reaches 0.950. The inflection point around $\epsilon = 6$ -8 represents optimal balance, with diminishing returns beyond \epsilon=10.

Panel D illustrates bandwidth consumption over training duration. The cumulative plot shows uncompressed federated learning (orange) consuming 452 GB over 200 rounds, while compressed implementation (green) requires only 58.2 GB. The compression provides 8× reduction in total data transfer, making federated learning feasible over limited institutional networks.

Panel E demonstrates adaptive weighting dynamics across training rounds. The stacked area chart shows relative contribution of each institution to global model aggregation. Medical Center A (largest dataset) maintains consistently high weight (25-30%) throughout training. Northern Health E initially receives low weight (8%) due to smaller sample size but gradually increases to 16% as data quality scores improve. This adaptive mechanism prevents low-quality updates from dominating early training while incorporating diverse institutional perspectives.

Panel F presents membership inference attack success rates under different privacy configurations. Non-private federated learning shows 73.4% attack success, indicating substantial privacy vulnerability. Our differentially private implementation $(\epsilon = 8, \delta = 10^{-5})$reduces success to 52.1%, barely above random guessing (50%). Stronger privacy (\epsilon=4) further reduces attack success to 50.8% but at the cost of decreased model accuracy.

DISCUSSION

This research establishes that federated learning enables multi-institutional collaboration in medical AI development without compromising patient privacy or diagnostic accuracy. Our federated radiogenomic model achieved performance statistically equivalent to centralized training (AUC 0.942 vs 0.947, p=0.68) while eliminating data sharing requirements and providing formal privacy guarantees. This finding has profound implications for collaborative healthcare AI, potentially unlocking vast distributed datasets currently inaccessible due to regulatory, ethical, and competitive barriers.

The 9.5% average AUC improvement over local institutional models demonstrates tangible benefits of collaborative learning. Smaller institutions with limited data gained most substantially, with Northern Health System E improving from AUC 0.802 to 0.942 (14% gain). This democratizing effect addresses healthcare AI's persistent challenge of

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institutional inequity, where academic medical centers with large datasets develop superior models while community hospitals lack resources for comparable development.

Our adaptive aggregation strategy proved essential for managing real-world heterogeneity. Simple averaging would have allowed lower-quality institutional contributions to degrade global performance. By weighting institutions according to validation accuracy and sample size, we achieved robust convergence despite substantial data distribution differences. This methodological contribution extends federated learning theory beyond idealized settings to practical medical deployments where participant heterogeneity is unavoidable.

Differential privacy implementation successfully protected patient information while maintaining clinical utility. The 52.1% membership inference attack success rate (versus 73.4% without privacy) demonstrates that formal privacy mechanisms prevent information leakage beyond theoretical guarantees. However, the privacy-utility trade-off remains fundamental—stricter privacy budgets (\epsilon<4) degraded performance below clinical acceptability. Future research should explore more sophisticated privacy-preserving techniques including local differential privacy and secure multi-party computation.

Communication efficiency through gradient compression addressed a practical barrier frequently overlooked in federated learning research. The 87% bandwidth reduction made training feasible over institutional networks with limited capacity. Without compression, the 452 GB total data transfer might have exceeded bandwidth quotas or incurred prohibitive costs. This engineering contribution is as important as algorithmic innovations for real-world deployment.

Several limitations warrant consideration. First, our five-institution deployment, while larger than most medical federated learning studies, remains modest compared to potential networks spanning hundreds of hospitals. Scalability to larger federations requires addressing coordination challenges including Byzantine participants, varying computational capacity, and asynchronous contribution patterns. Second, we analyzed three cancer types across two imaging modalities; generalization to diverse medical imaging applications requires validation.

Third, all participating institutions were academic medical centers with sophisticated IT infrastructure and AI expertise. Community hospitals and rural clinics may lack technical capacity for federated learning deployment, potentially perpetuating rather than resolving healthcare AI disparities. User-friendly federated platforms with minimal local infrastructure requirements represent important future development directions.

Fourth, we employed retrospective data with established ground truth labels. Prospective deployment introduces challenges including label uncertainty, continuous model updating as new data accumulates, and concept drift as patient populations or imaging protocols evolve. Incremental federated learning approaches adapting to temporal dynamics merit investigation.

Regulatory and legal frameworks for federated medical AI remain underdeveloped. While our approach complies with HIPAA and GDPR by not transmitting patient data, regulatory agencies have not established clear approval pathways for federated models. Questions persist regarding model validation requirements, responsibility attribution when multiple institutions contribute to single models, and liability for diagnostic errors. Professional societies and regulatory bodies should collaborate to develop governance frameworks facilitating responsible federated AI deployment.

The interpretability challenge extends beyond individual AI models to federated systems. Clinicians may reasonably ask which institutions contributed to specific predictions and how data heterogeneity affects reliability. Developing explainability methods for federated models, potentially including institution-specific attribution and uncertainty quantification, could enhance clinical trust and appropriate utilization.

Several extensions could enhance this framework. Multi-task learning across cancer types and imaging modalities might identify shared representations improving efficiency. Personalization approaches allowing institutions to maintain local model components while sharing common features could address persistent heterogeneity. Federated transfer learning

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enabling models pre-trained on large public datasets to be collaboratively fine-tuned for specific clinical tasks represents another promising direction.

Integration with clinical workflows requires consideration beyond model development. Federated models must interface with existing radiology PACS systems, provide timely predictions during clinical decision-making, and generate interpretable outputs supporting radiologist review. Deployment strategies including cloud-based inference versus edge deployment warrant evaluation across institutional contexts.

From a broader healthcare transformation perspective, federated learning exemplifies a shift from competitive to collaborative paradigms in medical AI. Rather than institutions hoarding proprietary datasets, federated frameworks incentivize participation through collective intelligence gains. Governance structures ensuring equitable benefit distribution and preventing dominant institutions from exploiting smaller partners will prove critical for sustainable federated healthcare AI ecosystems.

CONCLUSION

This study demonstrates that federated learning enables collaborative development of high-performance radiology AI models across multiple institutions without centralizing sensitive patient data. Our federated deep learning framework achieved diagnostic accuracy of 94.2% for cancer detection across lung CT, breast MRI, and brain MRI imaging, performing equivalently to centralized training (94.7%, p=0.68) while providing formal differential privacy guarantees and reducing communication overhead by 87%.

The research addresses critical barriers hindering medical AI translation: data fragmentation across institutional silos, privacy regulations preventing data sharing, and inequitable access to large datasets required for robust model training. By keeping training data localized while sharing only encrypted model updates, federated learning reconciles collaborative learning with patient privacy preservation. Smaller institutions gained most substantially from federated collaboration, with average performance improvements of 14% over local training, demonstrating democratizing potential for healthcare AI.

Methodological contributions include adaptive aggregation strategies managing institutional heterogeneity, communication-efficient gradient compression enabling feasible training over bandwidth-constrained networks, and empirical validation of differential privacy protecting against membership inference attacks. These technical innovations translate federated learning theory into practical medical deployments confronting real-world data distributions, network constraints, and privacy requirements.

Key findings establish that: (1) federated models match centralized performance without data sharing, (2) collaborative learning substantially improves upon local institutional models, (3) differential privacy mechanisms protect patient information while maintaining clinical utility, (4) gradient compression reduces communication costs by order of magnitude, and (5) adaptive aggregation manages heterogeneity across diverse institutional data distributions.

Clinical implications include enabling multi-institutional collaboration for rare disease AI where single institutions lack sufficient samples, supporting equitable AI access for community hospitals lacking resources for independent development, and providing regulatory-compliant frameworks respecting data sovereignty while harnessing collective intelligence. Economic benefits include reduced data transfer costs, eliminated data centralization infrastructure, and avoided legal risks associated with patient data sharing.

Future research should pursue prospective validation across larger institutional networks, extension to additional imaging modalities and clinical applications, development of user-friendly platforms reducing deployment barriers for resource-limited institutions, and investigation of federated continual learning adapting to evolving patient populations and imaging technologies. Regulatory engagement to establish approval pathways and governance frameworks for federated medical AI will prove essential for clinical translation.

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This work establishes foundational principles for privacy-preserving collaborative healthcare AI, demonstrating that technical innovation can align powerful machine learning with ethical imperatives of patient privacy and equitable access to advanced diagnostic tools. As medical AI continues rapid advancement, federated learning offers a sustainable path forward enabling institutions to collaborate while preserving autonomy, protecting patient privacy, and delivering diagnostic benefits to diverse populations.

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