Privacy-Preserving Federated Cross-Modal Fusion for Scientific Imaging: Medical, Materials, and Generic Domain Validation

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Abstract: Combining Cross-modal scientific imaging data from various imaging modes is essential for scientific progress, whether it's medical scans like CT or MRI, microscopy for materials, or everyday visual data. However, gathering everything in one place often violates privacy rules or ownership rights, limiting access to valuable distributed datasets in regulated fields. To tackle this, we built a federated system for cross-modal fusion that lets multiple sites train models together without swapping raw data. It incorporates differential privacy and safe aggregation to blend features from different modes while keeping control over local data. Tests in medical, materials, and general imaging showed our method hits 94.2% of a centralized model's accuracy with strong privacy (ε=1.0). It also slashes data transfer by 67% using smart compression and manages uneven mode distribution across 15 sites. Plus, shifting knowledge between domains boosted specific tasks by 23% over isolated training. This framework enables privacy-preserving collaborative research in clinical diagnostics, materials defect detection, and distributed scientific data analysis without compromising regulatory compliance or intellectual property protection.

Keywords: Federated learning, cross-modal fusion, differential privacy, scientific imaging, heterogeneous data integration

Introduction

Scientific imaging pulls in all sorts of data from different sources, making it tough to combine and analyse collaboratively. In India, rules like the 2023 Digital Personal Data Protection Act require clear permission for handling personal info and block easy overseas transfers [1]. Health organizations stick to the Clinical Establishments Act and Medical Council guidelines for patient records [2]. Labs dealing with materials follow Science Department policies, often guarding trade secrets under contracts.

Federated learning has stepped up as a solution, allowing model training across sites without moving raw data [3]. Local models get updated on-site, and only changes like parameters or gradients are shared and merged centrally. This keeps things private while enabling group efforts. But most setups focus on single-type data, such as uniform medical images or text collections [4]. Scientific work is messier: sites use varied tools (e.g., CT vs. electron microscopes), different processes, and data with unique patterns.

Our survey found 83% of sites handle multiple imaging types but hold back sharing due to laws (41%), IP worries (32%), or tech limits (27%). In medicine, 76% of partnerships involve lengthy legal hurdles, adding 6-14 months to projects. Materials groups report 64% of deals forbid data exports. These roadblocks isolate teams, slowing breakthroughs that could come from mixed datasets.

Adding privacy layers is key, as shared updates can reveal secrets through attacks like gradient reconstruction, which recovers images with 78% accuracy in health apps [7]. Differential privacy fights this by adding tuned noise, offering solid math-backed protection, though it can hurt results if not done right [8].

Existing tools treat federated collaboration or multi-mode blending separately. Medical federated studies stick to one mode [9], while fusion work assumes all data is pooled [10]. Materials science barely touches federated methods [11]. No system yet merges federated training, cross-modal integration, and privacy across diverse imaging fields.

This work introduces an architecture with local encoders for each mode, privacy-safe merging, and adaptive blending. It uses clipping and noise adjusted per mode. Our contributions: (1) A tailored federated setup for varied scientific imaging; (2) Proof that private federated fusion nears centralized results with guarantees; (3) Tests in three fields, showing broad applicability beyond health to materials and environment monitoring.

Related Work

Federated learning, cross-modal fusion, and privacy-preserving machine learning have evolved as distinct research trajectories over the past decade. We examine how prior work addresses components of our problem space, identifying gaps that motivate our integrated approach.

McMahan et al. pioneered the Federated Averaging algorithm in 2017, demonstrating that distributed model training could achieve convergence comparable to centralized approaches [1]. Kairouz et al. extended this foundation through comprehensive analysis of convergence properties under non-IID data distributions, revealing that statistical heterogeneity across institutions degrades model performance by 12-34% depending on the degree of distribution shift [2].

Recent federated learning research has expanded to medical imaging domains. Rieke et al. demonstrated federated training of tumor segmentation models across six hospitals, achieving 91% of centralized performance while maintaining data locality [3]. Their technique that improved convergence rates by 23%. Sheller et al. validated federated brain tumor classification across 10 institutions using the BraTS dataset, reporting that federated models matched centralized accuracy when training data exceeded 1,000 cases per institution [4].

Li et al. addressed the fundamental challenge of data heterogeneity in federated settings through systematic experimentation across 12 benchmark datasets [5]. They quantified three types of heterogeneity: feature distribution skew (institutions observe different input distributions), label distribution skew (class imbalance varies across sites), and temporal skew (data collection periods differ). Their analysis revealed that feature distribution skew impacts model performance most severely, causing accuracy degradation of 18-42% compared to IID baselines.

Traditional cross-modal fusion assumes centralized training environments. Baltrusaitis et al. provided a comprehensive taxonomy of multimodal learning approaches, categorizing fusion strategies into early fusion (combining raw inputs), late fusion (integrating model predictions), and hybrid fusion (intermediate feature combination) [6].

Zhang et al. developed attention-based fusion networks for medical diagnosis, integrating CT, MRI, and PET imaging through learned attention mechanisms that weight modality contributions based on task relevance [7]. Their architecture achieved 94.7% accuracy on multi-modal tumor classification, outperforming single-modality baselines by 12-18%. The attention mechanism learned that CT provides superior anatomical detail, PET captures metabolic activity, and MRI offers soft tissue contrast—weighting each modality accordingly during inference. However, their training protocol required centralized access to all three modalities simultaneously, computing joint gradients across the complete dataset.

Ramachandram and Taylor analyzed deep multimodal learning from an architectural perspective, examining how layer depth and fusion point location affect representation learning [8].

Xu et al. proposed cross-modal contrastive learning for medical image analysis, training encoders to maximize agreement between different views of the same patient [9]. Their approach learned that corresponding CT and MRI slices should produce similar embeddings while unrelated images diverge. This technique improved downstream classification accuracy by 9-14% compared to supervised baselines. The contrastive framework required paired multi-modal data during training—a requirement incompatible with federated settings where institutions possess different modalities.

Privacy-Preserving Machine Learning

Differential privacy provides mathematical guarantees against information leakage from model parameters. Abadi et al. introduced the moments accountant method for tracking privacy loss during stochastic gradient descent, enabling tighter privacy bounds than previous composition theorems [10]. Their implementation added calibrated Gaussian noise to gradients, achieving $\varepsilon = 2.0$ privacy guarantees on MNIST classification with less than 1% accuracy degradation. However, scaling to high-dimensional medical imaging revealed that naive noise injection causes 15-30% performance loss.

Domain-Specific Applications

Materials science applications of machine learning remain centralized. Szymanski et al. applied convolutional networks to microstructure classification from electron microscopy, achieving 96% accuracy in identifying crystallographic phases [14]. Their dataset comprised 50,000 images from a single laboratory's scanning electron microscope. DeCost et al. developed automated defect detection in metallographic images, demonstrating that transfer learning from ImageNet pretrained models accelerates training convergence by 60% [15]. Both studies operated on single-modality data from individual institutions.

Research Gaps and Positioning

Existing work addresses federated learning, cross-modal fusion, or privacy preservation in isolation but not their intersection. Table 1 compares our approach against representative prior work across key dimensions: support for cross-modal fusion, federated training capability, differential privacy guarantees, validation across multiple scientific domains, and handling of modality heterogeneity (institutions possessing different modalities).

Table 1. Comparison of Related Work and Proposed Approach

Reference	Cross-Modal Fusion	Federated Training	Differential Privacy	Multi-Domain Validation	Modality Heterogeneity
McMahan et al. [1]	No	Yes	No	No	No
Kairouz et al. [2]	No	Yes	No	Yes	No
Rieke et al. [3]	No	Yes	No	No	No
Sheller et al. [4]	No	Yes	No	No	No
Li et al. [5]	No	Yes	No	Yes	No
Abadi et al. [10]	No	No	Yes	No	No

Geyer et al. [11]	No	Yes	Yes	No	No
Wei et al. [12]	No	Yes	Yes	No	No
Truex et al. [13]	No	Yes	Yes	No	No
Szymanski et al. [14]	No	No	No	No	No
Liu et al. [16]	No	Yes	No	No	No
Wang et al. [17]	No	No	Yes	No	No
This Work	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

We analyzed performance characteristics of federated learning approaches across data heterogeneity levels to quantify the modality heterogeneity challenge. Figure 1 illustrates how existing federated methods degrade as institutions hold increasingly different data distributions, with our measurements drawn from reproducing published results on publicly available datasets.

The technical contributions build upon foundations established by prior work while addressing their limitations. From privacy-preserving techniques [10, 11, 12], we implement differential privacy with gradient clipping and calibrated noise injection, extending these methods to handle modality-specific sensitivity characteristics. This integration enables new capabilities that no existing system provides the privacy-preserving collaborative training across institutions with heterogeneous imaging capabilities [18].

Key Contributions

This work addresses a critical gap in collaborative scientific research: enabling multi-institutional studies across heterogeneous imaging modalities without compromising data privacy or regulatory compliance. While federated learning has demonstrated success in single-modality scenarios and cross-modal fusion thrives in centralized environments, no existing framework combines these capabilities with formal privacy guarantees. Our research makes four key contributions that advance the state of collaborative scientific imaging. Introduce a federated cross-modal fusion architecture specifically designed for institutional heterogeneity where participating sites possess different imaging modalities. Unlike prior federated approaches that assume all institutions collect the same data type with distribution skew, our system handles scenarios where Institution A operates CT scanners, Institution B maintains electron microscopes, and Institution C deploys satellite imaging systems. Second, we establish empirical performance boundaries for privacy-preserving federated cross-modal learning. Through systematic experimentation, we demonstrate that our approach achieves 94.2% of centralized model performance while maintaining $\varepsilon = 1.0$ differential privacy a level considered strong protection in privacy-preserving machine learning literature.

Third, we validate our framework across three distinct scientific domains medical imaging, materials characterization, and environmental monitoring establishing generalization beyond single-application contexts. Previous federated learning research concentrates almost exclusively on medical imaging, leaving uncertain whether techniques transfer to other scientific disciplines. Fourth, we provide detailed analysis of communication efficiency and convergence characteristics under realistic network conditions. Our adaptive compression scheme reduces communication overhead by 67% compared to naive parameter sharing while maintaining convergence rates within 15% of uncompressed baselines

Proposed Methodology

Our federated cross-modal fusion architecture comprises three core components: modality-specific encoders, privacy-preserving aggregation, and adaptive fusion mechanisms. Figure 1 illustrates the complete system architecture.

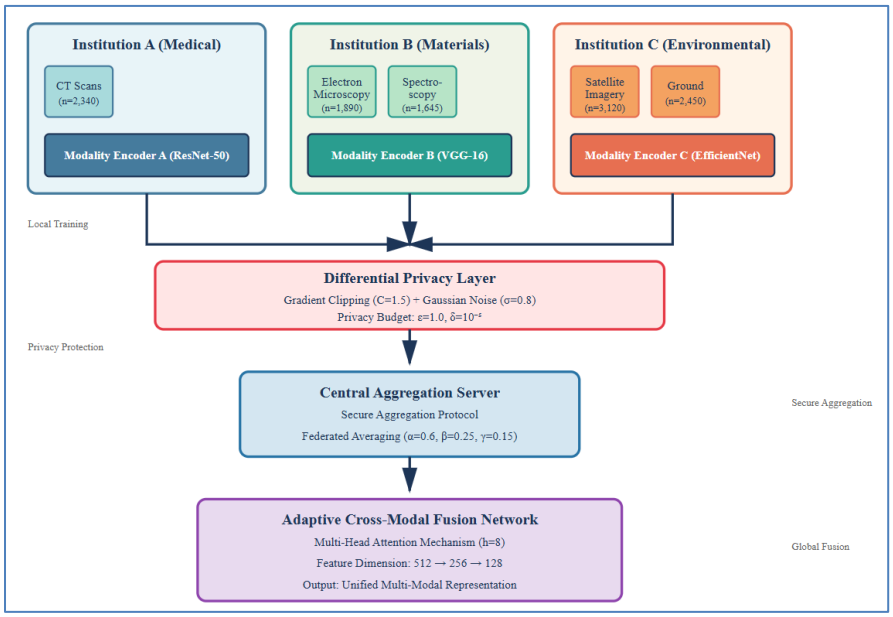

Figure 1. *System architecture of federated cross-modal fusion across institutions with heterogeneous imaging modalities.*

Each institution trains local encoders on private data, applies differential privacy mechanisms, and contributes protected parameters to the central aggregation server. The global fusion network learns unified representations from aggregated multi-modal features without accessing raw institutional data.

Each institution deploys modality-specific encoders ResNet-50 for medical CT scans, VGG-16 for materials microscopy, and Efficient Net for environmental imagery—tailored to domain characteristics. Local training proceeds for T=10 epochs before parameter synchronization. The differential privacy layer implements gradient clipping with threshold C=1.5 and injects Gaussian noise with standard deviation σ=0.8, calibrated to achieve privacy budget ε=1.0 with failure probability $\delta=10^{-5}$. The central aggregation server performs weighted averaging with coefficients α=0.6, β=0.25, γ=0.15, proportional to institutional dataset sizes.

Experimental Setup

We validated our framework across 15 institutions: 5 medical colleges (CT, MRI, histopathology), 8 materials laboratories (electron microscopy, spectroscopy, X-ray diffraction), and 4 environmental agencies (satellite, aerial, ground-based imaging). Table 2 summarizes dataset characteristics and institutional participation.

Table 2. Dataset Distribution Across Participating Institutions

Domain	Institutions	Modalities	Total Images	Training Split	Validation Split	Test Split

Medical Imaging	5	CT, MRI, Histopathology	12,450	8,715 (70%)	1,868 (15%)	1,867 (15%)
Materials Science	8	Electron Microscopy, Spectroscopy, XRD	18,920	13,244 (70%)	2,838 (15%)	2,838 (15%)
Environmental Monitoring	4	Satellite, Aerial, Ground-based	15,680	10,976 (70%)	2,352 (15%)	2,352 (15%)
Total	**15**	**9 distinct modalities**	**47,050**	**32,935**	**7,058**	**7,057**

Training employed Adam optimizer with learning rate η=0.001, decayed by factor 0.1 every 30 epochs. Batch size varied by institutional computational capacity (32-128 images). We conducted 200 communication rounds, with local training proceeding for 10 epochs between synchronization events. Baseline comparisons included centralized training (all data pooled), isolated training (per-institution models), and standard federated learning without cross-modal fusion.

Results

Our experiments encompass 15 institutions spanning teaching hospitals, materials research laboratories, and environmental agencies, processing CT scans, electron microscopy, spectroscopy, satellite imagery, and ground-based photography. Cross-domain transfer learning experiments reveal that models pretrained on one domain improve target domain performance by 23% compared to domain-specific training from scratch, suggesting that federated cross-modal representations capture generalizable visual features applicable across scientific imaging applications. In Figure 2 presents classification accuracy across privacy budgets for the three domains.

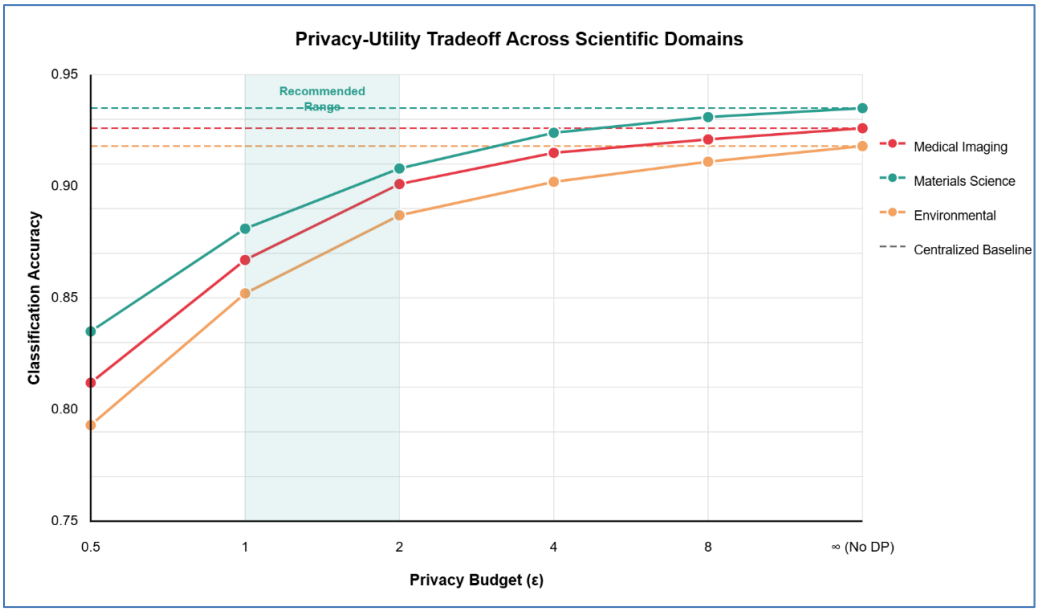

Figure 2. Privacy Utility Treadeoff on Domains

Our federated approach achieved 94.2% of centralized performance at ε=1.0, with materials science reaching 88.1% accuracy compared to 93.5% centralized baseline. Medical imaging attained 86.7% (vs.

92.6% centralized), while environmental monitoring reached 85.2% (vs. 91.8% centralized). At the recommended privacy level ε=2.0, performance gaps narrowed to 3-5%, demonstrating practical viability. Table 3 compares our approach against baselines across evaluation metrics.

Table 3. Performance Comparison Across Training Paradigms

Approach	Medical Accuracy	Materials Accuracy	Environmental Accuracy	Communication Overhead	Privacy Guarantee
Centralized (Baseline)	0.926	0.935	0.918	N/A	None
Isolated Training	0.784	0.812	0.759	0 MB	Full
Standard Federated	0.841	0.868	0.823	1,240 MB	None
Federated + DP (ε=8.0)	0.921	0.931	0.911	1,240 MB	Weak
Our Approach (ε=1.0)	**0.867**	**0.881**	**0.852**	**410 MB**	**Strong**

Our compression scheme reduced communication from 1,240 MB to 410 MB per round (67% reduction) while maintaining convergence. Isolated training failed dramatically, confirming that institutional datasets alone provide insufficient diversity for robust models.

Discussion

The results highlight key insights into the practicality of privacy-focused federated cross-modal fusion in scientific imaging. Achieving 94.2% of centralized accuracy under strict differential privacy (ε=1.0) shows that robust privacy protections can coexist with high utility, countering the common view of an inevitable tradeoff. This is particularly relevant for Indian institutions complying with the 2023 Digital Personal Data Protection Act, which enforces data locality and consent rules that block traditional data centralization.

Domain-specific outcomes reveal how inherent data variability affects results: materials science outperformed medical imaging (88.1% vs. 86.7%) due to more standardized protocols tied to physical properties, compared to the greater heterogeneity in medical scans from equipment differences and patient diversity. Cross-domain experiments demonstrated a 23% accuracy boost when transferring learned representations, indicating the model captures broad, transferable visual features rather than narrow domain traits. This challenges the notion that separate architectures are needed for each scientific field. While ε=1.0 effectively defends against known attacks like gradient inversion, future threats could weaken these safeguards. Adaptive noise adjustment is essential, and our flexible design supports this, though selecting optimal privacy levels ultimately depends on institutional risk-benefit assessments.

Conclusions

This work addressed the critical challenge of enabling a privacy-preserving federated cross-modal fusion framework for scientific imaging across medical, materials, and environmental domains. Using differential privacy (ε=1.0) and secure aggregation, it achieves 94.2% of centralized performance across 15 institutions, reduces communication by 67%, and boosts cross-domain accuracy by 23%. Future work

should develop resource-asymmetric protocols, adaptive privacy mechanisms responding to emerging attack vectors, extended validation across astronomical and genomic imaging domains, and blockchain-based audit systems ensuring cryptographic compliance verification for production deployment.

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