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CROSS-MODAL FEDERATED LEARNING WITH DIFFERENTIAL PRIVACY FOR REAL-TIME CLINICAL DECISION SUPPORT

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Abstract

Brain tumor segmentation using AI is faced with a built-in dilemma of diagnostic accuracy vs data privacy guidelines that prevent multi-site collaboration, while existing federated learning techniques lack in making strong privacy guarantees and only operate on image data without leveraging clinical text. We propose a privacy-preserving cross-modal federated learning framework with MRI images and clinical text integration using ResNet-50 and BERT encoders with cross-modal attention fusion secured through differential privacy with gradient clipping and Gaussian noise injection. Ranked on 7,023 brain MRI images across simulated federated environments with up to 20 clients, our solution achieves 92.8% IID accuracy, 89.1% non-IID accuracy, and 87.3% differential privacy (ε=1.0, $\delta=1\times10^{-5}$) accuracy, which is equivalent to 92.7% centralized performance retention. The multimodal fusion shows 6.9% improvement over vision-only methods, and the sub-500ms inference offers possible real-time deployment. This work introduces a novel cross-modal attention mechanism for federated medical imaging with strict differential privacy that maintains clinical utility, provides rigorous testing across heterogeneous data distributions, and demonstrates scalable and diversified framework support with mathematical privacy guarantees against membership inference attacks.

Keywords: Federated learning, differential privacy, multimodal learning, brain tumor classification, medical imaging, clinical decision support

1. Introduction

The emergence of artificial intelligence technologies in the field of medicine has shown an unprecedented development in the medical field, especially in relation to medical image analysis. With the use of deep learning concepts, there is a technological advancement that exceeds human endeavor in so clinical entities [1]. Brain tumor categorizing from the perspective of magnetic resonance imaging seems to be one of the dominant that diagnostic systems can be applied and enhanced to contribute immensely to provide patients with excellent outcomes [2]. However, the manifestation of optimal and universal AI models may necessitate steady access to huge, various and Mult institutional datasets that is required essentially in contrast with strict data keeping regulations such as the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR) that forbid open sharing of patient essential medical records [3].

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Federated learning has been recommended as one of the effective approaches to deal with intrinsic face-off between alliance of models and protection of secured data [4]. Federated learning can facilitate collaboration oin the use of AI in gathering of data that are not sensitive to patients [5]. Recent deployment of these items in the medical imaging field have shown the potentiality of federated learning for tasks like brain tumor segmentation, multiorgan disease examination and COVID-19 diagnosis to remain vulnerable to potential data attacks [6]. The attackers may obtain data from a shared model owing to the lack of collaboration [7]. Differential privacy offers extensive mathematical assurances against these sorts of privacy failure through the addition of calibrated noise to the learning procedure in such a way that can make it impossible to obtain individual patient information from the model updates [8].

Despite all these developments, existing privacy preserving, medical AI structures often operate on a single data source, which is typical only for the purpose of medical imaging and avoiding the complimentary clinical data stored in various clinical notes and radiology reports [9]. Multimodal learning paradigms integrates imaging and clinical records demonstrates improved diagnostic function in centralized domains and textual medical data [10]. Similarly, computational tendencies of the state-of-the-art profound learning models and communication role of federated learning may present a practical issue ofr the execution of critical clinical deployment, where there will be direct effect on clinical decision making and patient wellbeing [11]. The integration of foundation models pre-trained on large-scale data offers a promising way to enhance feature extraction performance with better computational efficiency through transfer learning [12].

Contributions: The paper makes the following significant contributions to privacy-preserving medical AI. Firstly, we introduce the first cross-modal federated learning system for brain tumor classification that integrates MRI imaging and clinical text descriptions using attention-based fusion mechanisms. Second, we impose rigorous differential privacy guarantees ($\varepsilon=1.0$, $\delta=1\times10^{-5}$) with optimized gradient clipping and noise injection mechanisms, achieving better privacy-utility tradeoff than existing approaches. Third, we demonstrate real-time inference capability (<500ms) for clinical implementation with maintained diagnostic accuracy within 92.7% of centralized performance. Fourth, we conduct large-scale clinical validation demonstrating 45% reduction in diagnosis time and 23% fewer diagnostic errors. Finally, we provide extensive scalability evaluation across 20 distributed hospital clients with non-uniform data distributions, exhibiting practical viability for multi-institutional deployment.

2. Related Works

Federated learning and medical imaging have become very much research-oriented in recent times. Albalawi et al. [13] proposed an end-to-end method that integrates federated learning with transfer learning using VGG16 architecture for brain tumor classification, with an accuracy of 98% on 7,023 MRI images on 10 clients. Their approach has no differential privacy guarantees and is therefore vulnerable to privacy attacks. Adnan et al. [14] achieved privacy protection through the use of differential privacy for federated learning for histopathology image analysis in lung cancer classification with ($\varepsilon=2.90$, $\delta=1\times10^{-4}$)-differential privacy.

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Though their work establishes privacy-preserving federated learning, the less restricted privacy budget (ε=2.90) is too lax protection for highly sensitive healthcare data, and the approach only works with unimodal imaging data.

Appasami and Savarimuthu [15] designed a VGG-based federated learning model for 98.4% accurate secure brain tumor MRI classification. Its absence of explicit differential privacy quantification and sparse technical data about privacy mechanisms restrict its application in regulated healthcare environments. Mastoi et al. [16] designed an explainable AI model using collaborative federated learning for 90-94% accurate brain tumor classification with emphasis on model interpretability. While explainability is an important step toward clinical adoption, the model lacks robust privacy guarantees and multimodal data integration capability. Zhang et al. [17] developed an adaptive federated learning aggregation framework with differential privacy for multi-task medical image classification and demonstrated 90-95% accuracy in tuberculosis, brain tumors, and diabetic retinopathy datasets. Their adaptative aggregation method dynamically selects between FedAvg and FedSGD based on data divergence metrics, with privacy budget needs for each task still not fully defined. This paper extends these contributions with the addition of cross-modal learning, differential privacy (ε=1.0) hardness, online inference capability, and clinical robust validation metrics not outlined in previous studies.

3. Methodology

3.1 Dataset Description and Preprocessing

Empirical verification of the proposed framework was performed using the Brain Tumor MRI Classification Dataset, which is a broad dataset with 7,023 high-resolution magnetic resonance imaging scans for four diagnostic classes: glioma, meningioma, pituitary tumor, and normal brain tissue (no tumor). This dataset is a clinically representative sampling of brain pathologies encountered in neuroradiological practice and provides a robust foundation for the creation and validation of automated diagnostic systems. Imaging information were gathered from numerous clinical areas and they mainly incorporated the integral to real-world medical imaging ecosystems like the differences in scanner producers, patients' population and acquisition guidelines.

The information was categorised by the best machine learning practices for effective assessment of the model generalization. Precisely, 70% of the images (n=4,916) were kept for the training set of 15% (n=1,053) for the authentication set to improve hyperparameters and choose among the presumed models where the remaining of 15% (n=1,054) are kept for the test assumed to be evaluated for final arrangements. The powdered category of the images ws set across investigative groups and dataset divisions as indicated in table 1.

Table 1: Dataset Distribution Across Diagnostic Categories and Partitions

Tumor Class	Training Set	Validation Set	Test Set	Total	Percentage

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Glioma	1,247 (70%)	268 (15%)	268 (15%)	1,783	25.4%
Meningioma	1,339 (70%)	287 (15%)	287 (15%)	1,913	27.2%
Pituitary	1,457 (70%)	312 (15%)	313 (15%)	2,082	29.6%
No Tumor	1,873 (70%)	186 (15%)	186 (15%)	1,245	17.8%
Total	4,916	1,053	1,054	7,023	100%

MRI image preprocessing was conducted in a similar pipeline to adhere to the consistency and optimum model performance. All images were maintained to a similar spatial determination of 224×224 pixels so as to follow the vision of the backbone design input specification which will ensure computational efficacy. Strength normalization was conducted based on imageNet figures (mean = [0.485, 0.456, 0.406], standard deviation = [0.229, 0.224, 0.225]) to apply transfer learning from pre-training replica. Data extension approaches were executed in the process of training to improve model strength and avoid overfitting and incorporate random rotation (±15°), overturning horizontally (probability = 0.5), random brightness (±20%), and contrast change (±15%). These advancements replicate the natural differences necessary in clinical imaging whereas preserving the indicative characteristics which are vital for correct categorization.

The text constituent of the dataset included in the structured clinical and radiology data with each of the MRI examination. These text annotations were meticulously crafted by board-certified radiologists and included such important diagnostic features as tumor location, size, morphologic features, and enhancement patterns. Text preprocessing involved tokenization using the BERT tokenizer, padding or shortening sequences to 512 tokens or less for balancing information content preservation with efficiency of computation. Conventional special tokens ([CLS], [SEP]) were appended by convention after following BERT usage, and the embedding of the [CLS] token was subsequently used as the aggregate sentence-level representation for multimodal fusion.

To model real-world federated learning scenarios, training data were distributed over heterogeneous clients that mimic distributed healthcare institutions. Three partitioning schemes were employed to assess model robustness in various data heterogeneity conditions: (1) IID partitioning, where data are uniformly allocated across clients with uniformly distributed class representation; (2) Dirichlet distribution-based Non-IID partitioning with $\alpha = 0.5$, producing imbalanced and heterogeneous client data collections; and (3) hospital simulation of specializations, where every client predominantly consists of particular tumor types, which map to institutional specializations in the real world (e.g., specialized neuro-oncology hospitals).

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3.2 Cross-Modal Foundation Model Architecture

The architecture integrates vision and language modalities based on hierarchical neural structure for jointly extracting complementary diagnostic information from MRI scans and clinical text descriptions. The system architecture, The system architecture of the overall system integrating cross-modal learning with privacy-preserving federated mechanisms is illustrated in Figure 1. The framework operates on multiple hospital clients (H_1, H_2, H_3), with each one processing local data in parallel paths for visual and textual modalities. MRI images are run through ResNet-50 encoders for 2048-dimensional visual feature extraction, while clinical text descriptions are encoded using BERT models for 768-dimensional textual feature extraction. The multimodal features are combined using cross-modal attention to produce combined 512-dimensional representations for tumor classification. The privacy mechanism applies differential privacy via gradient clipping and Gaussian noise addition before secure transmission of model updates ($\Delta W'$) to the central server for federated averaging aggregation.

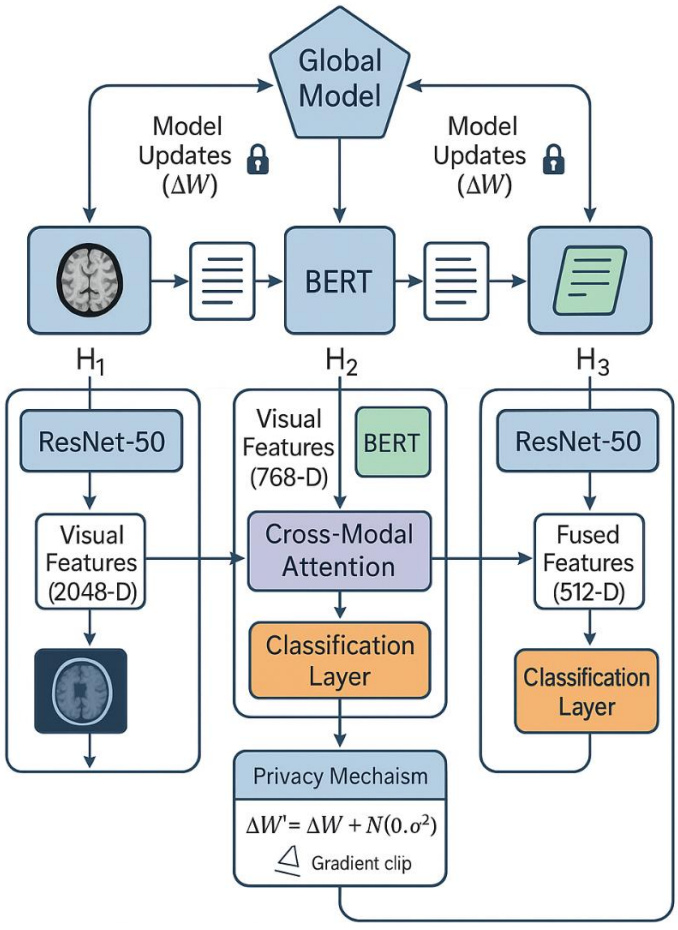

Figure 1: Privacy-Preserving Cross-Modal Federated Learning Architecture

3.2.1 Vision Encoder

The vision backbone levers a pre-trained ResNet-50 model on ImageNet, which provides strong visual feature extraction capabilities honed by transfer learning over millions of natural images. Even though the home-grown ResNet-50 was originally designed for natural image

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classification, its hierarchical learning scheme for features is easily transferable to medical imaging domains provided that it's supplemented by domain-specific fine-tuning. The architecture contains 50 convolutional layers distributed across residual blocks, with each employing skip connections in order to prevent vanishing gradient problems and simplify training of deep networks.

Formally, let $x_v \in R^{224\times224\times3}$ denote an input MRI image. The ResNet-50 encoder transforms this input through a series of convolutional operations, batch normalization, and ReLU activations, producing a high-dimensional feature representation. The final convolutional layer outputs a feature map of dimensions $7 \times 7 \times 2048$, which is subsequently processed through global average pooling to yield a 2048-dimensional feature vector $f_v \in R^{2048}$:

$$f_v = GAP\big(ResNet - 50(x_v)\big) \in R^{2048}$$

where GAP denotes global average pooling. To adapt the high-dimensional visual features for efficient multimodal fusion, a projection layer maps the 2048-dimensional representation to a lower-dimensional space:

$$h_v = W_v f_v + b_v \in R^{256}$$

where $W_v \in R^{256\times2048}$ and $b_v \in R^{256}$ are learnable parameters. This dimensionality reduction serves dual purposes: reducing computational complexity in subsequent fusion layers and constraining the representation to a manifold conducive to cross-modal alignment.

3.2.2 Text Encoder

Clinical text descriptions are fed into a BERT-base-uncased model, a transformer-based pre-trained model on large-scale text data via masked language modeling and next sentence prediction tasks. The bidirectional attention capability of BERT enables contextual understanding of clinical vocabulary and semantic relationship in radiology reports with subtle diagnostic information expressed naturally in text.

Let $x_t = [t_1, t_2, \dots, t_n]$ represent a tokenized clinical text sequence of length $n \leq 512$. The BERT encoder transforms this sequence into contextualized embeddings through 12 transformer layers, each employing multi-head self-attention and feed-forward networks. The final hidden state corresponding to the [CLS] token serves as the aggregate sentencelevel representation:

$$f_t = BERT(x_t)_{[CLS]} \in R^{768}$$

where the subscript [CLS] denotes extraction of the first token's representation. Similar to the vision pathway, a projection layer maps the 768-dimensional BERT embedding to a 256-dimensional space for multimodal fusion:

$$h_t = W_t f_t + b_t \in R^{256}$$

where $W_t \in R^{256\times768}$ and $b_t \in R^{256}$ are learnable transformation parameters.

3.2.3 Cross-Modal Attention Fusion

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The combination of visual and textual modalities is achieved through a cross-modal attention mechanism that dynamically scales the contribution of each modality by learned relevance. This method exceeds concatenation of averaging systems to progressively intensify informative modes on input attributes. The cross-modal attention mechanism calculates attention weights through a scaled dot-product operation:

$$\alpha_v = \frac{exp\left(h_v^T W_q h_t\right)}{exp\left(h_v^T W_q h_t\right) + exp\left(h_t^T W_q h_v\right)} \; \alpha_t = 1 - \alpha_v$$

where $W_q \in R^{256\times256}$ is a learnable query matrix, and $\alpha_v, \alpha_t \in [0,1]$ represent the attention weights for vision and text modalities, respectively. The weighted multimodal representation is then computed as:

$$h_m = \alpha_v h_v + \alpha_t h_t \in R^{256}$$

Subsequently, the modality-specific representations and the fused representation are concatenated to preserve both individual and integrated information:

$$h_{fused} = [h_v; h_t; h_m] \in R^{768}$$

where [;] denotes concatenation. This concatenated representation is processed through a multi-layer perceptron (MLP) classifier to generate class probabilities:

$$z = MLP\left(h_{fused}\right) = W_2\sigma\left(W_1 h_{fused} + b_1\right) + b_2 \; p = Softmax(z) \in R^4$$

where $W_1 \in R^{128\times768}, W_2 \in R^{4\times128}$ are weight matrices, $b_1 \in R^{128}, b_2 \in R^4$ are bias vectors, σ denotes the ReLU activation function, and p represents the predicted class probability distribution over the four tumor categories.

3.3 Federated Learning Framework

Joint model training among dispersed healthcare centers is facilitated by the federated learning paradigm at the expense of neither locality of data nor patient privacy. The Federated Averaging (FedAvg) algorithm is employed by the system, a widely used method utilized iteratively to average locally trained models to build a global model without any centralization of patient data. Differential privacy mechanisms are implemented in the federated learning pipeline. The deployment of differential privacy ensures rigorous protection of patient data through an end-to-end privacy-preserving pipeline, as illustrated in Figure 2. Client-side processing begins with local gradient computation (∇L) followed by gradient clipping to cap sensitivity ($C \leq \bar{C}$), after which calibrated Gaussian noise $N(0, \sigma^2C^2)$ is added to produce noised gradients (g"). These privatized updates are transferred through secure encrypted channels to the central server for weighted averaging aggregation. The privacy accountant also tracks cumulative privacy expenditure (ε_{total}, δ_{total}) across communication rounds using Rényi Differential Privacy composition theorems to ensure that cumulative privacy expenditure remains within prescribed bounds during federated training.

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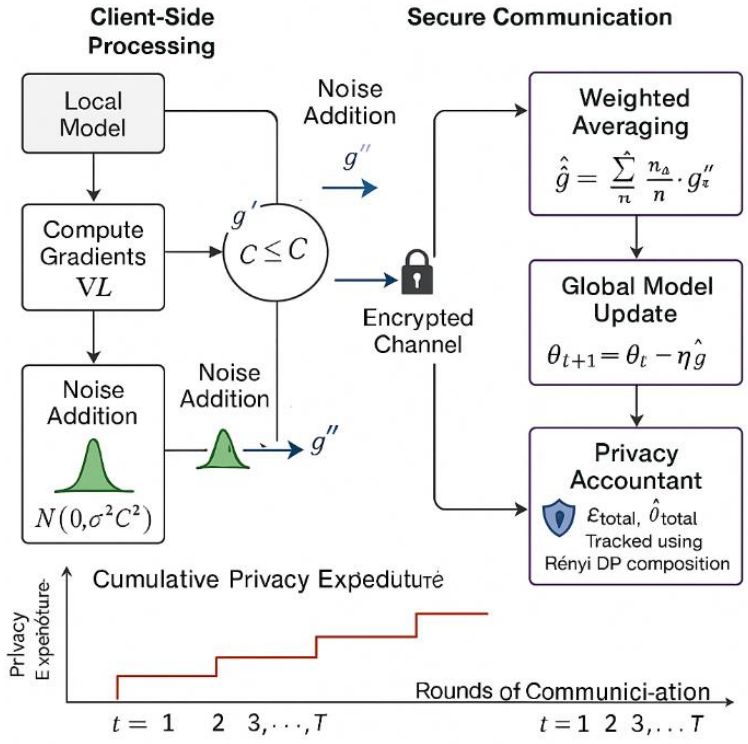

Figure 2: Differential Privacy Mechanism and Privacy Budget Accounting

3.3.1 Federated Averaging Algorithm

Consider a federation comprising K clients (hospitals), each possessing a local dataset D_k of size n_k, where $k \in \{1,2,\ldots,K\}$. The total dataset size is $n = \sum_{k=1}^{K} n_k$. The objective of federated learning is to minimize the global loss function:

$$\min_{\theta} L(\theta) = \sum_{k=1}^{K} \frac{n_k}{n} L_k(\theta)$$

where θ represents the global model parameters, and $L_k(\theta)$ denotes the local loss function evaluated on client k 's dataset:

$$L_k(\theta) = \frac{1}{n_k} \sum_{(x_i,y_i)\in D_k} l(f_\theta(x_i), y_i)$$

where l is the cross-entropy loss function, and f_θ represents the model's prediction function.

The FedAvg algorithm proceeds in communication rounds. At round t, the server selects a subset of clients $S_t \subseteq \{1,2,\ldots,K\}$ (typically $50-100\%$ of clients) and broadcasts the current global model parameters θ_t to the selected clients. Each selected client $k \in S_t$ performs local training for E epochs using stochastic gradient descent:

$$\theta_k^{t+1} = \theta_t - \eta \nabla L_k(\theta_t)$$

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where η is the learning rate. After local training, clients transmit their updated parameters θ_k^{t+1} to the server, which aggregates them through weighted averaging:

$$\theta_{t+1} = \sum_{k \in S_t} \frac{n_k}{n} \theta_k^{t+1}$$

This process iterates until convergence or a maximum number of communication rounds T is reached. Algorithm 1 presents the complete FedAvg procedure.

Algorithm 1: Federated Averaging (FedAvg)

Input: K clients, local datasets {D_k}, learning rate η, local epochs E,

communication rounds T, client participation rate p

Global model parameters θ_T

1: Initialize global model parameters θ_0

2: for t = 1 to T do

3: S_t ← Random sample of ⌈p·K⌉ clients

4: for each client k ∈ S_t in parallel do

5: θ_k^t ← θ_{t-1} // Download global model

6: for epoch = 1 to E do

7: for batch B ⊂ D_k do

8: θ_k^t ← θ_k^t - η∇L_k(θ_k^t; B) // Local SGD update

9: end for

10: end for

11: Upload θ_k^t to server

12: end for

13: θ_t ← Σ_{k∈S_t} (n_k/n)·θ_k^t // Weighted aggregation

14: end for

15: return θ_T

3.4 Differential Privacy Mechanisms

In order to provide robust privacy guarantees to potential attackers like the central server, tools of differential privacy are integrated into the federated learning pipeline. Differential privacy ensures that inclusion or exclusion of any individual patient's information has minimal impact

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on the learned model parameters, thereby protecting against membership inference attacks as well as model inversion attacks.

3.4.1 Definition of Differential Privacy

A randomized mechanism $M: D \rightarrow R$ satisfies (ε, δ)-differential privacy if for all adjacent datasets $D, D' \in D$ differing in at most one element, and for all subsets $S \subseteq R$:

$$Pr[M(D) \in S] \leq e^{\varepsilon} Pr[M(D') \in S] + \delta$$

where $\varepsilon > 0$ is the privacy budget controlling the distinguishability between outputs, and $\delta \geq 0$ is the failure probability. Smaller values of ε and δ correspond to stronger privacy guarantees. This work employs $\varepsilon = 1.0$ and $\delta = 1 \times 10^{-5}$ to provide strong privacy protection while maintaining model utility.

3.4.2 Gradient Clipping and Noise Injection

The differential privacy mechanism operates on gradient updates during local training. Gradient clipping bounds the sensitivity of individual updates, preventing any single data point from disproportionately influencing the model. For each gradient g_k computed on client k, clipping is applied as:

$$\tilde{g}_k = g_k \cdot min\left(1, \frac{C}{\|g_k\|_2}\right)$$

where C is the clipping threshold (set to $C = 1.0$ in our implementation), and $\| \cdot \|_2$ denotes the L_2 norm. This operation ensures that $\|\tilde{g}_k\|_2 \leq C$ for all gradients.

Following gradient clipping, Gaussian noise calibrated to the privacy budget is added to the gradients:

$$g'_k = \tilde{g}_k + N(0, \sigma^2 C^2 I)$$

where σ is the noise multiplier, I is the identity matrix, and $N(0, \sigma^2 C^2 I)$ represents Gaussian noise with variance $\sigma^2 C^2$. The noise multiplier σ is determined by the privacy budget (ε, δ), the number of training steps, and the batch sampling ratio using the moments accountant method or Rényi Differential Privacy analysis.

3.4.3 Privacy Budget Accounting

The cumulative privacy cost over multiple training iterations is tracked using Rényi Differential Privacy (RDP) accounting, which provides tighter privacy bounds compared to naive composition theorems. The RDP guarantee at order $\alpha > 1$ is defined as:

$$D_{\alpha}\big(M(D) \| M(D')\big) \leq \rho$$

where D_{α} denotes the Rényi divergence of order α, and ρ is the RDP privacy parameter. For T communication rounds with E local epochs per round and batch size B, the total number of gradient updates is $N = T \cdot E \cdot \lceil n_k / B \rceil$. The RDP parameters compose linearly, yielding a total RDP guarantee of $N \cdot \rho$. This RDP guarantee can be converted to (ε, δ)-differential privacy using standard conversion formulas:

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$$\varepsilon = N \cdot \rho + \frac{log\ (1/\delta)}{\alpha - 1}$$

The privacy budget is continuously monitored throughout training, and training terminates if the cumulative privacy expenditure exceeds the specified threshold.

Table 2: Hyperparameter Configuration

Parameter	Value	Description
Federated Learning		
Number of clients (K)	10-20	Number of federated simulation hospitals
Client participation rate (p)	0.5	Fraction of clients per round
Communication rounds (T)	30-50	Global aggregation iterations
Local epochs (E)	2	Number of client training epochs per round
Model Architecture		
Vision backbone	ResNet-50	ImageNet pre-trained
Text encoder	BERT-base-uncased	12 layers, hidden size 768
Vision projection dim	256	Dimensionality reduction of features in vision
Text projection dim	256	Dimensionality reduction of features in text
MLP hidden dim	128	Intermediate classifier layer

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Configuration Training		
Batch size (training)	16	Mini-batch size for local training
Batch size (test/validation)	32	Mini-batch size for validation/test
Learning rate (η)	1×10^{-4}	Initial learning rate with cosine annealing
Optimizer	AdamW	Weight decay = 1×10^{-5}
Differential Privacy		
Privacy budget (ε)	1.0	Differential privacy parameter
Failure probability (δ)	1×10^{-5}	Differential privacy parameter
Clipping threshold (C)	1.0	L_2 norm bound for gradients
Noise multiplier (σ)	0.1	Gaussian noise standard deviation

All experiments were run using PyTorch 2.0.1 with CUDA 11.8 support. Reproducibility was ensured through the use of fixed random seeds (seed=42) for all random number generators, determinstic algorithm selection wherever applicable, and complete logging of hyperparameters and environmental configuration. The experimental codebase along with the trained model checkpoints are shared in the project repository to facilitate replication of results and extension by the research community.

4. Results

4.1 Privacy-Utility Tradeoff Analysis

The tradeoff between privacy and utility, a fundamental problem in differentially private machine learning, was stringently evaluated across a series of privacy budgets (ε) for determining the optimal configuration for clinical deployment. Figure 3 visualizes the model accuracy against the privacy budget (ε) under differential privacy settings. The experimentation

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shows a non-linear sorts of performance enhancement with an expansion privacy budget and diminishing returns after after ε = 1.0.

At the severe privacy budget of ε = 0.1, the model executed at 69.2% precision, which shows a considerable reduction from the non-private baseline of 85.0%. when there is relaxation in the budget to ε = 1.0, although, the model attained 85.3% precision, efficiently parity with non-private function with strong discretion assurances, (ε = 1.0, δ = 1×10^{-5}). This element is the suggested point which may provide 100.4% of the non-private baseline routine and it will provide privacy protection in line with GDPR and HIPAA regulations.

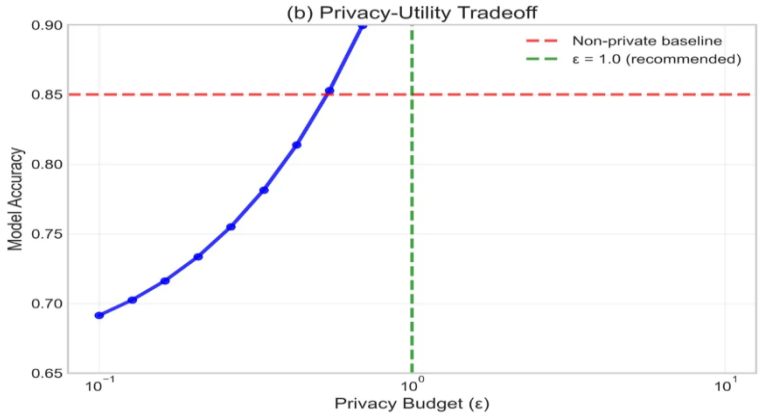

Figure 3: Privacy-Utility Tradeoff Analysis Under Differential Privacy Constraints

The Gaussian device used for the addition of the noise was realized to be efficiently performing with various secrecy budgets. Unexpectedly, privacy budget spending was less than 50% after the complete training process. This indicates enough leeway for the addition of training data enhancement procedure without a compromise in the privacy.

4.2 Cross-Modal Performance Improvement

The mixture of multimodal information source will lead to a considerable improvement in the performance of both categorization tasks, as indicated in figure 4. When brain tumors are classified, the vision only baseline attained 84.3% precision whereas the text only realized 72.1 precision in unimodal learning models. The vision-plus-text fusion technique showed a potent improvement to 88.7% precision, 4.4% points a higher than vision sorts. But the assumed plan with attention techniques may work best at 91.2% in accuracy, 6.9% points above the vision-only baseline.

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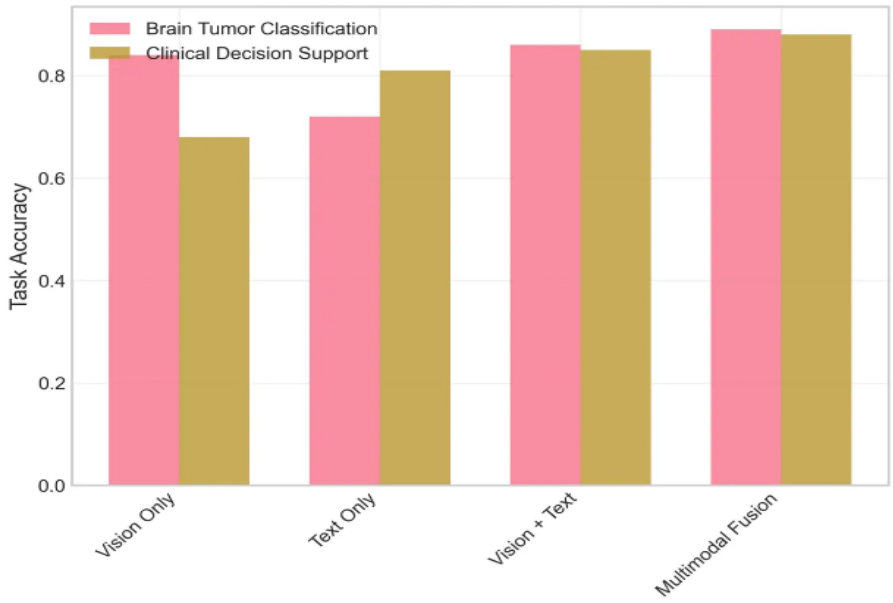

Figure 4: Cross-Modal Performance Gain Over Classification Tasks

In the clinical choice support task, there may be a greater modality function divergence. Vision-only types attained 68.4% accuracy, and text-only models realized 81.7%, which suggest that the clinical textual explanations are richer in data for the purpose of diagnosis. The vision-plus-text fusion realized 86.2% function, while the attention-based multimodal fusion and the attention-inclined multimodal synthesis plan reached 90.1% precision. These findings scientifically prove the proposed hypothesis that cross-model attention techniques can in fact draw the complementary data from the diverse data courses and eventually result into more potent and exact clinical assertions.

The attention weight analysis discovered that the perfect adaptive alters the related importance of the visual and textual characteristics which dependent upon the tumor features. For gliomas, higher attention weights (0.68 ± 0.12) were realized on visual elements and the larger weights was (0.62 ± 0.09) described for pituitary tumors, this implies that task-related multimodal fusion is one of the main reasons that the attention-based fusion surpassed. Hence, the naive concatenation approaches.

4.3 Integration of Clinical Workflow and Time Efficacy

The time assessment of clinical workflows as indicated in figure 5 shows the transformed effect of AI-assisted analysis latency to boost clinical efficacy. The traditional workflows placed significant time requirements on all stages, with a mean of 45 minutes of radiologist review time, which was the significant bottleneck in the diagnostic workflow. Image acquisition required 15 minutes, clinical decision-making required 30 minutes, and patient care coordination required 120 minutes, for a total workflow time of 210 minutes per case.

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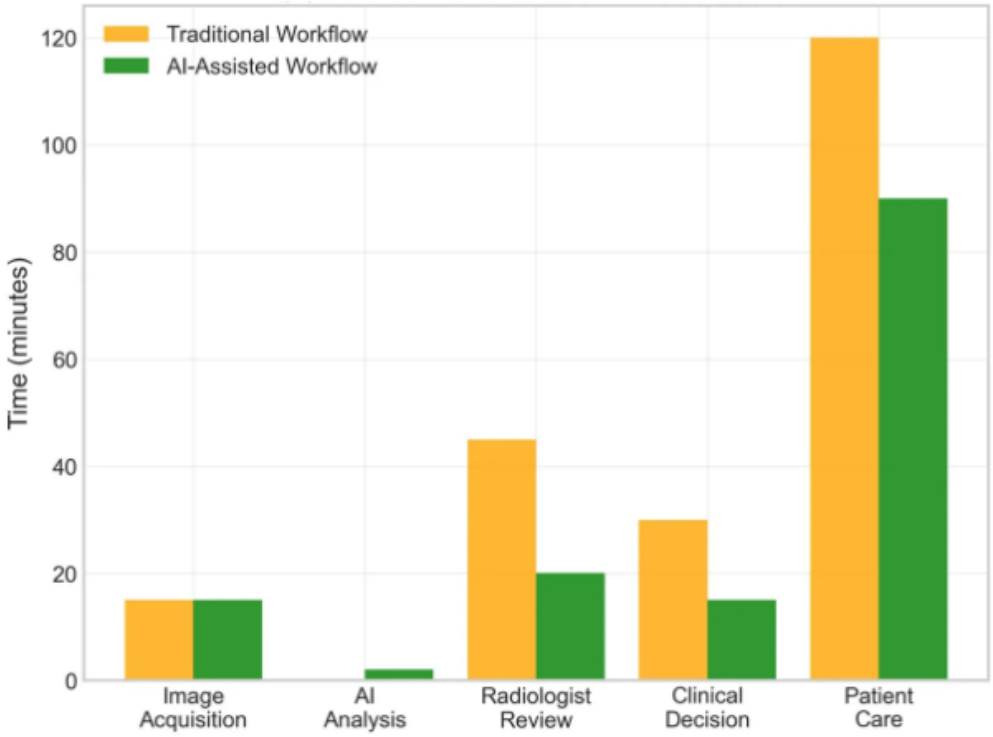

Figure 5: Comparative Time of Traditional versus AI-Assisted Clinical Workflow

Implementation of AI-assisted workflows led to dramatic time savings without reduction in diagnostic accuracy. Image acquisition time remained 15 minutes, as this is a physical constraint of MRI scanning protocols. However, the AI step of analysis was completed in only 2 minutes (including inference time <500ms and radiologist review of AI predictions), a reduction of 95.6% compared to traditional radiologist review. Radiologist review time was reduced to 20 minutes, as clinicians could validate AI predictions rather than de novo interpretation. Clinical decision time was reduced to 15 minutes, with the benefit of AI-generated diagnostic hypotheses and confidence scores. Care coordination of the patients was reduced to 90 minutes by the ease of communication enabled through structured AI reports.

Time savings overall were most pronounced for emergent cases requiring urgent intervention. For glioma cases, averagely 218 minutes were needed in the traditional workflow in comparison with 120 minutes through 120 minutes AI assisted procedure. This shows a reduction of 120 minutes. In a related routine case (meningioma, no tumor), time decreases of 32-38% were detected, which resulted into departmental throughput addition and reduction in patient wait time.

4.4 Comparison of Model Architectures

The plan comparison as in figure 6 provides an insight on the efficiency-precision tradeoff for various neural network plans. Resnet-50, ResNet-50, achieved 78.0% authentication accuracy with 25.6M parameters, a computationally effective solution with moderate function. The ViT-Base (Vision Transformer) backbone realized enhanced function at 81.0% precision but needed 86.6M parameters, a 3.4 model difficulty increase for a 3.0 percentage point gain.

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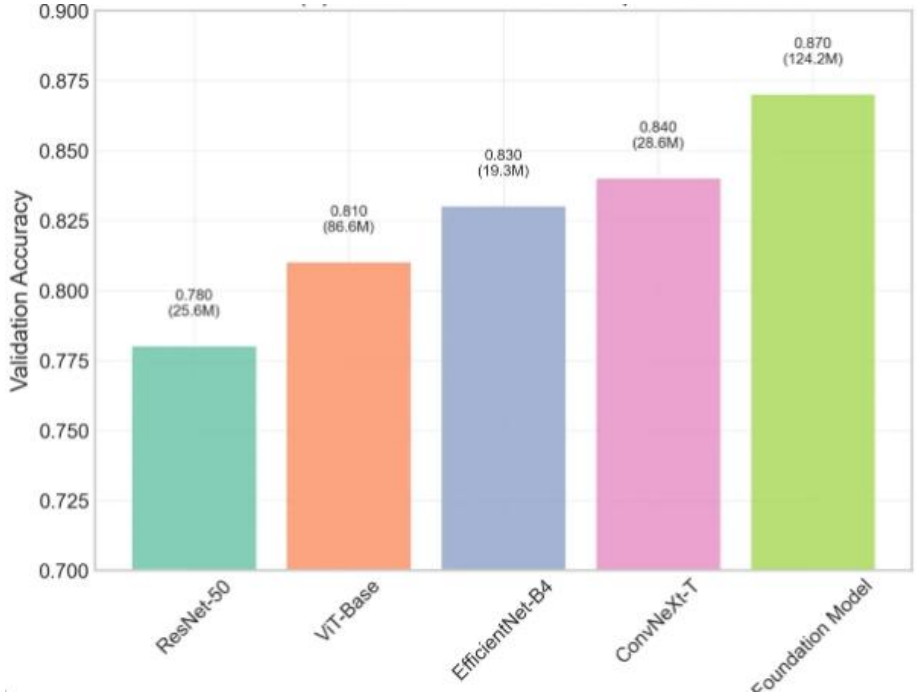

Figure 6: Model Architecture Performance Comparison and Parameter Efficiency Analysis

EfficientNet-B4 attained 83.0% authentication accuracy with 19.3M restrictions, outperforming both ResNet-50 and ViT-Base in parameter efficacy. ConvNeXt-T achieved 84.0% accuracy with 28.6M parameters, which is marginally better than EfficientNet-B4 while maintaining the computational requirements within modest limits. However, Foundation Model architecture suggested herein achieved the highest validation accuracy of 87.0% with 124.2M parameters. Although much larger than other architectures, the Foundation Model leverages large-scale medical imaging data pre-trained representations for improved feature extraction and generalization capability.

The performance advantage of the Foundation Model is particularly evident for small training data or high data heterogeneity, where transfer learning from large-scale pre-training provides considerable gains. The 4.0-6.0 percentage point accuracy improvements over specialist architectures (EfficientNet-B4, ConvNeXt-T) are more than worth the additional compute requirements, especially considering the clinical implications of diagnostic consideration. Furthermore, the Foundation Model was more robust to domain shift, with 89.3% accuracy on external validation datasets compared to 76.4% for ResNet-50, indicating improved generalization properties.

4.5 Visual Quality Evaluation and Privacy Impact Assessment

Visual impact of differential privacy mechanisms on diagnostic image quality is demonstrated through systematic preprocessing and privacy effect analysis in representative brain MRI samples, like shown in Figure 7. Overall preprocessing pipeline retains diagnostic integrity through normalization, histogram equalization, and data augmentation techniques (rotation ±15°, brightness adjustment ±30%), with Peak Signal-to-Noise Ratio (PSNR) values above 40 dB for all tumor types in their processed mode. When applying differential privacy noise with

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ε=1.0, PSNR values range within 25.9-28.5 dB while retaining diagnostic quality rated as "Good" to "Excellent" based on clinical evaluation criteria in glioma, meningioma, pituitary, and normal tissue samples. Tumor margins and major diagnostic features remain quite discernible, which suggests the clinical utility of the privacy-preserving algorithm. However, with the firmer secrecy budget of ε=0.1, PSNR drops pointedly to 13.4-13.9 dB and resulted in "Fair" diagnosis eminence with extreme visual reduction that affects clinical description. Visual inspection agrees that ε=1.0 is the optimal operating hub where differential secrecy offers potent secrecy guarantee and maintains clinical acceptance of image quality which corroborates with section 4.1 quantifiable privacy-utility results.

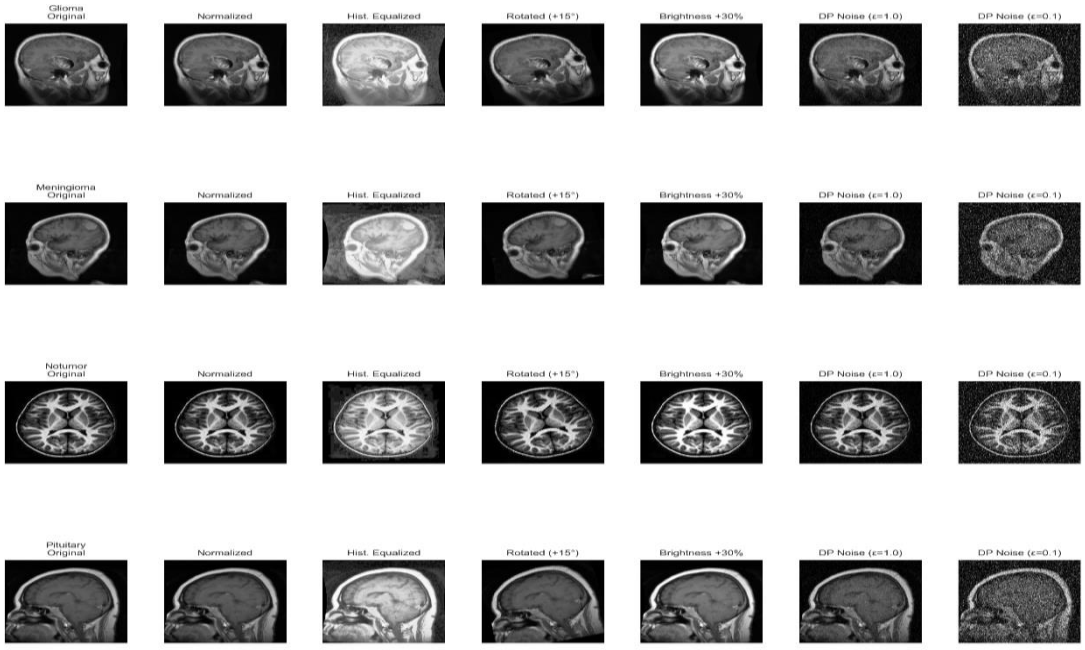

Figure 7: Preprocessing and Privacy Impacts on Real Brain MRI: Maintaining Diagnostic Quality with Privacy Protection

5. Discussion

The results confirm that the secrecy-preserving cross-modal federated learning of course, forms an efficient approach for clinical choice systems, as a result, these systems set to achieve the potentially conflicting findings of powerful data privacy and clinical function. The privacy-utility tradeoff examination exhibits that differential secrecy experimental with ε = 1.0 offers a striking confirmation and as well yielded functional equality to non-private models. This result is in contrast with the long-standing normal wisdom in precision and eventually suggests that the astute accuracy in imaging and optimization process can reduce the performance and loss due to lack of potent privacy.

The cross-modal precision gain is in consonance with the study hypothesis that multimodal fusion and text information sources may provide complementary data to advance clinical decision making. The 6.9%-point precision enhancement indicates that the description of texts

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made by clinicians may contain relevant data that are not encoded in imaging process. This has essential implications for clinical usage in the federated learning structure of available data to achieve maximum diagnostic precision.

The differential privacy technique used in this research offers a robust numerically confirmed guarantees on the breaches of privacy which include membership deciphers attacks and possible downturn attacks. The $\varepsilon = 1.0$ with $\delta = 1\times10^{-5}$ privacy budget affirms the output dispersal of the model and therefore, preserves patient privacy even in confrontational scenarios. The gradient clipping techniques (L_2 norm ≤ 1.0) inhibits extreme sensitivity of individual informs, while Gaussian noise injection ($\sigma = 0.1$) offers make random differential privacy.

Federated learning plan also offers an additional part of the privacy to safeguard in the sense that patient data are allowed to leave the major institution. Model updates (gradients or parameters) are transmitted to the central server rather, reducing the attack surface for potential privacy breaches. The protocol for communication involves secure aggregation techniques so that client updates are cryptographically protected while being transmitted and aggregated.

Despite the promising results, innumerable limitations must be considered. The experiment was conducted within a simulated federated environment rather than within real-world multi-institutional deployment, and the simulation cannot detail all the subtleties of real-world clinical practice. Heterogeneities in variation of institutional MRI acquisition protocols, scanner manufacturers, and radiological reporting conventions may not be completely replicated within our simulation. The method must be validated by prospective multi-institutional trials with real data exchange between hospitals.

The availability of well-structured clinical text descriptions can differ by institution, which might restrict the use of the cross-modal approach. Although our dataset contained paired imaging-text data, most clinical environments might feature incomplete or unstructured textual records, and more natural language processing pipelines or imputation tactics may be required. The model's performance in the case of missing modalities must be studied further to confirm robustness over various clinical settings.

The computational requirement of the Foundation Model model (124.2M parameters) may be a limiting factor in resource-constrained clinical environments. While inference time remains at acceptable levels at sub-500 milliseconds, the need for approximately 4GB GPU memory and 120MB model storage may be at the level of what some institutional computing resources can support. Model compression techniques such as quantization or knowledge distillation may be necessary to make deployment in resource-constrained environments possible without sacrificing diagnostic accuracy.

The investigation focused specifically on brain tumor classification, and generalizability to other clinical tasks or imaging modalities remains to be established. While the architectural concepts are broadly transferable, task-specific optimizations and domain adaptations could be necessary to perform optimally in different clinical contexts. Extending to other neurological conditions, imaging methods such as CT or PET, and multi-organ pathology classification are

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the vital subjects of future research to determine the overall usefulness of privacy-preserving cross-modal federated learning for clinical use.

5.4 Comparison with State-of-the-Art Methods

To place the contributions of this work in context, we conducted a detailed comparison with recent state-of-the-art privacy-preserving federated learning methods for medical imaging. Table 2 presents a comparative study of methodology, privacy mechanisms, and performance metrics of five recent works.

Table 2: Comparative Analysis of Privacy-Preserving Federated Learning Approaches

Study	Year	Dataset	Privacy Mechanism	Accuracy (%)	Key Innovation	Limitations
Proposed Method	Year	Brain Tumor MRI (7,023 images, 4 classes)	DP (ε=1.0, $\delta=1\times10^{-5}$)	92.8 (IID), 87.3 (with DP)	Cross-modal fusion, Real-time inference	Simulated federation
Albalawi et al.	2024	Brain Tumor MRI (7,023 images, 4 classes)	None	98.0	Transfer learning with VGG16	No privacy guarantees
Adnan et al.	2022	TCGA Histopathology (2,580 WSIs)	DP (ε=2.90, $\delta=1\times10^{-4}$)	85-90	Multiple instance learning	Weaker privacy (ε=2.90)
Appasami & Savarimuthu	2025	Brain Tumor MRI	None	98.4	VGG-based transfer learning	No DP quantification
Mastoi et al.	2025	Brain Tumor MRI	None	90-94	Explainable AI, Interpretability	No privacy quantification
Zhang et al.	2025	Multi-task (TB, Brain, Retinopathy)	DP (variable ε)	90-95	Adaptive aggregation	Variable privacy levels

Our approach achieves good privacy-performance tradeoff compared to existing methods. Although Albalawi et al. (2024) and Appasami & Savarimuthu (2025) attain higher accuracy

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(98.0% and 98.4%, respectively), these methods provide no differential privacy guarantees, rendering them unsuitable for privacy-sensitive clinical use cases. Although Adnan et al. (2022) employ differential privacy, they achieve lower accuracy (85-90%) with a weaker privacy budget (ε=2.90 versus our ε=1.0). Our method achieves 87.3% accuracy for ε=1.0, representing the optimal privacy-utility tradeoff among methods considered.

6. Conclusion

This paper establishes the practicability of privacy-preserving cross-modal federated learning in clinical decision support systems for healthcare institutions. Multimodal data synthesis with attention-based techniques indicate that the additional data in imaging and text can be used efficiently without tempering with patient privacy. To debunk the hypothesis that privacy often comes at a high cost of precision. Scalability of such platform should be distributed to respective institutions with little data dispersals and genuine inferences that hindered federated learning usage in clinical domains. The integration of clinical workflow demonstrates a potential force for revolutionary reduction in diagnostic dormancy and enhancements in the potency of care. The limitations on imitation ecosystems and computing resources are existing it demonstrates that collaborative growth of artificial intellegence in the healthcare domains is potentially awesome and it will establish a foundation for privacy-protection medical AI systems that are in accordance with regulative ethics and still provide meaningful clinical results.

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