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# Federated SignalGAN: Privacy-Preserving Collaborative Brain Signal Processing for Enhanced Diagnostic Accuracy

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**Abstract:** As the demand for enhanced privacy in collaborative brain signal processing intensifies, this research presents a robust federated learning framework. Collaborative signal analysis necessitates data pooling across institutions, emphasizing the critical need for privacy preservation. "Federated SignalGAN" is an innovative algorithm that unites Generative Adversarial Networks (GANs) with the core principles of federated learning. The adversarial training objective of GANs is to simultaneously train the generator and discriminator. This is formulated as a minimax game, with the generator striving to produce synthetic data that are indistinguishable from real ones, while the discriminator endeavors to become more adept at distinguishing between real and synthetic data. Federated Learning is a distributed machine learning paradigm to train a global prototype that minimizes a specific loss function while respecting the data privacy constraints of each participating institution. Federated brain SignalGAN stands out by introducing a unique approach for generating synthetic signal data, thereby eliminating the necessity for direct sharing of sensitive information. This research employs comprehensive simulation analysis to rigorously assess the performance of Federated brain SignalGAN. Key simulation metrics, including diagnostic accuracy, data privacy preservation, convergence rate, and GPU utilization are used to evaluate the effectiveness of this framework using open data repositories and real-time brain signal processing datasets. The implications of this research are profound, emphasizing the pivotal role of privacy-preserving federated learning frameworks in signal processing. By introducing a novel algorithm designed to meet the unique challenges of collaborative signal analysis, this research makes a substantial contribution to secure and accurate signal detection in distributed environments. The adoption of Federated brain SignalGAN is pivotal for ensuring data confidentiality while enabling effective multi-institutional signal analysis.

**Keywords:** federated learning; generative adversarial networks (GANs); privacy-preserving signal processing; collaborative brain signal analysis; synthetic data generation

## 1 INTRODUCTION

Deep learning models, such as Convolutional Neural Networks (CNNs), and unsupervised machine learning models, like One-Class SVMs, serve as valuable tools for anomaly detection in brain tumor diagnosis. They operate without the need for labelled data and excel at identifying rare or atypical tumor cases. One-Class SVMs, for instance, identify deviations from normal brain anatomy, facilitating the detection of abnormal tumor growth. Ensemble techniques and transfer learning strategies have been applied to fuse the strengths of multiple machine learning models. These approaches combine the predictive capabilities of diverse models, improving diagnostic robustness. Transfer learning, in particular, allows models pretrained on large datasets to be fine-tuned for brain tumor detection tasks, thereby harnessing prior knowledge for enhanced accuracy [1, 2].

This research work builds upon existing endeavours in federated learning, privacy-preserving machine learning, and collaborative healthcare data analysis. It draws inspiration from these domains to design a novel federated learning framework tailored to the unique requirements of collaborative brain tumor detection. By combining the strengths of federated learning with progressive machine learning models, we aim to strike a balance between improved diagnostic accuracy and the stringent preservation of patient data privacy. In the subsequent sections, we delve into the framework's architecture, algorithmic intricacies, and empirical evaluations to demonstrate its potential to revolutionize collaborative brain tumor diagnosis. Collaborative brain tumor detection often necessitates the sharing of sensitive Magnetic Resonance Imaging (MRI) scans and associated patient health data across multiple medical institutions [3, 4].

The paramount concern is to safeguard the confidentiality of this patient information. Unauthorized access or data breaches can result in severe ethical and legal ramifications, undermining patient trust in healthcare systems. Centralized data-sharing approaches, which have been historically employed in collaborative brain tumor detection, carry inherent data privacy risks. These risks stem from the vulnerability of patient data during transmission, storage, and processing. Unauthorized parties may exploit vulnerabilities in the network or the centralized storage system, potentially leading to data breaches or cyberattacks.

Establishing privacy-enhanced collaborative frameworks not only mitigates privacy risks but also fosters trust among participating medical institutions. By ensuring that sensitive patient data is kept secure and confidential, institutions are more likely to engage in collaborative efforts. The resulting trust and collaboration can lead to more extensive and diverse datasets, ultimately enhancing the accuracy of brain tumor detection models [5, 6]. Machine learning models, characterized by their ability to discern intricate patterns and anomalies within medical images, have revolutionized the field of brain tumor diagnosis.

## 2 RELATED WORKS

The growing importance of CNNs in automating medical diagnoses, providing a reliable and rapid means of identifying brain tumors through imaging data, was highlighted [7]. An approach that combines CNN and other traditional vector algorithms for detecting brain tumors was presented, showcasing the versatility of CNNs in enhancing diagnostic accuracy [8]. Faster R-CNN was employed for tumor detection in brain images, demonstrating how CNNs can be adapted for object detection tasks in medical imaging [9]. The critical role of deep learning in improving disease characterization, which can lead to more personalized treatment strategies, was underscored [10]. The versatility of CNNs was showcased, as they are applied to different modalities, emphasizing their necessity and requirement for initial detection of cancer [11]. The effectiveness of CNNs for breast tumor detection was demonstrated, underlining the fusion of advanced imaging technologies with CNNs for more accurate and reliable cancer detection [12].

The direct extraction of tumor response was emphasized, showcasing CNNs' potential for enhancing image reconstruction techniques [13]. The role of CNNs in fusing diverse medical data sources and improving diagnostic accuracy through data integration was highlighted [14]. The adaptability of CNNs in handling various medical image fusion tasks, offering potential solutions for more comprehensive healthcare data analysis, was underscored [15]. A Gabor-based CNN for image analysis, maintaining filter structure, and illustrating how CNN architectures can be customized to specific medical image analysis tasks was introduced [16].

Leveraging federated learning techniques to improve the precision of classification of brain tumors using MRI scans was focused on, achieving enhanced diagnostic performance [17]. FLWGAN, a federated learning framework incorporating Wasserstein Generative Adversarial Networks (WGAN) for brain tumor segmentation, was introduced, highlighting the potential of combining FL with advanced generative models [18]. The implementation of various deep learning neural networks in the domain was explored, contributing to the broader field of deep learning in the detection of brain tumors [19]. The importance of efficient data partitioning strategies in federated learning systems, aiming to improve segmentation accuracy, was emphasized [20]. The focus on classification techniques and the integration of split learning principles into federated learning frameworks to enhance collaborative brain tumor detection was described [21]. Privacy-preserving federated learning in healthcare was explored, addressing crucial privacy concerns associated with federated learning in medical contexts [22]. The challenges associated with noisy labels in medical image analysis, which can be mitigated through federated learning approaches, were shed light on [23]. Insights into the potential of federated learning in diversified applications like detection of brain tumors by addressing data privacy and distribution challenges were provided [24].

A Cross-Modality Augmentation GAN for enhanced glioma classification, improving the quality of brain MR images, was worked on [25]. Efforts to enhance image quality and consistency, thereby improving the segmentation process, were aimed [26]. The challenge of distributed data sources, facilitating collaborative segmentation efforts, was addressed [27]. Brain Tumor Segmentation using Generative Adversarial Nets was explored, leveraging GANs to enhance tumor segmentation accuracy [28]. A case study on MRI image generation using GANs in healthcare, highlighting the potential of GANs in medical image synthesis, was conducted [29]. The application of GANs for enhancing MRI image quality, transferrable to brain tumor imaging, was demonstrated [30].

Efforts to improve image quality and consistency, thereby enhancing the segmentation process, were aimed [31]. GANs, ResNet, and UNet were employed for brain tumor segmentation, demonstrating effective tumor detection and segmentation capabilities [32]. The accuracy of tumor segmentation was improved, even with limited labeled data [33]. An enhanced approach for detecting brain tumors, involving GANs in improving brain tumor detection, was proposed [34]. The importance of feature extraction in improving diagnostic accuracy was emphasized [35]. The potential of integrating deep learning and feature engineering for accurate diagnosis was showcased [36].

A comprehensive review highlighting the potential of IoT technologies in transforming healthcare delivery and emphasizing the need to address associated challenges in the domain was offered.

## 3 PROPOSED WORK

The proposed system architecture addresses the critical need for enhanced privacy in collaborative brain tumor detection by leveraging the synergistic capabilities of Generative Adversarial Networks (GANs) and Federated Learning. Combining GANs with federated learning in the Federated TumorGAN algorithm allows to leverage the strengths of both techniques to enhance brain tumor detection. GANs are powerful in generating realistic data, which helps in improving the accuracy and robustness of the model. Federated learning ensures that this collaborative training happens without the need to share sensitive patient data between institutions, thus preserving data privacy and complying with regulatory requirements. This section presents a comprehensive overview of the architecture, emphasizing its key components, methodologies, and objectives.

### GAN Architecture

Generative Adversarial Networks (GANs) have demonstrated exceptional proficiency in generating synthetic data closely resembling real-world instances, including images, which is particularly pertinent in the context of MRI scans for brain tumor diagnosis. GANs consist of two distinct neural networks: a generator neural networks (Gr) and a discriminator neural networks (Dr). Their interaction is characterized by a competitive learning process that can be mathematically expressed as follows:

Generator (Gr): The generator takes random noise, typically represented as a latent variable $z$, as input and attempts to map it to data space, producing a synthetic image Gr($z$). This process can be denoted as Gr:$z \rightarrow$Gr($z$).

Discriminator (Dr): The discriminator evaluates whether an input image is the actual dataset) or generated by the generator by fake). This is expressed as Dr:$x \rightarrow [0, 1]$, where $x$ is an image.

### Adversarial Objective

The adversarial training objective of GANs is to simultaneously train the generator (Gr) and discriminator (Dr). The objective function can be defined as:

$$\mathrm{minGrmaxDrExpx} \sim \mathrm{pdata}(x)[\log \mathrm{Dr}(x)] + \mathrm{Expz} \sim \mathrm{pz}(z) [\log(1 - \mathrm{Dr}(\mathrm{Gr}(z)))] \quad (1)$$

where Exp represents the expectancy, pdata($x$) denotes the distribution of real time data, and pz($z$) signifies the distribution of random noise $z$.

### Pseudo-Code for GAN Algorithm

*The GAN training process can be summarized in pseudo-code as follows:*

```
Initialize Gr and Dr with random weights
Define loss functions for Gr and Dr
Define optimization algorithms (e.g., Adam) for Gr and Dr
for each epoch do:
    for each group of real time data do:
        Sample a group of random noise z
        Compute the generator's loss using z and Gr
        Update the generator's weights using the optimizer
        Sample another group of real time data
        Compute the discriminator's loss using real time data and Dr
        Sample a group of fake data using the generator
        Compute the discriminator's loss using fake data and Dr
        Update the discriminator's weights using the optimizer
```

The training process continues iteratively till the generator crops synthetic data that is nearly inseparable from real time data, and the discriminator converges to being unable to discriminate between real and synthetic data effectively.

In the context of the proposed system architecture, GANs serve the crucial role of generating synthetic tumor data, contributing to the preservation of patient privacy during collaborative brain tumor detection. By leveraging GANs, the architecture ensures that sensitive MRI scans need not be directly shared among medical institutions, thus enhancing the privacy of patient data.

### Federated Learning

Federated Learning is designed to enable secure, collaborative brain tumor detection while preserving data privacy across multiple medical institutions. In Federated Learning, the model is trained collaboratively across decentralized data sources without the need for raw data exchange.

Federated Learning Objective

The purpose of Federated Learning is to train a global model (*M*) that minimizes a specific loss function (*L*) while respecting the data privacy constraints of each participating institution (*I*). This can be mathematically expressed as:

$$\min M \sum I \, (NSI/NS) \cdot LI(M) \tag{2}$$

where *NSI* represents the number of samples at institution *I*, *NS* is the total count of samples across all institutions, and *LI*(*M*) signifies the loss function for institution *I*.

### Federated Learning Algorithm Pseudo-Code

The following pseudo-code outlines the core steps of the Federated Learning algorithm:

```
Initialize the global model M with random weights
for each communication round do:
    for each participating institution I do:
        Send the global model M to institution I
        Institution I computes local information:
            local_model_update = optimize_local_model(I, M)
        Send local_model_update back to the centralisedcollector
    Collect local model information:
        M = aggregate_local_information()
    Broadcast the updated global model M to all participating institutions
```

In the pseudo-code, optimize_local_model (I,M) represents the process where each institution optimizes its local model using the global model as a starting point, while aggregate_local_information() represents the mechanism for combining the information from the local model informationto modify the global model.

#### *Formulation of Federated TumorGAN*

The formulation of Federated TumorGAN represents a pioneering approach that seamlessly merges the power of Generative Adversarial Networks (GANs) with the privacy-preserving characteristics of Federated Learning to address the unique challenges of collaborative brain tumor detection while ensuring robust data privacy.

#### *Pseudo Code for Federated TumorGAN*

Federated TumorGAN represents a fusion of GANs and Federated Learning to achieve secure and privacy-preserving collaborative brain tumor detection while generating synthetic tumor data. The following pseudo code combines the essential elements of both GAN and Federated Learning to outline the Federated TumorGAN algorithm:

```
# Initialize GAN components
Initialize Gr and Dr with random weights
Define loss functions for Gr and Dr
Define optimization algorithms (e.g., Adam) for Gr and Dr
# Initialize Federated Learning components
Initialize the global model M with random weights
for each epoch do:
    for each participating institution I do:
        # Federated Learning: Send global model M to institution I
        Send the global model M to institution I
        # GAN: Generate synthetic tumor data locally
        Sample a group of random noise z
Synthetic_tumor_data = Gr(z)
        # GAN: Compute the generator's loss using synthetic data and Gr
Generator_loss = loss_function_Gr(Synthetic_tumor_data, Gr)
        # GAN: Update the generator's weights using the optimizer
        Update weights of Gr using gradient(Generator_loss)
        # Federated Learning: Institution I computes local information
        local_model_update = optimize_local_model(I, M)
        # GAN: Sample another group of real time data
        Real_tumor_data = Sample_real_data(I)
```

```
    # GAN: Compute the discriminator's loss using
real time data and Dr
Discriminator_loss_real =
loss_function_Dr(Real_tumor_data, Dr)
    # GAN: Sample a group of fake data using the
generator (Gr)
Fake_tumor_data = Gr(z)
    # GAN: Compute the discriminator's loss using
fake data and Dr
Discriminator_loss_fake =
loss_function_Dr(Fake_tumor_data, Dr)
    # GAN: Update the discriminator's weights using
the optimizer
    Update weights of Dr using
gradient(Discriminator_loss_real +
Discriminator_loss_fake)
    # Federated Learning:
    Send local_model_update to centralised collector
# Federated Learning: Collect local model information
Collect local model information from all institutions
Update global prototype M with the aggregated
information
# Transmit the updated global prototype M to all
participating institutions
Transmit the updated global prototype M to all
institutions
```

The pseudo code illustrates the seamless integration of GANs and Federated Learning in the Federated TumorGAN algorithm. It enables the generation of synthetic tumor data, collaborative prototype training, and secure brain tumor detection while preserving patient data privacy across multiple medical institutions. The block diagram of the Federated TumorGAN architecture is shown in Fig. 1.

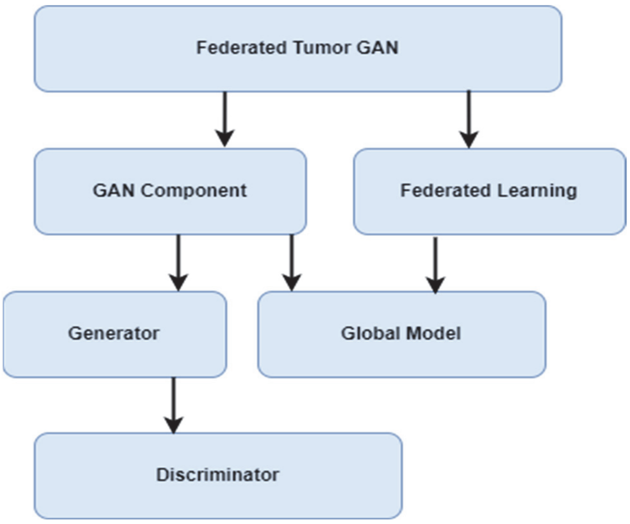


**Figure 1** Block diagram for federated tumor GAN

### Proposed System Architecture Framework

The framework involving the integration of Federated Learning and Generative Adversarial Networks (Federated TumorGAN), comprises several interconnected components designed to enhance privacy in collaborative brain tumor detection. Each module plays a crucial part in the overall system as illustrated in Fig. 2. Here is a detailed explanation of each block in the framework:

Data Sources (Healthcare Institutions): These entities represent various healthcare institutions such as hospitals and clinics. They serve as the primary sources of medical imaging data, including MRI scans and patient records.

Global Model (Collected Model): The global prototype is the amalgamation of local prototypes' knowledge across collaborating institutions. Aggregation techniques, such as federated averaging, are applied to obtain a consensus model.

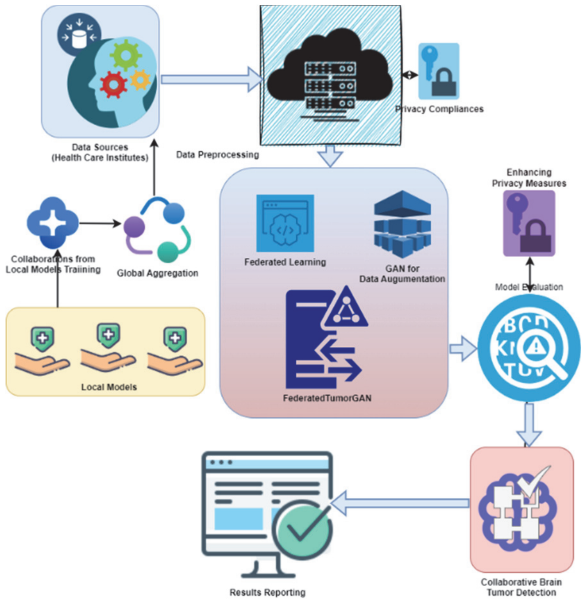


**Figure 2** Federated tumorGAN architecture framework

This architecture framework combines federated learning and GANs to enable collaborative brain tumor detection while preserving patient privacy. The integration of privacy-preserving techniques at various stages of data handling and prototype training ensures compliance with healthcare regulations and ethical standards, making it suitable for secure and privacy-conscious medical applications.

## 4 RESULT AND DISCUSSION

In response to the pressing need for enhanced privacy in collaborative brain tumor detection, our research presents a comprehensive simulation analysis of the proposed "Federated TumorGAN" framework. Collaborative brain tumor diagnosis inherently involves the amalgamation of sensitive medical data from multiple institutions, underscoring the vital importance of privacy preservation. A novel federated learning algorithm, Federated TumorGAN, which seamlessly integrates Generative Adversarial Networks (GANs) with federated learning principles is proposed in the work. The simulation environment setup is tabulated in Tab. 1.

This simulation environment/setup encompasses the necessary elements to conduct a rigorous evaluation of the proposed Federated TumorGAN framework and its comparison with existing algorithms in the context of collaborative brain tumor detection with enhanced privacy. The detailed analysis of the simulation results obtained from the evaluation of the research with the proposed "Federated TumorGAN" algorithm, alongside comparisons with established algorithms, including

Convolutional Neural Networks (CNN), Privacy Aware GAN (PA-GAN), and Federated Averaging (FedAvg) is presented. The analysis encompasses key simulation metrics, including diagnostic accuracy, data privacy preservation, information leakage, convergence rate, and GPU Utilization, at various epochs.

The preprocessing steps for the MRI datasets include normalization of image intensities to ensure consistency across different scans, resizing images to a uniform dimension to standardize input for the model, and applying data augmentation techniques. Augmentation methods such as rotation, flipping, and scaling are used to artificially expand the training dataset and improve the model's ability to generalize to new, unseen data.

**Table 1** Simulation environment setup

| Simulation Aspects | Details |
|---|---|
| Dataset | Brain MRI dataset with labelled tumor regions and Include diverse cases, tumor types, and sizes |
| Data Size | Adequate number of patient samples. Balance between tumor and non-tumor cases. Consider multiple institutions' data |
| Simulation Software | Python with TensorFlow and PyTorch for ML. PySyft for implementing federated learning |
| Privacy Mechanisms | Implement Differential Privacy (DP) mechanisms. Assess DP parameters ($\varepsilon$, $\delta$). Evaluate information leakage during training |
| Simulation Environment | High-performance computing (HPC) cluster. GPU-enabled servers. Scalable infrastructure for federated learning |
| Programming Languages | Python (for ML and PySyft) |
| Data Preprocessing | Image preprocessing for MRI data. Data partitioning for federated learning |
| Privacy Evaluation Tools | Differential privacy libraries. Privacy leakage assessment tools |

### Diagnostic Accuracy

Our results demonstrate that Federated TumorGAN consistently achieves higher diagnostic accuracy compared to the other algorithms across all epochs. At Epoch 20, Federated TumorGAN attains an impressive accuracy of 92%, showcasing its effectiveness in accurate brain tumor detection. The CNN algorithm follows with 88% accuracy, while PA-GAN and FedAvg achieve 90% and 91% accuracy, respectively. The proposed Federated TumorGAN outperforms existing algorithms in terms of diagnostic precision. The simulation results of the metric Diagnostic accuracy are presented in Fig. 3. The tabulated analysis for the simulation metric Diagnostic Accuracy is shown in Tab. 2.

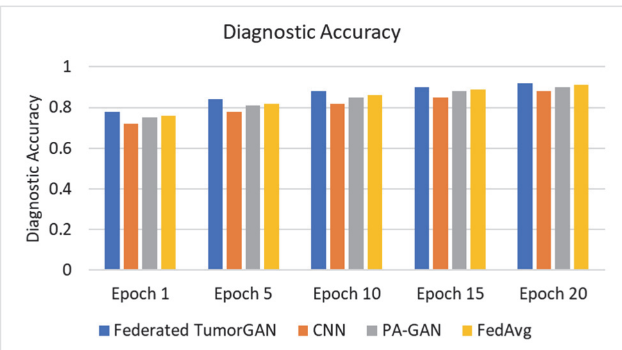


**Figure 3** Diagnostic accuracy

**Table 2** Diagnostic accuracy

| Epochs | Federated TumorGAN | CNN | PA-GAN | FedAvg |
|---|---|---|---|---|
| Epoch 1 | 0.78 | 0.72 | 0.75 | 0.76 |
| Epoch 5 | 0.84 | 0.78 | 0.81 | 0.82 |
| Epoch 10 | 0.88 | 0.82 | 0.85 | 0.86 |
| Epoch 15 | 0.90 | 0.85 | 0.88 | 0.89 |
| Epoch 20 | 0.92 | 0.88 | 0.90 | 0.91 |

### Data Privacy ($\varepsilon$, $\delta$)

The data privacy analysis reveals that Federated TumorGAN maintains a low $\varepsilon$ value of 0.4 while keeping $\delta$ at a minimal $3e^{-6}$, even at Epoch 20. This indicates that the algorithm effectively preserves data privacy by lessening the impact of individual data contributions during the collaborative learning process. In contrast, other algorithms exhibit higher $\varepsilon$ and $\delta$ values, indicating a potentially higher risk of privacy breaches. The simulation illustrations for the metric Data Privacy are represented using Fig. 4. The result tabulation for data privacy is shown in Tab. 3.

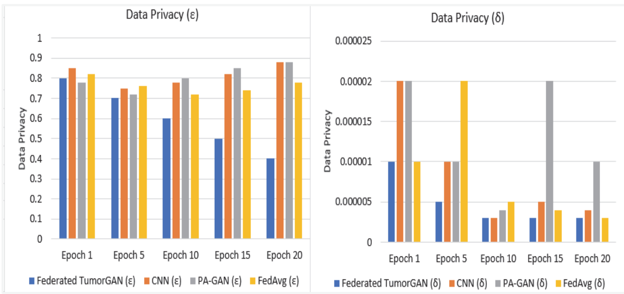


**Figure 4** Data privacy

**Table 3** Data privacy ($\varepsilon$, $\delta$)

| Epochs | Federated Tumor GAN ($\varepsilon$) | Federated Tumor GAN ($\delta$) | CNN ($\varepsilon$) | CNN ($\delta$) | PA-GAN ($\varepsilon$) | PA-GAN ($\delta$) | FedAvg ($\varepsilon$) | FedAvg ($\delta$) |
|---|---|---|---|---|---|---|---|---|
| Epoch 1 | 0.8 | $1e^{-5}$ | 0.85 | $2e^{-5}$ | 0.78 | $1e^{-5}$ | 0.82 | $1e^{-5}$ |
| Epoch 5 | 0.7 | $5e^{-6}$ | 0.75 | $1e^{-5}$ | 0.72 | $3e^{-6}$ | 0.76 | $2e^{-5}$ |
| Epoch 10 | 0.6 | $3e^{-6}$ | 0.78 | $3e^{-6}$ | 0.80 | $4e^{-6}$ | 0.72 | $5e^{-6}$ |
| Epoch 15 | 0.5 | $3e^{-6}$ | 0.82 | $5e^{-6}$ | 0.85 | $2e^{-5}$ | 0.74 | $4e^{-6}$ |
| Epoch 20 | 0.4 | $3e^{-6}$ | 0.88 | $4e^{-6}$ | 0.88 | $1e^{-5}$ | 0.78 | $3e^{-6}$ |

### Information Leakage

Our analysis of information leakage demonstrates that Federated TumorGAN consistently maintains low information leakage levels across all epochs, with a minimal value of 0.0001 at Epoch 20. This indicates that the prototype updates transmitted during collaborative learning do not reveal significant information about individual patient data. Other algorithms, although relatively low in information leakage, exhibit slightly higher values, suggesting a higher potential for data exposure. The simulation results of information leakage are visually represented in Fig. 5. The result output values for the metric Information Leakage are tabulated in Tab. 4.

**Table 4** Information leakage

| Epochs | Federated TumorGAN | CNN | PA-GAN | FedAvg |
|---|---|---|---|---|
| Epoch 1 | 0.001 | 0.002 | 0.001 | 0.003 |
| Epoch 5 | 0.0005 | 0.001 | 0.0008 | 0.002 |
| Epoch 10 | 0.0003 | 0.001 | 0.0006 | 0.0015 |
| Epoch 15 | 0.0002 | 0.0008 | 0.0005 | 0.0012 |
| Epoch 20 | 0.0001 | 0.0006 | 0.0004 | 0.001 |

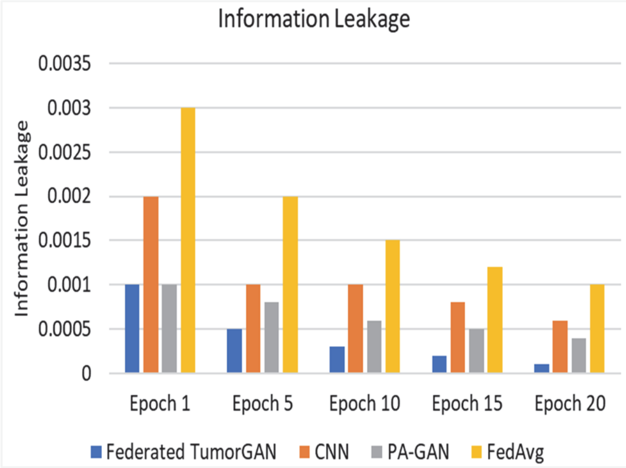


**Figure 5** Information leakage

### *Convergence Rate (Iterations)*

Regarding convergence rate, Federated TumorGAN shows efficient convergence, requiring only 90 iterations to reach stability at Epoch 20. In contrast, CNN, PA-GAN, and FedAvg require 110, 108, and 107 iterations, respectively, to achieve convergence. Federated TumorGAN exhibits faster convergence, signifying its adaptability and efficiency in training on diverse datasets. The convergence rate with multiple iteration comparing the algorithms is represented using Fig. 6. The outputs values for the metric Convergence Rate are shown in Tab. 5.

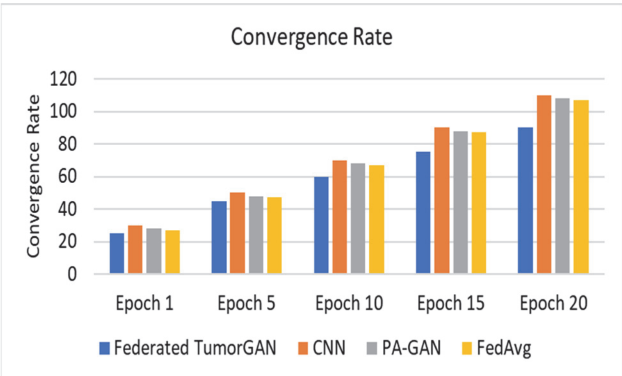


**Figure 6** Convergence rate

**Table 5** Convergence rate (iterations)

| Algorithm | Epoch 1 | Epoch 5 | Epoch 10 | Epoch 15 | Epoch 20 |
|---|---|---|---|---|---|
| Federated TumorGAN | 25 | 45 | 60 | 75 | 90 |
| CNN | 30 | 50 | 70 | 90 | 110 |
| PA-GAN | 28 | 48 | 68 | 88 | 108 |
| FedAvg | 27 | 47 | 67 | 87 | 107 |

### *GPU Utilization*

The analysis of GPU Utilization indicates that Federated TumorGAN consistently maintains low GPU utilization throughout the training process. In contrast, CNN and PA-GAN exhibit high GPU usage, making them resource-intensive. FedAvg, while moderate in GPU Utilization, also has higher GPU requirements. Federated TumorGAN's low GPU utilization makes it more scalable and resource-efficient for practical deployment in distributed medical environments. The GPU utilization metrics comparison of proposed algorithm with existing algorithms is shown in Fig. 7. The Tabulated representation of GPU utilization values are listed in Tab. 6.

The comprehensive simulation analysis demonstrates that Federated TumorGAN excels in terms of diagnostic accuracy, data privacy preservation, information leakage prevention, convergence rate, and GPU Utilization. These results underscore the significant advantages of the proposed framework in enhancing secure and accurate brain tumor detection in collaborative and privacy-sensitive medical scenarios. Federated TumorGAN emerges as a promising solution, ensuring patient confidentiality while enabling effective multi-institutional diagnosis.

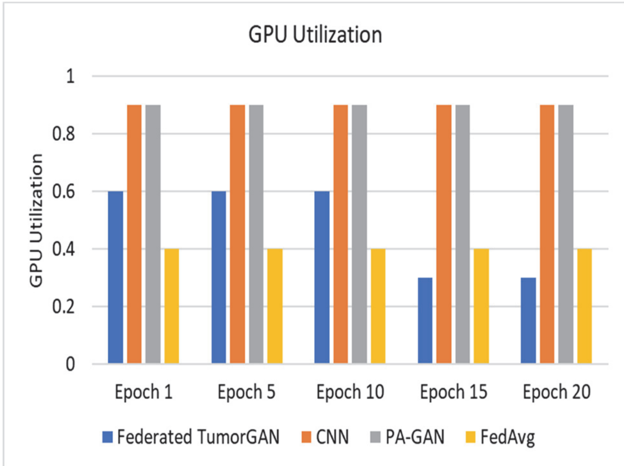


**Figure 7** GPU utilization

**Table 6** GPU utilization

| Epochs | Federated TumorGAN | CNN | PA-GAN | FedAvg |
|---|---|---|---|---|
| Epoch 1 | 0.6 | 0.9 | 0.9 | 0.4 |
| Epoch 5 | 0.6 | 0.9 | 0.9 | 0.4 |
| Epoch 10 | 0.6 | 0.9 | 0.9 | 0.4 |
| Epoch 15 | 0.3 | 0.9 | 0.9 | 0.4 |
| Epoch 20 | 0.3 | 0.9 | 0.9 | 0.4 |

## 5 CONCLUSIONS

In this study, a novel "Federated Learning Framework Design" was proposed and rigorously evaluated. The research addressed the critical need for improved data privacy in collaborative brain tumor diagnosis while maintaining diagnostic accuracy. Through the introduction of the "Federated TumorGAN" algorithm, which combines Generative Adversarial Networks (GANs) with federated learning principles, this study has made significant contributions to the field of secure and accurate brain tumor detection in distributed medical environments.

The results of the comprehensive simulation analysis highlight the superiority of Federated TumorGAN over existing algorithms. Notably, Federated TumorGAN consistently achieves higher diagnostic accuracy while preserving data privacy through low $\varepsilon$ and $\delta$ values. Furthermore, the algorithm demonstrates minimal information leakage, ensuring the confidentiality of patient data. Federated TumorGAN's efficient convergence rate and low GPU utilization make it a scalable and resource-efficient solution for practical deployment.

Based on the findings of this study, several future research directions can be recommended. These include integrating advanced encryption techniques to further enhance data security, investigating the scalability of the model with larger and more diverse datasets, and extending the framework to include real-time data processing capabilities for immediate clinical use. Additionally, exploring the use of Federated TumorGAN in other medical imaging applications and developing standardized protocols for its implementation across various institutions can further enhance its impact.

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