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RESEARCH ARTICLE

Medical Image Classification with Privacy: Centralized and Federated Learning Comparison

Classificação de Imagens Médicas com Privacidade: Comparação entre Aprendizado Centralizado e Federado

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Abstract: The use of different techniques in image-based medical diagnostic computing has positively impacted the healthcare industry. Diseases such as colon and lung cancer can be detected using image classification strategies. In this context, Federated Learning (FL) has emerged as an enabling approach to disease detection with security and privacy when handling sensitive patient data. This study aimed to compare the centralized and FL classifications of histopathological images of lung and colon cancer. We compared the performance of FL with that of centralized learning, and the results indicated that FL outperformed centralized approaches in scenarios with heterogeneous datasets. These findings highlight the potential of FL as an alternative to medical image classification, particularly in privacy-sensitive applications.
Keywords: Federated Learning — Centralized Learning — Image Classification — Cancer — Deep Learning

Resumo: O uso de diferentes técnicas de computação no diagnóstico médico baseado em imagem impactou positivamente o setor de saúde. Doenças como câncer de cólon e pulmão podem ser detectadas usando estratégias de classificação de imagem. Nesse contexto, o aprendizado federado surgiu como uma abordagem facilitadora para detecção de doenças com segurança e privacidade ao lidar com dados sensíveis de pacientes. Este estudo teve como objetivo comparar as classificações centralizada e federada de imagens histopatológicas de câncer de pulmão e cólon. Comparamos o desempenho do aprendizado federado com o do aprendizado centralizado, e os resultados indicaram que o aprendizado federado superou as abordagens centralizadas em cenários com conjuntos de dados heterogêneos. Essas descobertas destacam o potencial do aprendizado federado como uma alternativa à classificação de imagens médicas, particularmente em aplicações sensíveis à privacidade.
Palavras-Chave: Aprendizado Federado — Aprendizado Centralizado — Classificação de Imagens — Cancer — Aprendizado Profundo

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1. Introduction

Colorectal and lung cancers are among the most prevalent and deadly forms of cancer worldwide. According to the World Health Organization (WHO), lung cancer is the leading cause of cancer-related deaths among men globally and the second leading cause among women. Similarly, colorectal cancer is one of the most common cancers, affecting both men and women [1][2].

Analysis of medical images, such as histopathological slides, is essential for accurate diagnosis and treatment planning. However, the sheer volume of data generated in modern medical practice presents significant challenges for pathologists [3] [4]. In this sense, computer-aided diagnosis systems based on image processing and AI techniques enable the accurate diagnosis of diseases from medical images, facilitating earlier detection and personalized treatment for patients. Moreover, these techniques are financially attractive, particularly in developing countries [3][5].

Nevertheless, the increasing reliance on centralized learning models, which require the aggregation of vast amounts

of sensitive medical data in a central server, raises significant concerns regarding patient privacy and data security [4][6][7]. To overcome these concerns, Federated Learning (FL) has emerged as a promising alternative that offers a decentralized approach in which models are trained across multiple institutions or devices without the need to share raw data. This paradigm not only addresses privacy concerns but also leverages the computational power distributed across the network, potentially reducing latency and increasing the robustness of the model [8][9].

FL has been successfully applied in various domains, including healthcare [6], agriculture [10], and cybersecurity [11], demonstrating the effectiveness of this technique in addressing privacy and computational challenges. Despite these advantages, a gap remains in the understanding of how FL compares with traditional centralized learning in the context of medical image classification, particularly regarding performance, scalability, and privacy preservation [4].

Therefore, the main goal of this paper is to compare centralized and FL approaches for medical image classification. Our evaluation includes histopathological image dataset, focusing on the classification performance, efficiency of the training environment, and preservation of data privacy. Our main contributions are: (i) comparing FL with centralized learning, training, and testing the AI model on different datasets; (ii) evaluation of the robustness of the AI model in heterogeneous environments; and (iii) preserving data privacy ensures that sensitive patient data remain localized, enhancing privacy while maintaining the classification performance.

The remainder of this paper is organized as follows. Section 2 surveys the related work. Section 3 describes the material and methods. Section 4 presents and discuss the results. Finally, conclusion and future work are presented in Section 5.

2. Related Work

The use of FL for disease detection has been widely explored in various medical scenarios. For instance, the model proposed by Rehman et al.[12] aims to classify different types of cancer, such as prostate, lung, and breast cancer, using a structure called FedCSCD-GAN, which combines FL with Generative Adversarial Networks (GANs). In addition, the study defines hospitals as distributed clients to evaluate data from different institutions. The approach achieved an accuracy of 97.80% for lung cancer, 96.95% for prostate cancer, and 97% for breast cancer.

Adnan et al. [13] investigated lung cancer and the effects of Independent and Identically Distributed (IID) and non-Identically Distributed (non-IID) data using The Cancer Genome Atlas (TCGA) dataset, which contains images of various types of lung cancer. The study examines the impact of different domains on histopathological image sources and demonstrates performance and privacy guarantees in distributed training using Multiple Instance Learning (MIL). The model achieved approximately 80% accuracy in lung cancer classification in both IID and non-IID contexts.

Nergiz [14] proposed an approach for colorectal cancer classification using deep learning, FL, and centralized learning techniques. The model employs a structure called Big Transfer, which is a method of General Visual Representation Learning, alongside the VGG deep learning architecture as a classifier. The results demonstrate the potential of FL in generalizing well in various medical scenarios, providing a robust evaluation of medical images.

Tan et al. [15] proposed using FL for breast cancer classification, ensuring patient data privacy by avoiding information sharing between hospitals. The approach employs Transfer Learning to extract features from mammography images, improving diagnostic accuracy. Additionally, it applies the synthetic minority oversampling technique (SMOTE) to balance the dataset and enhance model performance. The experimental results show that the proposed approach achieved a classification accuracy of approximately 98%.

Subashchandrabose et al. [16] proposed an approach based on FL for multiorder lung cancer classification. They integrated conventional machine-learning models, specifically Support Vector Machine (SVM) and Neural Networks, trained on diverse datasets containing lung cancer images. Agbley et al. [17] proposed an approach that combines different magnification factors of histopathological images using a residual network and information fusion in FL to support the automatic classification of breast cancer. Hossain et al. [18] used the same dataset considered in our study and evaluated the an Inception-V3 with FL. However, their approach only addressed IID data, unlike our study, which examined a more complex non-IID scenario.

In contrast to previous studies, our study compares federated and centralized learning in different contexts. By focusing on non-IID data, we provide a more comprehensive assessment of FL in real-world medical environments where data heterogeneity is common. FL offers a promising framework for disease detection, allowing institutions to keep data locally for privacy and security, while benefiting from a global model trained on distributed data from multiple sources, such as hospitals or healthcare units.

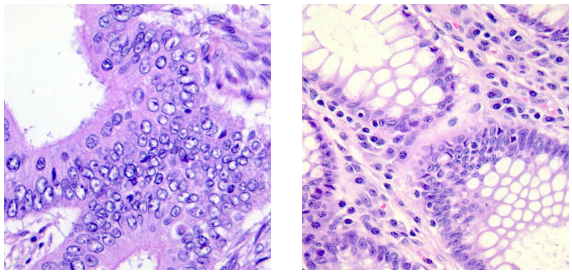
3. Material and Methods

3.1 Dataset

We obtained the images used in this work from the Lung and Colon Cancer Histopathological Images (*LC*25000)[1] [19] and are in RGB format. The colon images have two classes: normal (10,000 images), and cancer (10,000 images) as illustrated in Fig. 1.

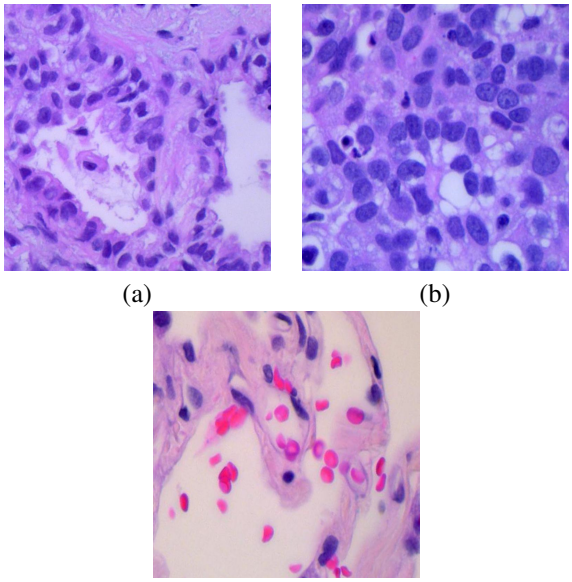
The lung dataset contained three classes: benign lung tissue (5,000 images), lung adenocarcinoma (5,000 images), and lung squamous cell carcinoma (5,000 images) [20] as illustrated in Fig. 2. For this study, we considered all images of adenocarcinoma and squamous cells as cancer classes.

[1] ⟨https://www.kaggle.com/andrewmvd/lung-and-colon-cancer-histopathological-images⟩



(a) Cancer (b) Normal

Figure 1. Colon dataset.



(a) (b)

(c)

Figure 2. Lung Classes: (a) Cancer (Adenocarcinoma); (b) Squamous Cell (Cancer); (c) Normal.

3.2 Lightweight Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a multi-step image classification technique that incorporates spatial context and weight sharing among pixels to extract high-level hierarchical representations of the data [21] [22]. In this study, SqueezeNet [23] was selected because of its compact architecture and ability to perform accurately on low-cost computing devices, which are essential for resource-constrained environments such as mobile and edge computing [5]. Consequently, SqueezeNet is suitable for this study, as it facilitates efficient training and inference on non-IID distributed datasets, which are characteristic of FL scenarios where computational efficiency and model size are critical factors.

3.3 Federated Learning

FL is a decentralized approach for training machine learning models, where data remain locally on user devices, and only model parameters are shared. Instead of centralizing large volumes of data on a single server, FL distributes model training across multiple devices, which collaborate to build a global model [8][9]. This technique is useful in privacy-sensitive scenarios such as medical image classification, where data cannot be easily shared owing to legal or ethical constraints [7].

Each participating device, known as a client, trains a local model using its data and then sends the weight updates to a central server. The server aggregates these updates to form a global model, enabling the training process to benefit from diverse data sources without compromising data privacy [9] [24].

The Federated Averaging (FedAvg) [9] algorithm is a common method used in FL to aggregate locally trained models into global models. In this approach, each client independently trains a model using its local data and then sends the updated model weights to a central server. The server then computes a weighted average of these model weights, where the contribution of each client model is proportional to the size of its local dataset. The global loss function $L(\mathbf{w})$ is the weighted sum of the individual loss functions $L_i(\mathbf{w})$ from each client as defined by Eq. 1:

$$L(\mathbf{w}) = \sum_{i=1}^{N} \frac{n_i}{n} L_i(\mathbf{w}), \tag{1}$$

where n_i represents the number of data samples on client i, and $n = \sum_{i=1}^{N} n_i$ is the total number of samples across all clients. We consider a round an iteration where clients train their models locally and communicate updates to the central server. After each round of local training, the global model is updated by aggregating the local models using using Eq. 2:

$$\mathbf{w}_{t+1} = \sum_{i=1}^{N} \frac{n_i}{n} \mathbf{w}_i^{(t)}, \tag{2}$$

where $\mathbf{w}_{t+1}$ is the updated global model after round $t+1$. This process enables the system to leverage the data distributed across different clients, improving model performance while maintaining data privacy.

3.4 Evaluation Protocol

We measured the classification performance considering accuracy, precision, recall, and F1-score [25]. Where T_P is true positive, T_N is true negative, F_P is false positive and F_N is false negative. Accuracy is the hits of the classifier as whole. Precision is the hit rate per class for positive cases. Recall is the rate of a relevant sample being classified correctly. Finally, F1-Score is the harmonic mean of Recall and Precision.

Finally, Fig. 3 illustrates the steps of the proposed method. We aggregated all the data from the two medical image dataset sources into a single server for the centralized learning approach, where the model was trained and evaluated. By contrast, the FL approach involves two clients, C_1 and C_2, each performing local training on their data, and we used the non-IID strategy. We considered two clients because increasing the number of clients does not necessarily enhance accuracy performance, particularly in scenarios involving heterogeneous data [24]. The results from these clients are aggregated on a central server to update the model.

Our approach considers the distinct rounds of each environment, from data handling and local training to global model aggregation, highlighting the differences in data privacy, communication, and training processes between centralized and federated methods.

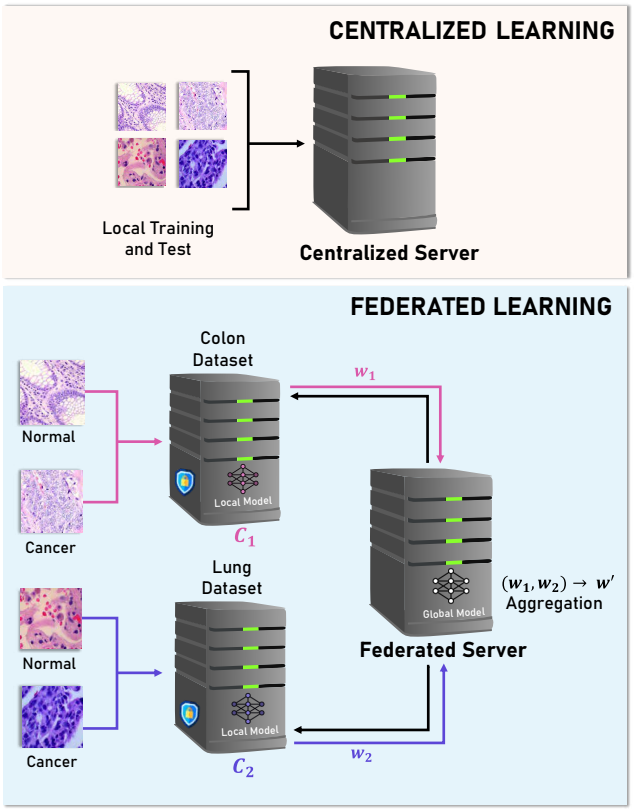


Figure 3. Proposed Comparison Method.

4. Results and Discussions

We conducted all experiments using the national-wide tested Fabric [26], on which we launched a virtual machine with 32 vCPU, 16 GB RAM, and an NVIDIA A30 GPU with 24 GB. We programmed the experiments using Python (version 3.11), PyTorch [27], and Flower FL framework [28].

Initially, the datasets were randomly partitioned into two subsets: 80% for training and 20% for testing. All images were resized to 224 × 224 pixels for input into SqueezeNet. We used the SGD optimizer with a learning rate of 0.001, batch size of 64, and 30 epochs. The decision to use only 30 epochs was based on preliminary experiments that showed convergence within this period. We implemented FL using the FedAvg algorithm with a setup comprising clients C_1, C_2, and one central server. During each round, a client performs local training on its dataset, and the server aggregates the model updates from all clients to form a global model. This setup enabled us to simulate a real-world scenario in which data are distributed across multiple devices, enhancing privacy by keeping the data local while still enabling collaborative model training.

In the centralized approach, we conducted several experiments considering six scenarios. The first is described by a training set with colon images, and testing with a hybrid set (colon and lung). In the second scenario, the training consists of lung images, and the test consists of hybrid images. In the third and fifth scenarios, the training set contains colon images, but in the third scenario's test set there are lung images, and in the fifth scenario's test set there are colon images. The training set contains lung images in the fourth and sixth scenarios, but the fourth scenario's test set has colon images and the sixth scenario's test set contains lung images. All experiments were conducted using SqueezeNet and the results are summarized in Table 1.

The results show that the FL strategy simulated a hospital institution during the detection of two different diseases. All disease images were grouped into a single class, called cancer, and healthy images were grouped into a normal class.

Fig. 4 shows the evolution of loss and accuracy during the training of clients C_1 and C_2 in different rounds. Each round represents a full iteration where clients train their models locally, send the updated model parameters to the central server, and the server aggregates these updates into a new global model. Notice that both clients converge quickly to low loss and high accuracy, suggesting that the models trained on each client fit well with the respective datasets. This indicates that the model is well-tuned and that the aggregation process in FL combines the updates from the clients efficiently, resulting in models that generalize well to the local data.

The training accuracy approaching 1 (100%) after just a few epochs across all rounds shows that the model can quickly learn and adjust to each client's local data, maintaining consistent performance across rounds. Furthermore, the stability of the loss and accuracy graphs in subsequent rounds (2 and 3) indicates that once the model is successfully trained in an initial round, updates in subsequent rounds do not result in significant changes in the model's performance. This suggests the model is already well-adjusted to each client's local data.

We considered three classification scenarios. In the first, the server has colon images and lung images. In the second scenario, the server is defined by colon images. In the third, the server has only lung images. In the last scenario, the model probably did not assimilate information well to generalize lung and colon classes. Therefore, this scenario was the one that presented the lowest results of the entire work.

The first scenario was the most challenging and best-performing since we trained the data on different clients and tested with random images from each colon and lung data. Thus, considering the non-IID aspect, where the data is not distributed identically, the approach overcame such challenges by achieving accuracy rates of 99.32%. In addition, it obtained a recall of 99.31% for positive cancer detections.

In the centralized approach, we noticed that when the model is trained on images of one type of cancer and tested on images of the other type (e.g., trained on colon and tested on lung), the performance is quite poor, with significantly lower

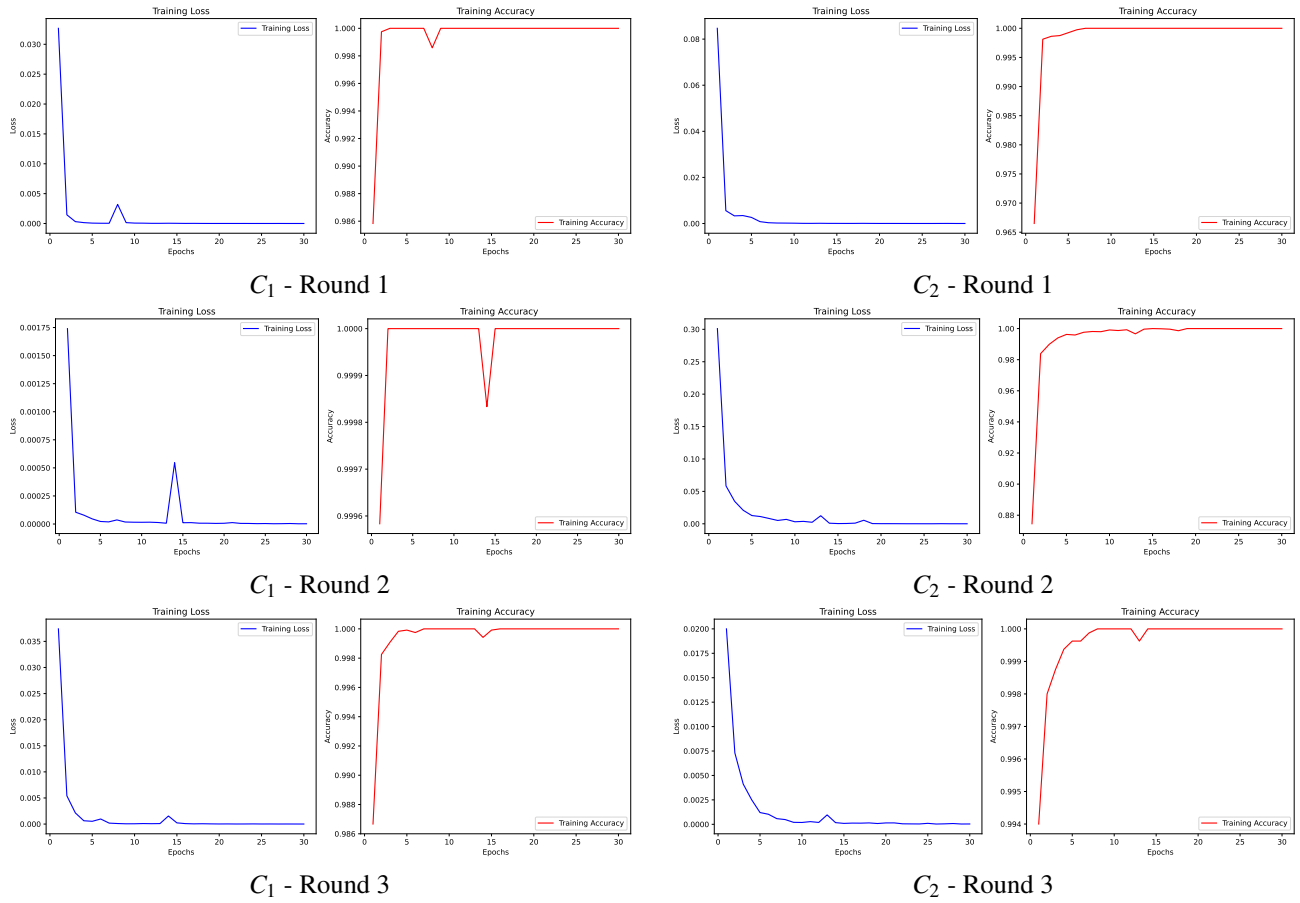


Figure 4. Evolution of loss and accuracy values throughout the training rounds of C_1 (lung dataset – left) and C_2 (colon dataset – right).

accuracy, precision, and other metrics. This is because the histopathological features of colon and lung cancer images are very different. Therefore, a model trained to identify one type of cancer does not generalize well when tested on images of another type.

Nevertheless, performance improves considerably when the model is trained and tested on the same type of cancer, especially for lung cancer, where accuracy reaches 100%. This may suggest that the lung cancer images in the dataset are more homogeneous or have more distinct visual features, making classification easier.

Training a model on colon cancer images and trying to predict lung cancer images is an interesting scenario because, even if the images are of different cancer types, the model can still capture some general features of cancerous tissue that could be useful for classification in other contexts. However, as the results show (Lung column for training with colon), the accuracy is only 50% or less, which confirms that these features are not sufficient for good generalization.

In the federated scenario, when testing with both cancer types (colon and lung), the accuracy, precision, recall, and F1-score reach 99%. This can be explained by combining data from both cancer types in training and testing, the model has access to a wider range of examples and can capture both the distinctive and general characteristics of cancerous tissues, improving overall performance.

In FL, since the data is distributed, each client can train on specific features (colon or lung), and combining the models on a central server helps improve generalization for both cancer types in the test set. The ability of FL to aggregate knowledge from different clients results in a more robust and accurate model when applied to a more diverse test set (colon + lung).

These results underscore the benefits of integrating data from diverse sources (in this case, cancer types) and employing FL to train the model, enabling better generalization compared to a centralized environment.

FL has demonstrated a clear advantage in scenarios involving heterogeneous datasets. This approach allows the global model to efficiently aggregate information from various data sources, resulting in a more robust and adaptable model. In contrast, centralized learning, which trains the model solely on a single type of data, fails to capture the diversity inherent in heterogeneous datasets, thus impairing its generalization capabilities.

Moreover, centralized learning performs poorly when tested on domains different from those used during train-

Table 1. Classification performance considering different approaches.

Environment	Training	Test	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Centralized	Colon	Colon + Lung	89.86	89.45	89.41	89.43
	Lung	Colon + Lung	60.00	30.00	50.00	37.50
	Colon	Lung	66.67	33.33	50.00	40.00
	Lung	Colon	50.00	25.00	50.00	33.33
	Colon	Colon	50.55	50.00	25.27	33.58
	Lung	Lung	100	100	100	100
Federated Learning	**C_1: Colon C_2: Lung**	**Server: Colon + Lung**	**99.32**	**99.28**	**99.31**	**99.32**
	C_1: Colon C_2: Lung	Server: Lung	98.43	98.85	97.64	98.21
	C_1: Colon C_2: Lung	Server: Colon	48.40	50.00	24.20	32.61

ing. For instance, in our experiments, the centralized model trained on colon cancer data showed significantly reduced performance when tested on lung cancer data. In contrast, FL proved effective in generalizing across diverse data, achieving high precision, recall, and F1-score metrics. Additionally, FL offers privacy-related benefits, as it keeps the data localized on the users' devices (clients) and transmits only model updates to the server. This ensures that users' raw data are never directly shared with the server, thus enhancing security and data protection.

5. Conclusion

In this paper, we propose an empirical comparison of FL and centralized learning for image-based disease classification. We combined different datasets to evaluate how CNN performs in a non-IID scenario, where the model encounters unseen samples. FL not only achieved superior performance but also effectively protects data privacy, as it ensures that patient images and other sensitive data remain decentralized on local devices. This privacy benefit applies broadly to all types of data, sensitive or not, by minimizing the need for direct data sharing with central servers

Furthermore, FL reduced the number of ambiguous detections by training multiple local models. By allowing models to learn locally and then combine the acquired knowledge centrally, FL achieves significantly better performance than traditional centralized learning when considering situations where data are heterogeneous.

This study will facilitate mutual integration between doctors and patients in image-based detection and provide security for data processing. Consequently, it is an interesting alternative for accurate disease diagnoses. In future work, we plan to optimize the hyperparameters, evaluate different medical imaging datasets, and employ more advanced techniques, such as differential privacy, to further improve both model performance and data protection in FL.

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Author contributions

LGFR: Conceptualization, Methodology, Software, Investigation, Validation, Visualization, Writing - original draft. GVGB: Conceptualization, Methodology, Validation, Writing - original draft. RM: Methodology, Investigation, Validation, Resources, Writing - Review & Editing. LFRM: Methodology, Validation, Visualization, Writing - Review & Editing. ARB: Supervision, Funding acquisition, Resources, Writing - Review & Editing, Project administration.

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