

PSO-based Client Selection to Improve Medical Image Classification in Federated Learning

Seleção de Clientes Baseada em PSO para Melhorar a Classificação de Imagens Médicas em Aprendizado Federado

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Abstract: Federated Learning (FL) offers an effective approach to enable collaborative model training across decentralized medical institutions while preserving patient privacy. However, FL faces challenges related to data heterogeneity and inefficient client participation issues. In this study, we introduce a novel client selection strategy based on Particle Swarm Optimization (PSO) to improve medical image classification in federated settings. Our method dynamically selects informative clients by evaluating their contributions to the global model, which reduces communication overhead and supports faster convergence. We performed experiments using three publicly available medical imaging datasets, Biglycan, ALL-IDB, and LC25000, focusing on binary classification tasks. The results show that the PSO-based approach improves performance over random client selection across all evaluated scenarios, with gains in accuracy, recall, precision, and F1-Score, even when selecting fewer clients. These findings indicate that incorporating PSO into FL frameworks helps address challenges related to data heterogeneity and communication efficiency while maintaining classification performance and privacy preservation.

Keywords: federated learning — particle swarm optimization — image classification — client selection — deep learning

Resumo: O Aprendizado Federado oferece uma abordagem eficaz para possibilitar o treinamento colaborativo de modelos entre instituições médicas descentralizadas, preservando a privacidade dos pacientes. No entanto, o Aprendizado Federado enfrenta desafios relacionados à heterogeneidade de dados e problemas de participação ineficiente de clientes. Neste estudo, introduzimos uma nova estratégia de seleção de clientes baseada em Otimização por Enxame de Partículas (PSO) para melhorar a classificação de imagens médicas em ambientes federados. Nosso método seleciona dinamicamente clientes informativos avaliando suas contribuições para o modelo global, o que reduz a sobrecarga de comunicação e promove convergência mais rápida. Realizamos experimentos utilizando três conjuntos de dados de imagens médicas publicamente disponíveis: Biglycan, ALL-IDB e LC25000, com foco em tarefas de classificação binária. Os resultados demonstram que a abordagem baseada em PSO melhora o desempenho em comparação com a seleção aleatória de clientes em todos os cenários avaliados, com ganhos em acurácia, revocação, precisão e F1-Score, mesmo quando seleciona menos clientes. Essas descobertas indicam que a incorporação do PSO em frameworks de Aprendizado Federado auxilia no enfrentamento dos desafios relacionados à heterogeneidade de dados e eficiência de comunicação, mantendo o desempenho da classificação e a preservação da privacidade.

Palavras-Chave: aprendizado federado — otimização por enxame de partículas — classificação de imagens — seleção de clientes — aprendizado profundo

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1. Introduction

Medical imaging plays a vital role in modern healthcare by enabling the early and accurate diagnosis of various diseases, including cancer and respiratory disorders [1, 2]. Techniques such as X-ray imaging, computer tomography (Computer Tomography) (CT), and microscopy generate rich visual data that support clinical decision-making. In recent years, the rapid digitization of medical records and imaging data has opened new possibilities for automated diagnostic tools [3].

Deep learning, particularly Convolutional Neural Network (CNN), has emerged as a powerful approach for analyzing medical images [4]. CNNs are effective at extracting hierarchical features from complex image data, achieving high accuracy in tasks such as disease detection and classification [3–5].

Despite these advancements, the development of robust deep learning models in healthcare is often hindered by privacy concerns and strict regulations regarding patient data sharing. Medical data are sensitive and subject to frameworks such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) [6]. Federated Learning (FL) addresses these challenges by enabling decentralized model training, where only model parameters—not raw data—are shared across institutions. This approach significantly reduces the risk of data breaches while ensuring patient confidentiality [6–8].

Nevertheless, FL faces challenges related to data heterogeneity and high communication costs. To mitigate these issues, intelligent client selection strategies have gained traction, especially those based on optimization techniques that prioritize participants with higher-quality or more representative data. Among these, Particle Swarm Optimization (PSO) stands out for its efficiency in guiding client selection based on swarm intelligence principles [9, 10].

In this study, we propose a novel approach that combines FL with PSO-based client selection to enhance medical image classification. Our method aims to (i) select the most informative clients using PSO to accelerate convergence and maximize data utility, (ii) improve classification performance through decentralized training over heterogeneous datasets, and (iii) to evaluate the proposed method through comprehensive experiments comparing selection strategies across varying FL configurations.

The remainder of this paper is organized as follows: Section 2 discusses related work on FL and client selection techniques. Section 3 describes the proposed approach based on PSO for client selection. Section 4 presents and discusses the experimental results. Finally, Section 5 provides the concluding remarks and directions for future work.

2. Related Work

Approaches based on FL have gained prominence in medical applications owing to their ability to preserve data privacy [6, 8].

Miao et al. [11] introduced FedSAF, targeting gastric cancer detection under non-IID conditions. Their model employs attention-based message passing and the Fisher Information Matrix to enhance accuracy while using model splitting to reduce the computational load.

Ning et al. [12] developed FedGCS, a generative client selection strategy that uses gradient-based optimization and metrics such as energy usage and latency. The approach selects optimal clients through continuous representations and improves global model performance by up to 15%, reducing communication delays in heterogeneous environments.

To mitigate communication overhead, De Souza et al. [9] proposed an adaptive client selection method based on each client’s contribution to the global model. Their approach reduced communication costs and improved personalization and convergence, particularly in nonindependent and identically distributed (non-IID) contexts.

Wu et al. [13] proposed a centralized federated deep fuzzy neural network combined with multi-objective neural architecture search for epistatic detection. Their method leverages heuristic optimization techniques to balance the model accuracy and architectural complexity. Experiments demonstrated superior performance over traditional federated approaches in genomic datasets, achieving improvements in both detection precision and computational efficiency.

Agarwal et al. [10] introduced a FL strategy that integrates dataset splitting and weighted averaging, optimized through PSO. Their method improved the global model accuracy and fairness in client contributions, especially under non-IID data distributions. Experiments showed that PSO-enhanced aggregation, at its best result, achieved 98.9% accuracy with AlexNet using ten clients.

Ouyang et al. [14] presented FedDPSO, a hybrid approach combining knowledge distillation and PSO for noisy label scenarios. It improved accuracy by up to 15% over Federated Averaging (FedAvg) and 11% over FOCUS on the CIFAR datasets.

In contrast to the aforementioned studies, our study introduces a client selection strategy based on PSO, which is specifically applied to medical imaging scenarios. Unlike prior applications of PSO for model aggregation or architecture search, we leverage PSO to dynamically select the most suitable clients for each communication round, thereby enhancing the global model performance and demonstrating the effectiveness of FL in preserving privacy and optimizing collaborative training across decentralized institutions with realistic and heterogeneous medical data.

3. Material and Methods

This section describes the proposed method. We describe the procedures and conditions under which our experiments were conducted and the metrics used for the evaluation.

3.1 Medical Image Datasets

This study evaluated three publicly available medical imaging datasets, Biglycan¹, ALL-IDB², and LC25000³, for binary classification tasks to distinguish between cancerous and healthy samples.

The Biglycan dataset comprises 336 images of breast tissue, categorized as 203 cancerous and 133 healthy, and curated to support biomarker-based cancer detection [15]. The ALL-IDB dataset includes 260 images of blood smears, evenly split between acute lymphoblastic leukemia (ALL) and healthy samples, and is widely used for benchmarking hematological malignancy detection [16]. Finally, the LC25000 dataset [17] contains colon and lung tissue image data. The colon subset included 10,000 normal and 10,000 cancerous images, whereas the lung subset comprised 15,000 images spanning benign, adenocarcinoma, and squamous cell carcinoma cases.

For consistency, only binary subsets (cancer vs. non-cancer) were used in this study. Examples of image samples from the datasets used in this study are presented in Fig. 1, including Biglycan (a, e), ALL-IDB (b, f), and LC25000 (c, d, g, h), with both cancerous and healthy samples.

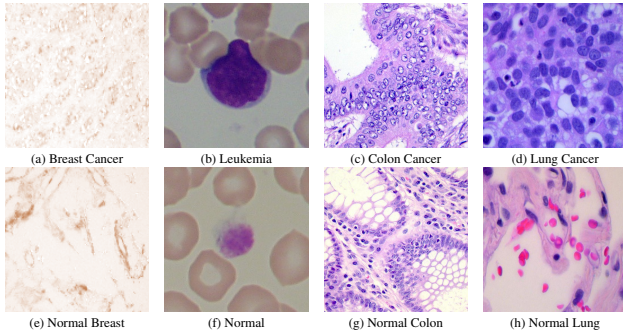


Figure 1. Examples of cancerous (top row) and healthy (bottom row) tissue images from different datasets.

3.2 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) have demonstrated remarkable capabilities in capturing spatial hierarchies within visual data, enabling the extraction of complex features across multiple layers. Recent studies have emphasized the importance of understanding spatial context in CNNs, particularly through explainable methods that enhance interpretability in applications such as remote sensing and environmental monitoring [18].

In this study, we opted for SqueezeNet because of its compact architecture and efficiency, making it well-suited for deployment on low-power and resource-constrained devices. Notably, SqueezeNet's design has been further optimized using techniques such as weight quantization, enhancing its applicability in embedded systems such as robot vacuums for indoor obstacle classification [19].

¹<https://data.mendeley.com/datasets/mpscwxb7/3>

²<https://scotti.di.unimi.it/all/>

³<https://www.kaggle.com/andrewmvd/lung-and-colon-cancer-histopathological-images>

3.3 Federated Learning

Federated Learning (FL) is a decentralized approach for training machine learning models, where data remain local to user devices, and only model parameters are shared. Rather than centralizing large volumes of data on a single server, FL distributes model training across multiple devices, which collaborate to build a global model [20][21]. This technique is particularly useful in privacy-sensitive contexts, such as medical image classification, where data cannot be easily shared owing to legal or ethical constraints [6].

Each participating device, referred to as a client, trains a local model using its data and then sends weight updates to a central server. The server aggregates these updates to form a global model, allowing the training process to benefit from diverse data sources without compromising data privacy [22].

One of the most widely adopted aggregation strategies in FL is the FedAvg algorithm [21]. In FedAvg, each client updates a local model using its dataset and transmits the resulting weights to a central server. Instead of simply selecting a model, the server computes a weighted mean of all received parameters, where the influence of each client is scaled according to the number of data samples it holds. 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:

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

where n_i is the number of training examples on client i , and $n = \sum_{i=1}^N n_i$ is the total number of samples across all the participating clients. Each communication round consists of local model updates, followed by global aggregation. The new global model after round $t + 1$ is computed using Eq. 2:

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

where $\mathbf{w}_i^{(t)}$ is the model obtained by client i in round t . This iterative procedure allows the system to benefit from decentralized training while preserving data locality and privacy guarantees.

3.4 Proposed Client Selection Approach

To improve the training performance of the federated model for medical image classification tasks, we propose a client selection strategy based on PSO, described in Algorithm 1.

PSO is a population-based optimization algorithm inspired by the social behavior of swarms, such as birds. It optimizes solutions by combining individual and shared experiences [23]. In our context, the PSO is employed to dynamically select the most promising clients for each communication round in a federated learning setup. Each client is represented as a particle in the search space, encoded by a binary position vector $x_i \in \{0, 1\}^N$, where 1 indicates the selection. The initial fitness value f_i of each particle is computed

Algorithm 1 PSO Client Selection

Require: Clients C with accuracy scores, number to select K
Ensure: Selected clients S

- 1: Initialize swarm $\mathcal{P}$ with random positions $x_i \in \{0, 1\}$ and velocities v_i
- 2: **for** each particle i **do**
- 3: Compute fitness $f_i \leftarrow \text{Evaluate}(x_i, C)$
- 4: Set $p_{\text{best},i} \leftarrow x_i$
- 5: **end for**
- 6: Set $g_{\text{best}} \leftarrow \arg \max(f_i)$
- 7: **for** each iteration **do**
- 8: **for** each particle i **do**
- 9: Update v_i and x_i using PSO equations
- 10: $f_i \leftarrow \text{Evaluate}(x_i, C)$
- 11: **if** $f_i > f(p_{\text{best},i})$ **then**
- 12: $p_{\text{best},i} \leftarrow x_i$
- 13: **end if**
- 14: **if** $f_i > f(g_{\text{best}})$ **then**
- 15: $g_{\text{best}} \leftarrow x_i$
- 16: **end if**
- 17: **end for**
- 18: **end for**
- 19:
- 20: **return** $S \leftarrow \text{Decode } g_{\text{best}}$

based on the validation accuracy of the corresponding client subset, which captures its contribution to the global model performance. During each iteration, the particle velocities and positions are updated using standard PSO equations, which are influenced by the personal best $p_{\text{best},i}$ and global best position g_{best} . These updates guide the search toward client subsets that maximize overall fitness, enabling a balance between the exploitation of high-performing clients and the exploration of alternatives. After convergence, the selected clients correspond to the indices marked in g_{best} , forming subset S for that round.

Algorithm 2 details the fitness evaluation function, which is invoked within the main PSO procedure (Algorithm 1). This function establishes a crucial link between the optimization search and FL objective. For each candidate solution, represented by a particle's binary position vector x_i , the function simulates a complete round of federated training using only the corresponding subset of the clients. This simulation involves distributing the current global model, performing local training on each client's private data, and aggregating the resulting model updates via FedAVG to form a new temporary global model. Finally, the new model was evaluated using a held-out validation dataset. The resulting accuracy is returned as the fitness score, which guides the PSO search toward the client combination that maximizes the global model performance.

The search behavior of the swarm, as outlined in Algorithm 1, is directed by several parameters. These parameters are utilized during the particle update step and include the

Algorithm 2 Fitness Evaluation Function

1: **function** Evaluate(particle position x_i , Clients C)
Require: Current global model M_g , Validation dataset D_{val}
Ensure: Fitness score (validation accuracy)

- 2: $C_{\text{selected}} \leftarrow \{c_j \in C \mid x_{ij} = 1\}$ {Decode binary vector to a client set}
- 3: $M_{\text{local\_updates}} \leftarrow \emptyset$
- 4: **for** each client c in C_{selected} **do**
- 5: Send M_g to client c
- 6: $M_{\text{local}} \leftarrow \text{TrainLocally}(M_g, \text{data}_c)$ {Client trains model on its local data}
- 7: Add M_{local} to $M_{\text{local\_updates}}$
- 8: **end for**
- 9: $M_{g'} \leftarrow \text{FederatedAverage}(M_{\text{local\_updates}})$ {Aggregate local models}
- 10: $\text{accuracy} \leftarrow \text{TestModel}(M_{g'}, D_{\text{val}})$ {Test new global model}
- 11: **return** accuracy
- 12: **end function**

inertia weight (w), which balances global and local exploration; the cognitive coefficient (c_1), which attracts a particle toward its personal best position (p_{best}); and the social coefficient (c_2), which pulls the particle toward the swarm's global best position (g_{best}). These parameters are integrated into the velocity update defined in Eq. 3 for each particle i .

$$v_i(t+1) = wv_i(t) + c_1r_1(p_{\text{best},i} - x_i(t)) + c_2r_2(g_{\text{best}} - x_i(t)), \quad (3)$$

where r_1 and r_2 are random numbers uniformly distributed in $[0, 1]$. Because the client selection problem is binary, the resulting continuous velocity vector is used to probabilistically update the particle's binary position, x_i . This is typically accomplished by applying a sigmoid function to the velocity to determine the probability of each element in the position vector being updated to 1.

The PSO parameters were configured as follows: cognitive (c_1) and social (c_2) coefficients were set to 2.0, following the standard formulation where these values provide balanced exploration-exploitation trade-offs [23]. The inertia weight ($w = 0.7$) was chosen to maintain swarm stability while preventing premature convergence. A population size of 30 particles proved sufficient to cover the search space without excessive computational overhead in our preliminary experiments.

The algorithm executed 100 iterations per communication round, ensuring convergence (typically achieved within 50-70 iterations) while maintaining FL efficiency. These settings collectively optimize the trade-off between selection quality and computational cost in federated scenarios. In each FL round, PSO dynamically selects only the most contributive client subset (typically 10-30% of available clients) for global model updates, as determined by their validation accuracy-based fitness scores.

This strategy enables adaptive and data-aware client selection while preserving scalability. Compared with static or random selection schemes, the PSO-based approach facilitates faster convergence, improved robustness to data heterogeneity, and better use of communication rounds in federated medical imaging tasks.

3.5 Evaluation Protocol

We measured the classification performance considering accuracy, precision, recall, and F1-score [24]. Finally, Fig. 2 illustrates the steps of the proposed method. We aggregated all data from the three sources of medical image datasets into a single server for the PSO-free approach where the model was trained and evaluated. By contrast, the FL approach involves n clients each performing local training on their data, and we used the non-IID strategy.

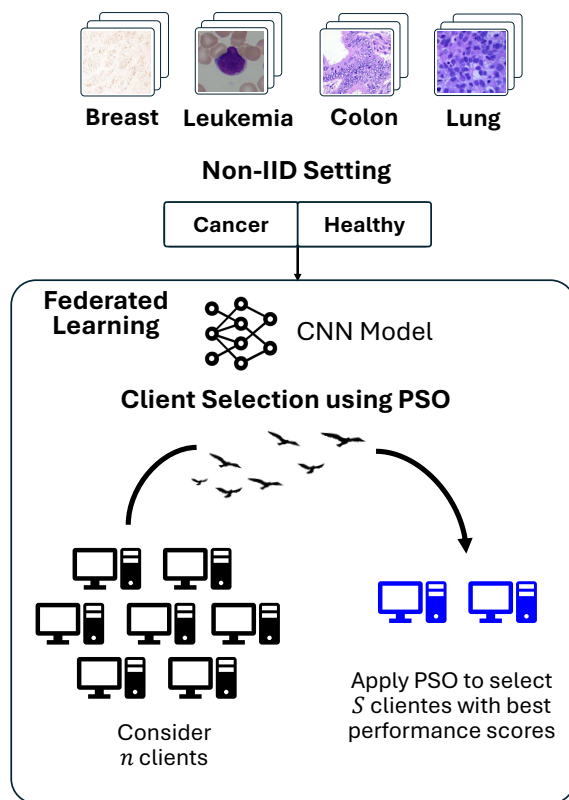


Figure 2. Steps of the Proposed Method.

4. Results and Discussion

All experiments were conducted in a virtual machine with 32 GB of RAM, 32 vCPU, and an NVIDIA Quadro RTX 6000 GPU on the Fabric testbed [25] with CUDA version 12.2. The experiments were programmed using Python 3.8.10, PyTorch 2.4.1, and Flower FL Framework 1.11.1.

To establish a performance baseline, we first implemented a FL setup using random client selection, where a fixed number of clients were chosen uniformly at random in each round without considering local performance or data quality. Model

updates from the selected clients were aggregated using the standard FedAvg algorithm, and no optimization heuristic was applied.

All datasets were combined into a global set using FL. Furthermore, were distributed in a non-IID manner across clients. Thus, both training and evaluation involve all datasets together, without distinguishing their individual contributions.

Table 1 summarizes the experimental results, including both the baseline configuration and the best-performing settings obtained through PSO-based client selection. The configurations shown reflect those that achieved the highest F1-Scores for each client group, highlighting the benefit of adaptive selection strategies over uniform sampling.

We compared the average values of the classification metrics across different numbers of communication rounds, as shown in Fig. 3. The results indicate that the model performance tends to improve and stabilize as the number of rounds increases, particularly when optimized client selection strategies, such as PSO are employed.

Figure 4 demonstrates PSO's superior convergence behavior, where the F1-Score consistently improves with additional communication rounds, especially in large-scale client setups. This reflects both reduced sensitivity to data heterogeneity and more efficient global model updates compared to random selection. This figure shows that FL performance does not depend linearly on the number of clients or rounds. When there are few clients, few rounds are sufficient. However, many rounds require a larger number of clients to mitigate the effects of heterogeneity.

The client selection behavior in the best-performing experimental configurations is illustrated in Fig. 5, where all clients are represented as blue dots and the best clients selected by PSO over the training rounds appear as red crosses.

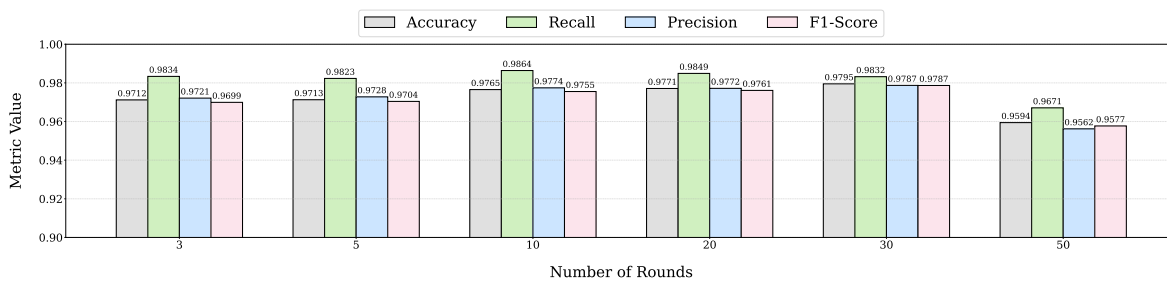
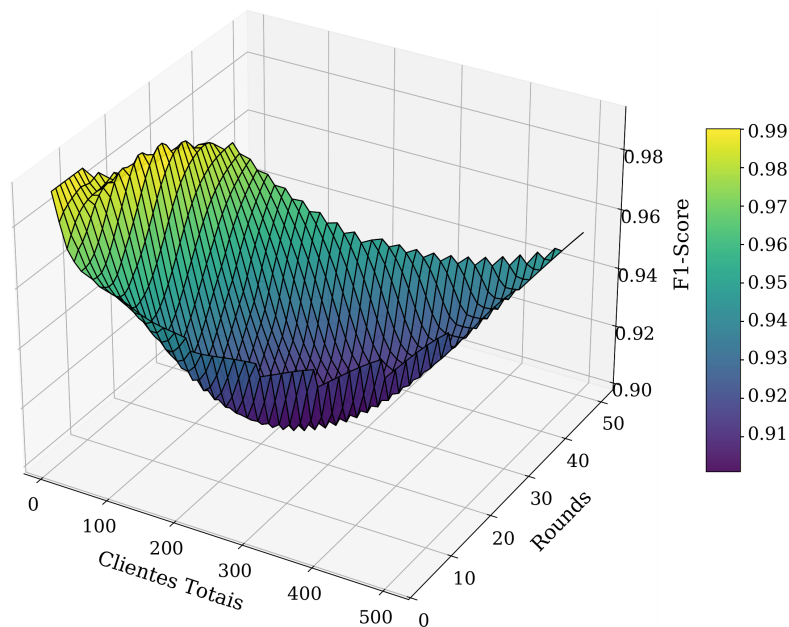
The results demonstrate that SqueezeNet provides client selection strategy most stable and consistent. With a small client population (e.g., 10), the model achieves rapid and stable convergence, even with few rounds and selected clients, indicating low sensitivity to the hyperparameters in homogeneous scenarios. As the number of clients increased (30, 50, 100), the performance variability increased, particularly in the early rounds and with limited client selection, reflecting the challenges posed by increased heterogeneity.

Rather than relying on random selection, PSO guides the process by favoring clients whose predicted probability vectors contribute significantly to the global performance, indicating better exploration of the solution space and mitigation of client variability, as can be seen in Figure 6. It shows the F1-Score values according to the number of total and selected clients, and the number of rounds of both comparisons.

PSO-based client selection strategy achieved higher F1-Scores across all tested configurations, from the smallest (10 clients, 2 selected, with perfect 0.9900 scores in all metrics) to the largest (500 clients, 30 selected, F1-Score: 0.9697). For example, in the configuration with 100 clients and 10 selected, the PSO approach maintained a high F1-Score of 0.9817.

Table 1. Comparison between the best-performing configurations using PSO and the baseline using Random selection.

Strategy	Total Clients	Selected Clients	Rounds	Accuracy	Recall	Precision	F1-Score
PSO	10	2	3	0.9900	0.9900	0.9900	0.9900
Random	10	2	3	0.9801	0.9800	0.9785	0.9792
PSO	30	2	10	0.9857	0.9984	0.9879	0.9851
Random	30	2	10	0.9797	97.88	0.9789	0.9789
PSO	50	5	10	0.9850	0.9971	0.9869	0.9843
Random	50	5	10	0.9584	0.9535	0.9625	0.9572
PSO	100	10	30	0.9824	0.9863	0.9819	0.9817
Random	100	10	30	0.9600	0.9600	0.9500	0.9600
PSO	500	30	50	0.9709	0.9749	0.9605	0.9697
Random	500	30	50	0.9670	0.9653	0.9660	0.9657

**Figure 3.** Metric comparison by number of rounds.**Figure 4.** 3D surface plot showing the F1-Score based on the number of clients and communication rounds.

Additionally, it significantly reduced training time-completing the largest configuration in just 12 hours compared to 24 hours for random selection. This demonstrates the method's scalability and practical advantages for real-world FL systems.

5. Conclusion

This study introduced a PSO-based client selection strategy to enhance federated learning in medical image classification tasks, particularly under non-IID data distributions. The proposed method demonstrated improvements over random

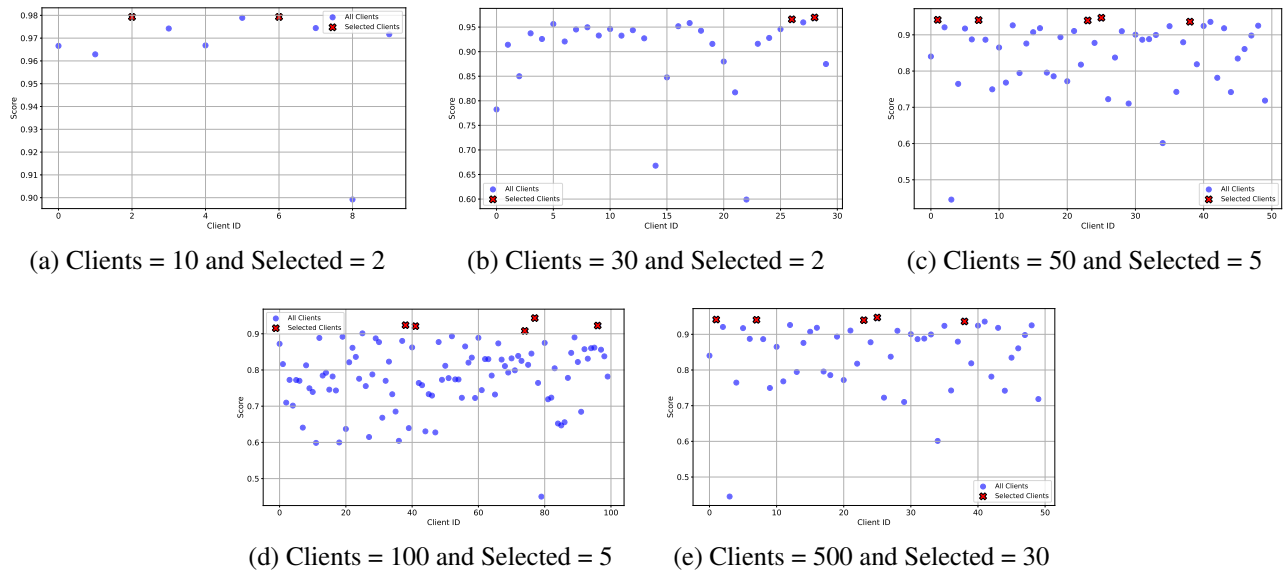


Figure 5. Selected clients in the best experiments with PSO.

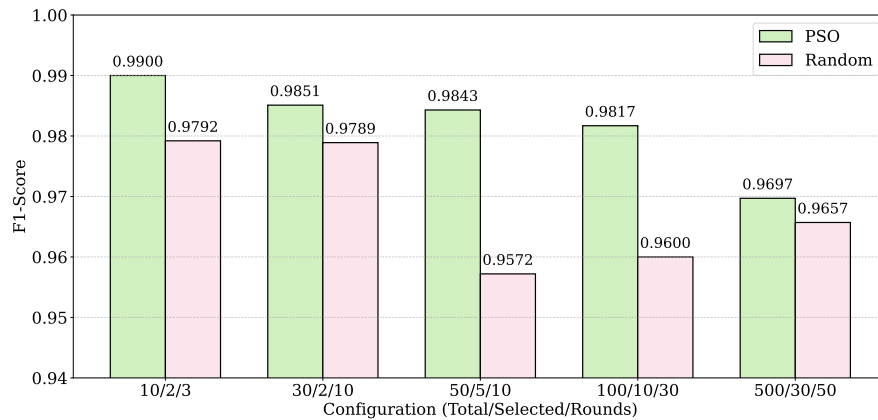


Figure 6. Comparison between evaluated strategies.

selection across a wide range of experimental configurations, achieving higher accuracy, recall, precision, and F1-Score.

Additionally, our approach maintained a strong performance even with a limited number of selected clients, while also reducing the training time in large-scale scenarios. These results validate the effectiveness of integrating heuristic optimization into the FL pipeline, offering a scalable and adaptive solution that addresses challenges such as convergence instability and data heterogeneity.

Although this study focused on the challenges of medical image classification, the proposed PSO-based selection mechanism is task-agnostic. It optimizes the selection based on performance feedback, a principle that is directly applicable to any classification task within an FL framework. This highlights the potential of our method as a valuable tool in other domains where data heterogeneity is a significant challenge, such as finance or the Internet of Things (IoT).

In future work, we intend to extend our investigation to

alternative metaheuristic strategies, including hybrid or adaptive algorithms that consider both client performance and data diversity. We also plan to evaluate the approach in real-world federated environments and analyze the trade-offs between optimization overhead and communication cost in dynamic or resource-constrained settings.

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Author Contributions

Leonardo Gabriel Ferreira Rodrigues contributed to experiments, statistical analysis, and prepared figures; Larissa Fer-

reira Rodrigues Moreira contributed to conception, design, writing, and funding; Rodrigo Moreira contributed to conception, design, and writing; André R. Backes contributed to supervision, writing, and funding.

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