Revista de Informática Teórica e Aplicada - RITA - ISSN 2175-2745
Vol. 33, Num. 2 (2026) 178-184

RESEARCH ARTICLE

Federated Semantic Segmentation of Synthetic UAV Imagery under Non-IID Conditions

Segmentação Semântica Federada de Imagens Sintéticas de VANT sob Condições Não-IID

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Abstract: Unmanned Aerial Vehicles (UAVs) rely on semantic segmentation for monitoring, inspection, and disaster response tasks. Traditional centralized training requires the transfer of large data volumes, which is often infeasible because of privacy, bandwidth, and decentralization constraints. Federated Learning (FL) offers a promising alternative; however, non-IID data hinder its effectiveness because UAVs operate in diverse environments with heterogeneous distributions. This study evaluated the adaptation of a semantic segmentation model to a federated setting using synthetic UAV imagery. We investigated four training configurations by varying the communication rounds, local epochs, and learning rates, and analyzed their effects on convergence and class-level accuracy. The results suggest that moderate communication with local training achieves balanced performance, whereas high learning rates or excessive synchronization cause instability and class-specific biases. These findings open avenues for designing robust federated UAV segmentation strategies under non-IID conditions.
Keywords: federated learning — semantic segmentation — UAV control — non-IID data

Resumo: Veículos Aéreos Não Tripulados (VANTs) dependem cada vez mais da segmentação semântica para tarefas de monitoramento, inspeção e resposta a desastres. O treinamento centralizado tradicional exige a transferência de grandes volumes de dados, o que muitas vezes é inviável devido a restrições de privacidade, largura de banda e descentralização. O Aprendizado Federado (AF) surge como uma alternativa promissora; no entanto, dados não-IID limitam sua eficácia, já que os VANTs operam em ambientes diversos com distribuições heterogêneas. Este estudo avaliou a adaptação de um modelo de segmentação semântica a um cenário federado utilizando imagens sintéticas de VANTs. Investigamos quatro configurações de treinamento, variando o número de rodadas de comunicação, épocas locais e taxas de aprendizado, e analisamos seus efeitos na convergência e na acurácia por classe. Os resultados indicam que uma comunicação moderada combinada com treinamento local proporciona desempenho equilibrado, enquanto taxas de aprendizado elevadas ou sincronização excessiva levam à instabilidade e a vieses específicos de classe. Esses achados abrem caminho para o desenvolvimento de estratégias robustas de segmentação federada em VANTs sob condições não-IID.
Palavras-Chave: aprendizado federado — segmentação semântica — controle de VANTs — dados não-IID

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DOI: http://dx.doi.org/10.22456/2175-2745.150921 • **Received:** 14/10/2025 • **Accepted:** 28/10/2025
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1. Introduction

Unmanned Aerial Vehicle (UAV) is increasingly employed in applications such as environmental monitoring, disaster response, precision agriculture, and infrastructure inspection [1, 2, 3]. These tasks often rely on semantic segmentation models to interpret aerial imagery at the pixel level, enabling the fine-grained recognition of terrain, vegetation, and man-made structures. Traditional approaches train such models in a centralized manner, requiring the collection and transmission of large-scale image datasets to a single server for processing. However, in UAV-based operations, this paradigm is impractical because of privacy constraints, limited bandwidth, and the decentralized nature of data acquisition across geographically distributed fleets [4].

Federated Learning (FL) has emerged as a promising alternative, enabling multiple clients to collaboratively train a shared model without directly exchanging raw data [5, 6, 7]. Although attractive in principle, applying FL to semantic segmentation tasks presents unique challenges. A major difficulty arises from non-Independent and Identically Distributed (non-IID) data, as UAVs operate in diverse environments with distinct visual characteristics. This heterogeneity can significantly hinder model convergence, exacerbate class imbalance, and reduce the generalization capacity of aggregated models [4, 8].

Although prior research has explored FL for image classification tasks [7, 9], studies targeting UAV semantic segmentation are scarce. Moreover, most existing studies focus on classification accuracy or communication efficiency, leaving open questions about how training-time hyperparameters, such as the number of communication rounds, local epochs, and learning rate, affect convergence under non-IID conditions. Addressing this gap is essential to understand the trade-offs between local computation and global synchronization and to design FL strategies that remain robust in real-world UAV deployments [4, 10].

To investigate these challenges, we rely on a recently proposed synthetic UAV dataset [2], generated using Robotic Operational System (ROS) [11] and Gazebo [12] with photo-realistic rendering and semantic labels. Synthetic data provide a controlled yet realistic environment for experimentation, overcoming the costs, risks, and annotation efforts associated with real-world UAV imagery. This choice enabled us to simulate non-IID client distributions while preserving fidelity to realistic aerial scenarios, thereby offering a solid foundation for analyzing the federated training convergence in semantic segmentation.

This study addresses the gap in understanding how FL performs in UAV semantic segmentation when the data are heterogeneous and synthetically generated. While most prior studies emphasize classification or communication efficiency, little attention has been paid to how hyperparameter configurations affect model convergence and class-level performance under non-IID conditions. To fill this gap, this study makes the following contributions.

- We design a federated training framework for semantic segmentation using synthetic UAV imagery, simulating non-IID client distributions to reflect realistic operating conditions.
- We evaluate the impact of hyperparameter configurations on model convergence, highlighting trade-offs between communication frequency and local computation.
- We analyze class-level performance using confusion matrices and macro-accuracy, revealing the asymmetric behavior of federated models under non-IID conditions and the bottlenecks caused by class imbalance and boundary ambiguity.

The remainder of this paper is organized as follows. Section 2 reviews the main works related on FL and semantic segmentation. Section 3 describes the proposed method. Section 4 presents and discusses the results. Finally, Section 5 concludes the paper and outlines the directions for future research.

2. Related Work

Ullah et al. [13] proposed a Split Federated Learning (SFL) framework for UAV-based aerial video event recognition, addressing spatiotemporal heterogeneity, resource constraints, and communication bottlenecks in distributed UAV networks. Although their focus was on temporal event recognition rather than semantic segmentation, their results confirmed that data heterogeneity and limited UAV resources remain critical challenges across UAV-based FL applications.

Miao et al. [14] proposed a federated framework for semantic segmentation that addresses class imbalance across clients by incorporating a modified cross-entropy loss and a local-to-global contrastive loss. Their approach demonstrated how tailored loss functions can mitigate performance degradation in scenarios where clients possess disjoint class distributions. Although they focused on pixel-level segmentation tasks, their strategies for handling class heterogeneity and evaluating per-class performance are highly relevant to our work.

Alshammari et al. [15] proposed a FL framework for semantic segmentation in autonomous driving, which combined a hybrid UNet-ResNet34 architecture with differential privacy mechanisms. Their experiments on the CARLA simulator demonstrated that FL can effectively handle decentralized training across heterogeneous clients while maintaining strong segmentation performance and safeguarding sensitive data.

Imandi et al. [16] developed a Fog-enabled UAV-as-a-Service platform that integrates FL for aerial image classification in disaster response scenarios. Although their focus is on image-level classification rather than dense prediction, their study highlights the importance of designing FL models that address privacy, communication, and sustainability constraints in UAV networks.

Godavarthi et al. [17] proposed a FL-based semantic segmentation framework for sustainable forest monitoring. Their method introduced a sequential client-training paradigm that improved performance over FedAvg when applied to aerial and satellite imagery of the Amazon and Atlantic forests. Using U-Net and DeepLabV3+ backbones, their approach achieved higher scores under non-IID conditions while preserving privacy and reducing the communication overhead.

Xie et al. [18] introduced a FL framework for semantic segmentation of terminal blocks in smart substations. Their approach integrates U-Net with a convolutional block attention module, combined with a privacy-preserving, anonymous authentication protocol and data augmentation to mitigate heterogeneity.

Table 1. Comparison with related work.

Work	Approach	UAV	Non-IID
[13]	Event recognition	✓	✓
[14]	Urban segmentation	×	✓
[15]	Autonomous driving	×	✓
[16]	Disaster classification	✓	✓
[17]	Forest monitoring	×	✓
[18]	Segmentation of terminal blocks	×	✓
Ours	**UAV clients + composite loss**	✓	✓

Table 1 compares recent FL approaches for UAV scenarios. Unlike prior work, our method combines UAV-based FL with composite loss for class-imbalanced, non-IID data. While previous studies have examined segmentation and privacy separately, few have evaluated UAV networks using class-level metrics. Our approach uses decentralized training with composite loss to enhance generalization and evaluate configurations for robustness.

3. Proposed Method

The proposed method adapts a high-resolution semantic segmentation network to a FL setting, in which multiple UAV clients are trained on heterogeneous synthetic datasets without sharing raw data. Each client performs local training and periodically communicates the model updates to a central server. The server aggregates these updates into a global model, which is redistributed to the clients for the next communication cycle. Fig. 1 illustrates our proposed method.

The FL environment consists of one federated server and four UAV clients, each holding a non-IID partition of the synthetic dataset. This design simulates realistic UAV operations in diverse environments where client data distributions differ significantly. The communication between the server and clients follows the standard Federated Averaging (FedAvg) procedure. The global model was optimized using a composite loss function that integrated three complementary terms: Dice Loss, Cross-Entropy Loss, and Boundary Loss. The combined objective is expressed in Equation 1.

$$\mathscr{L}_{total} = \alpha \cdot \mathscr{L}_{Dice} + \beta \cdot \mathscr{L}_{CE} + \gamma \cdot \mathscr{L}_{Boundary}, \quad (1)$$

Where $\mathscr{L}_{Dice}$ mitigates class imbalance by emphasizing underrepresented regions, $\mathscr{L}_{CE}$ enforces pixel-wise consistency with class weighting, and $\mathscr{L}_{Boundary}$ improves contour accuracy for fine UAV structures. The weights α, β, and γ were empirically tuned to balance accuracy and boundary precision, and optimization was performed with Adam.

The composite objective was designed to balance the pixel consistency (cross-entropy), region overlap incentives (Dice), and contour sensitivity (boundary-aware term).

For the segmentation backbone, we adopted the High-Resolution Network (HRNet) [19], which maintains high-resolution feature representations throughout the network by connecting multi-scale branches in parallel and repeatedly exchanging information. The HRNet preserves spatial details that are often lost in downsampling-heavy architectures, such as encoder–decoder models. The architecture was integrated into the FL pipeline, where each client trained its local copy of the model. After each round, the model weights were transmitted to the server and aggregated.

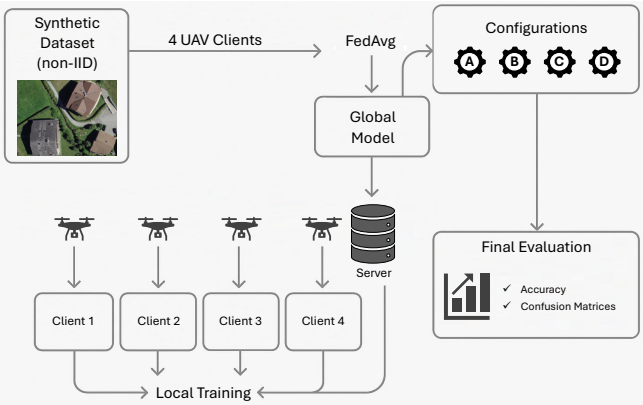


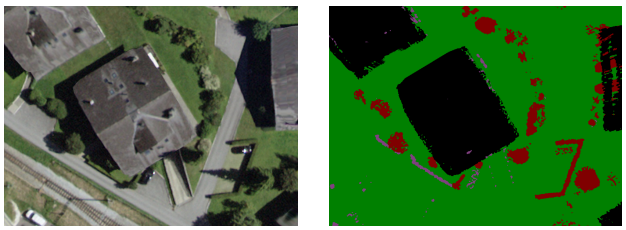
Figure 1. Proposed method.

We utilized the photorealistic synthetic UAV dataset proposed by Silva et al. [2], generated in ROS and Gazebo from Swiss geospatial data. The dataset covers diverse environments, such as forests, rivers, and urban areas, with images captured using different UAV models, altitudes, and camera angles. Each image contains pixel-level semantic labels and depth maps. Fig. 2 shows an example image and its segmentation map. For our study, we used 10,451 annotated images for training and 3,512 for validation, partitioned across four clients in a non-IID manner to emulate heterogeneous UAV conditions.

To investigate the effect of hyperparameters, we defined four configurations by varying the number of communication rounds, local epochs, and Learning Rate (LR) (Table 2). This comparison highlights the trade-offs between local computation and global synchronization under non-IID conditions.

As detailed in Algorithm 1, the server initializes a global model and runs R training rounds. At each round, the model is broadcast to four UAV clients, which train locally for E epochs using the composite loss (Eq. 1). The updated weights are then returned and aggregated via FedAvg, producing a weighted average without sharing the raw data.

After R rounds, the global model is evaluated on a held-out



(a) RGB image (b) Segmentation map

Figure 2. Example from the synthetic UAV dataset [2].

Table 2. Evaluated configurations.

Config.	Rounds	Epochs/Client	LR
A	3	50	0.001
B	3	70	0.0001
C	5	100	0.001
D	10	20	0.001

Algorithm 1 Federated Semantic Segmentation Method

Initialize global model $w^{(0)}$
for all config $\mathbf{c} \in \mathscr{C}$ **do**
  Set $(R, E, \eta) \leftarrow \mathbf{c}$
  for $t = 1$ to R **do**
    Broadcast $w^{(t-1)}$ to clients
    for all client k in parallel **do**
      Train E epochs on local $\mathscr{D}_k$ using $\mathscr{L}_{total}$
      Return w_k to server
    end for
    Aggregate $w^{(t)} \leftarrow \sum_k \frac{n_k}{\sum_j n_j} w_k$ ▷ FedAvg
  end for
  Evaluate $w^{(R)}$
end for

validation set using class-wise accuracy, macro-accuracy, and confusion matrices, which capture the overall performance and expose the asymmetric behavior across classes caused by data heterogeneity.

4. Results and Discussion

All experiments were conducted in five virtual machines with 32 GB of RAM, 32 *v*CPU, and an NVIDIA Quadro RTX 6000 GPU on the Fabric testbed [20] 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 [21].

The experimental evaluation assessed the adaptation of HRNet to a FL environment with synthetic UAV data, focusing on the interplay between training-time convergence, data heterogeneity, and hyperparameter optimization. The setup included four federated clients and one central server. The dataset was partitioned in a non-IID manner across clients to simulate UAVs operating in heterogeneous environments.

To examine the trade-offs between local computation and global communication, we explored four configurations, which are summarized in Table 2. Configuration **A** served as a baseline with few global rounds and a relatively high learning rate, intended to test the rapid convergence under limited communication. Configuration **B** increased the number of local epochs while reducing the learning rate ($LR = 0.0001$), aiming to stabilize client updates during aggregation, albeit at the cost of a longer training time to reach convergence. Configuration **C** simultaneously increased both the number of rounds and local epochs, allowing more frequent synchronization and richer local training, with the objective of mitigating client drift and improving convergence under non-IID conditions. Finally, configuration **D** emphasized frequent synchronization by increasing the number of communication rounds while reducing the local epochs, which was designed to investigate whether shorter local training could be compensated by more regular global updates.

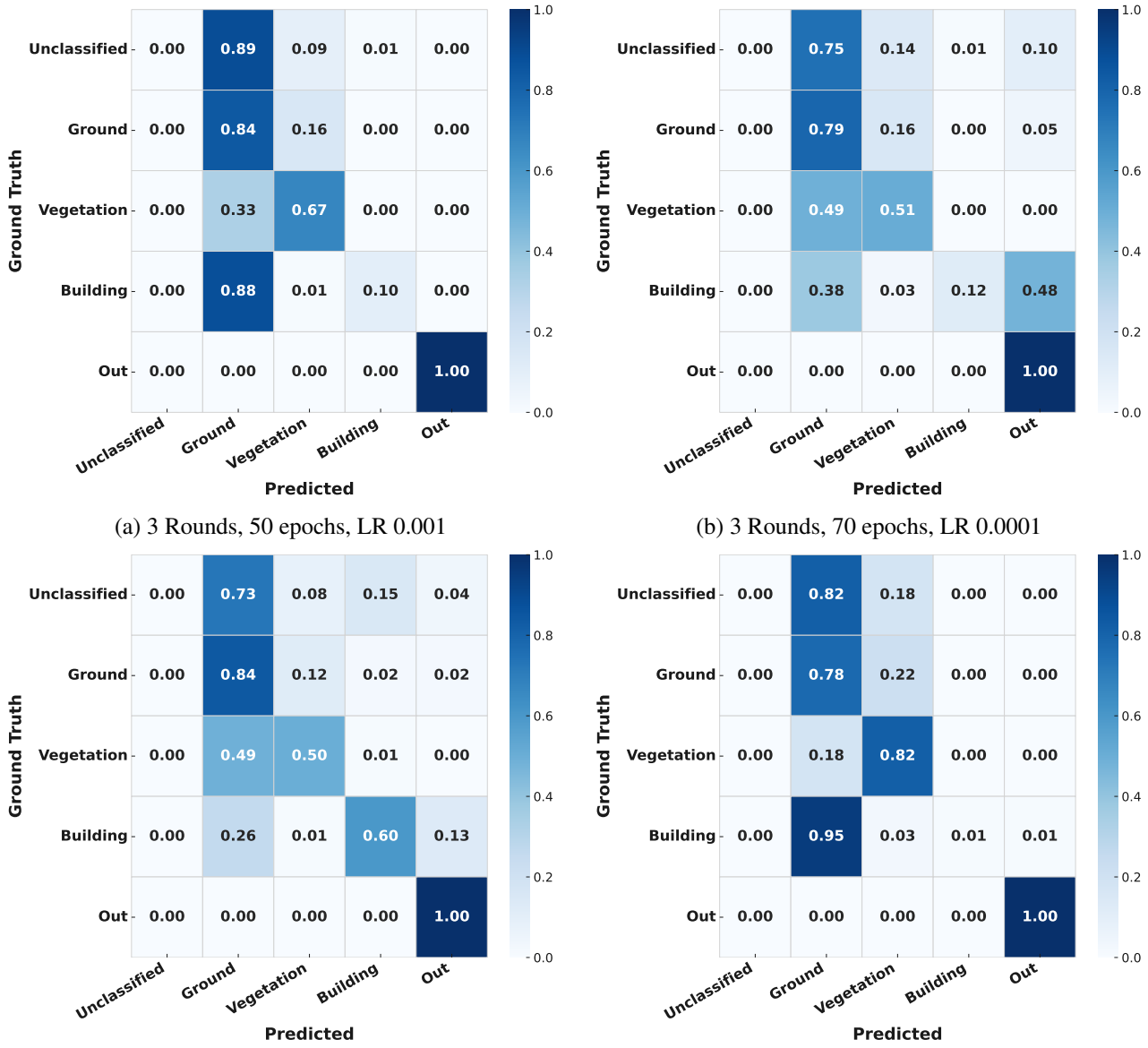
Together, these scenarios provide complementary insights into how hyperparameter tuning affects training-time convergence in a non-IID UAV setting. The experimental results suggest clear trade-offs between local training intensity, communication frequency, and learning rate stability. Configuration **A** achieved rapid convergence but exhibited oscillatory behavior owing to the relatively high LR in a heterogeneous scenario, indicating that aggressive updates amplify client drift under non-IID conditions. Configuration **B**, with an increased number of local epochs and a reduced LR (0.0001), aimed to stabilize the client updates during aggregation. This configuration yielded more stable convergence, although at the cost of slower progress toward competitive accuracy.

Configuration **C**, which simultaneously increased both the rounds and local epochs, achieved the most balanced outcome. The additional communication reduces the divergence between client updates, whereas longer local training enriches feature learning, leading to improved convergence and reduced variance across clients. In contrast, Configuration **D**, with ten rounds but fewer local epochs, demonstrated that frequent synchronization can partially compensate for shorter local training. However, its overall performance remained inferior to that of **C**, underscoring that communication alone cannot replace sufficient local optimization in complex segmentation tasks. Table 3 summarizes the class-wise accuracy and macro-accuracy for all experimental configurations. The results clearly show the sensitivity of federated UAV segmentation to the balance between the communication frequency, local training intensity, and learning rate.

This comparison indicates that the federated training convergence is strongly configuration-dependent. High LR accelerate early progress but destabilize aggregation under non-IID conditions, whereas very frequent communication can bias the performance toward certain classes. The confusion matrix analysis (Fig. 3) highlights the asymmetric performance across semantic classes. The model consistently recognized *Ground* (79% accuracy) and *Out* (100% accuracy), suggesting that spatially homogeneous and dominant patterns were captured. In contrast, *Vegetation* achieved only 51% accuracy, with nearly half of its samples misclassified as *Ground*, reflecting difficulties in separating fine-grained vegetation textures from soil.

Table 3. Results obtained for each configuration.

Config.	Ground	Vegetation	Building	Out	Macro-Acc.
A	84%	33%	10%	100%	56.8%
B	79%	51%	12%	100	60.5%
C	**84%**	**50%**	**60%**	**100%**	**73.5%**
D	78%	22%	95%	100%	73.8%



(a) 3 Rounds, 50 epochs, LR 0.001

(b) 3 Rounds, 70 epochs, LR 0.0001

(c) 5 Rounds, 100 epochs, LR 0.001

(d) 10 Rounds, 20 epochs, LR 0.001

Figure 3. Confusion matrices for configurations A-D.

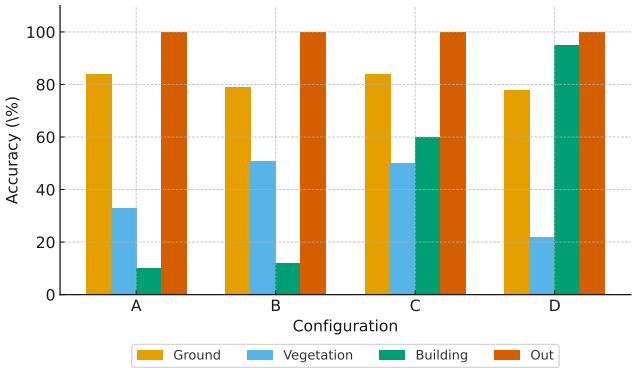


Figure 4. Class-wise accuracy for each configuration.

The most challenging case was *Building*, which reached only 12% accuracy and was frequently confused with *Ground* or *Out*. These results confirm that non-IID distributions restrict the ability of the global model to generalize structural and minority class features, indicating a critical bottleneck for FL. Overall, the confusion matrices highlight the asymmetric behavior of the federated HRNet, while the majority and homogeneous classes converge effectively, and the heterogeneous and structurally diverse classes suffer from poor generalization. These findings confirm that class imbalance and non-IID partitioning remain critical bottlenecks in UAV semantic segmentation with FL.

The balanced results were obtained when both communication rounds and local epochs were moderately increased

(Configuration C), highlighting the importance of tuning the trade-off between local computation and global synchronization in UAV segmentation tasks. As shown in Figure 4, the class-wise distribution of accuracies visually reinforces the imbalances presented in Table 3.

The per-class analysis under non-IID partitions reveals three recurring factors behind the observed asymmetries. First, *Vegetation* and *Ground* share texture and color statistics that induce mutual confusion, particularly when local training is short and global updates dominate. Second, Building is affected by minority frequency and thin edge structures, which increase boundary ambiguity and favor misclassification into *Ground* or *Out* when the global model aggregates diverging client updates. Third, *Out* remains robust owing to visual homogeneity and dominance in the scene. The configuration with moderate communication and sufficient local epochs (Configuration C) provides the most reliable balance across classes, as it reduces the client drift without overfitting any single client. The experimental results reveal how the FL trade-off between local training and global synchronization shapes the class-wise behavior under heterogeneity. Taken together, the evidence shows that moderate communication combined with sufficient local training consistently reduces client drift and yields the most reliable class balance without overfitting any single client. This approach is suitable for UAV deployments with bandwidth limits and skewed data distributions.

5. Concluding Remarks

This study evaluated the adaptation of the HRNet segmentation architecture to a FL environment using synthetic UAV imagery. The experiments showed that federated training under non-IID conditions is highly sensitive to hyperparameter configurations, with class-level performance varying significantly across setups. Configuration C (5 rounds, 100 epochs, $LR = 0.001$) yielded the most balanced results, improving both convergence and generalization across the dominant and minority classes. In contrast, configurations that emphasize a high LR or frequent synchronizations introduce instability and class-specific biases.

These findings confirm that federated UAV segmentation faces persistent challenges arising from class imbalance, boundary ambiguity, and heterogeneous data partitions. However, they also demonstrate that careful tuning of training-time parameters can mitigate some of these limitations. We recommend prioritizing moderate communication with sufficient local epochs to stabilize aggregation and improve minority and edge-sensitive classes as an actionable guideline for bandwidth-constrained deployments that sets a clear foundation for validation on real UAV datasets.

Future work will focus on extending the number of communication rounds and incorporating adaptive server-side optimizers (e.g., FedOpt and FedProx) to improve stability and reduce client drift under heterogeneous conditions. In addition, advanced data augmentation and synthetic balancing strategies will be investigated to alleviate class imbalance and strengthen the representation of minority categories, such as *Building* and *Vegetation*. Finally, personalized FL methods were explored to adapt the global model to client-specific distributions while preserving generalization.

Acknowledgments

The authors gratefully acknowledge the financial support from CAPES (Finance Code 001), FAPEMIG (Grant #APQ00923-24), CNPq (CNPq/ MCTI/FNDCT Nº 18/2021), and EMBRAPA Café (ConCafé #10.24.22.032.00.00/337 - supervisor Williams Ferreira). We are also grateful to Instituto de Inteligência Artificial e Computacional (Idata-UFV), FINEP (IA-AD-UFV #0284/22), and Cluster/UFV for providing GPU resources.

Author Contributions

All authors contributed equally to the development of this study.

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