Federated Learning for Urban Energy Efficiency: Detecting Thermal with UAV-based Imaging and AI

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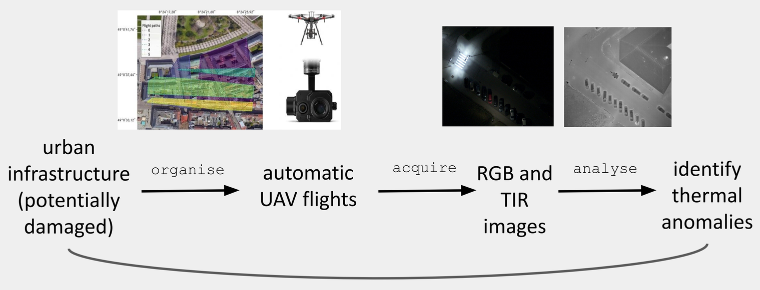
Abstract: The fast and accurate localization of heat loss areas to increase energy efficiency can be improved by automating the detection of thermographic anomalies through UAV-based thermal imaging combined with ***Deep Learning (DL)***. However, there are still challenges such as data sharing, resource constraints and privacy concerns in urban environments. Federated Learning (FL) offers a solution by enabling privacy-preserving model training on decentralized devices, making it suitable for resource-constrained applications. Using NVFlare and the U-NET segmentation model, we investigate ***Federated Learning (FL)*** for thermal hot spot detection based on urban features. The FL clients are selected based on the geographic location of the image and help district heating network operators detect leakages in underground pipelines via false alarm removal.

Motivation

Thermal Urban Feature Segmentation (TUFSeg)

- Identifying leakages in underground district heating networks by finding false alarms from common thermal urban features to sort out



Workflow for Identifying Thermal Anomalies in Urban Infrastructure. Source [3]

Application Motivation:

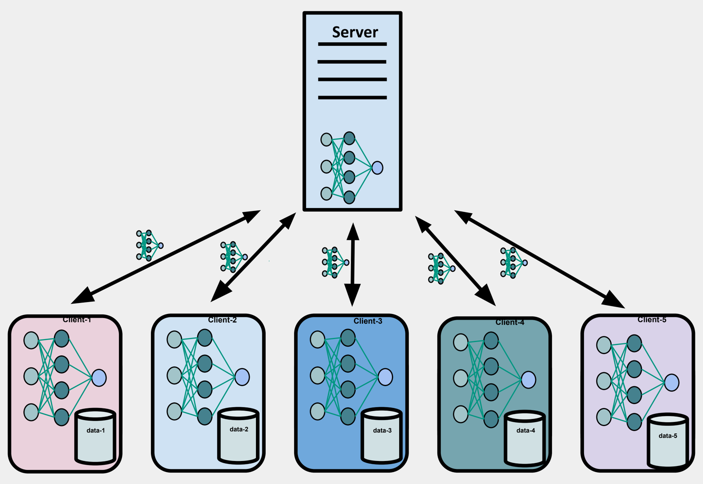
- **Usage:** Identifying thermal anomalies (hot spots) in urban environments to improve the efficiency of energy-related systems.

Challenges

- Data limitation: Sharing data from different cities and organizations can be beneficial. But this method poses several challenges, such as:
  - Data sharing and resource constraints
  - Data Privacy concern
  - Communication overhead
- Annotation is time consuming

Federated Learning

- A privacy-preserving machine learning paradigm introduced to address these challenges.
- Facilitates multiple peers to collaboratively learn a common prediction model by exchanging model weights while keeping the sensitive data on the local devices.



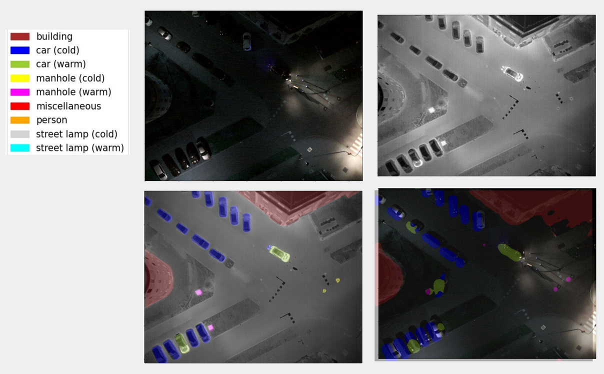
Scatter and Gather Workflow

Methods

TUFSeg Application

- Dual Camera is used to collect data: RGB + Thermal
- UAV-based: 90° pitch, high overlap
- Night-time flights in Karlsruhe (KA) & Munich (MU) (DE)
- 634 train, 159 test images
- Multi-class semantic segmentation
  - U-Net ResNet-152 backbone
  - Segmentation_models toolbox using Tensorflow and Keras
- Evaluation: precision, weighted precision (W Precision), IoU, weighted IoU (WIoU), weighted F1-score
- Model was trained for 35 epochs
- batch size of 8
- The MLflow instance provided by AI4EOSC [7] Project was used.

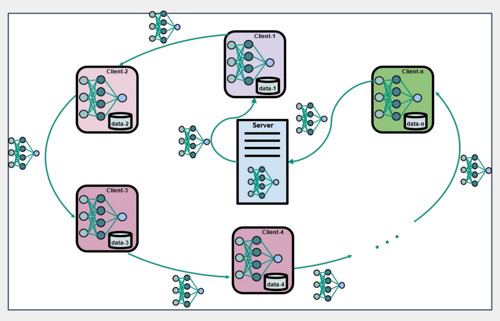
Equipment used for image acquisition. Source [3]



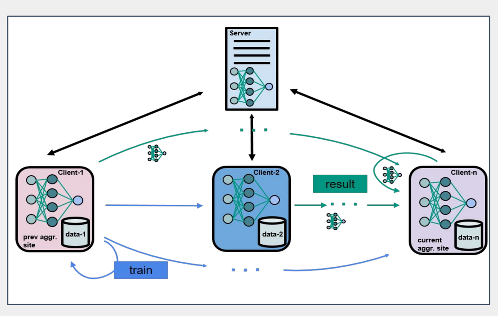
Example of thermal urban feature segmentation (l): combined RGB (top left) and TIR (top right) inputs, manual segmentation mask (bottom left), and U-Net model prediction (bottom right). Source [3]

Federated Learning Methods

- Federated Learning Categories based on architecture:
  - Centralized Federated Learning (CFL): server coordinates the training
  - Decentralized Federated Learning (DCFL): the communication is peer to peer.
  - FL WorkFlows:
    - Scatter & Gather (CFL): Global model parameters are distributed to client devices for local training; updated parameters are then aggregated.
    - Cyclic Learning (DCFL & CFL): The server selects a subset of clients. Training is done following a predetermined sequential order set by the server.
    - Swarm Learning (DCFL): Decentralized subset of FL where orchestration and aggregation is performed by the clients
- The HPC from KIT (Horeka) was used to do simulations
- Clients were selected based on the geographic location of the image (KA, MU).
- NVIDIA FLARE (NVFlare) framework was used:
  - Open source ML/DL framework-agnostic.
  - FL via Client API: few code changes from DL to FL version
- The results were simulated for two clients, KA and MU.
- Baseline here refers to the model trained using the entire dataset without FL.
- To ensure comparability with Centralised Learning (CL):
  - The model was trained for **4 rounds** and **9 epochs**.
  - The experiment used the same hyperparameter configuration as the baseline model.



CFL Cyclic Learning Workflow

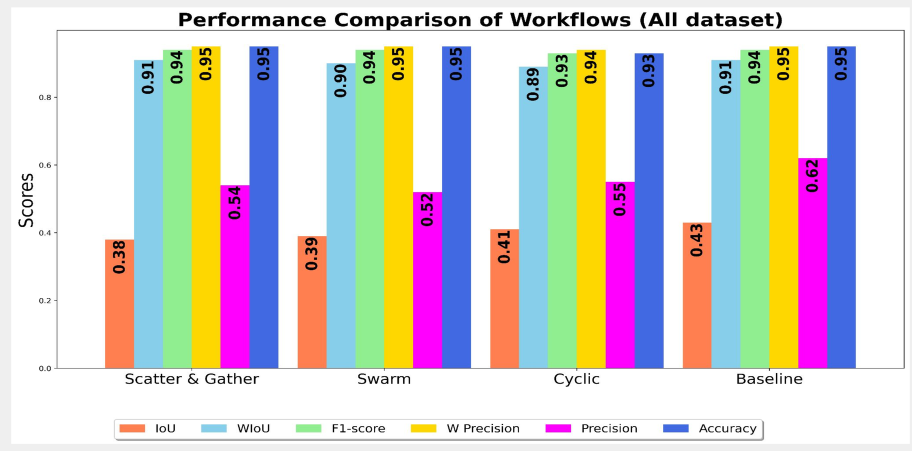


Swarm Learning Workflow

Results

Model Performance Across All Datasets

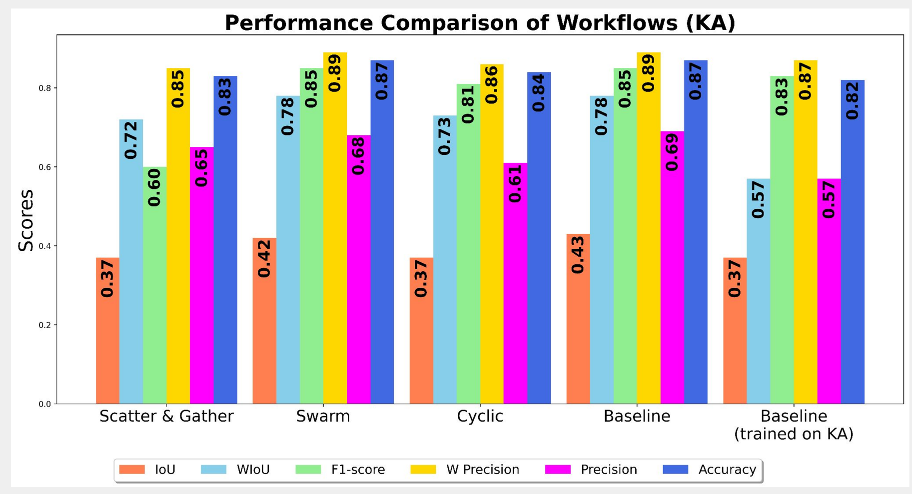
Workflow	IOU	W IOU	F1-score	W Precision	Precision	Accuracy
Scatter & Gather	0.38	0.91	0.94	0.95	0.54	0.95
Swarm	0.39	0.90	0.94	0.95	0.52	0.95
Cyclic (DCFL)	0.41	0.89	0.93	0.94	0.55	0.93
Baseline (CL)	0.43	0.91	0.94	0.95	0.62	0.95

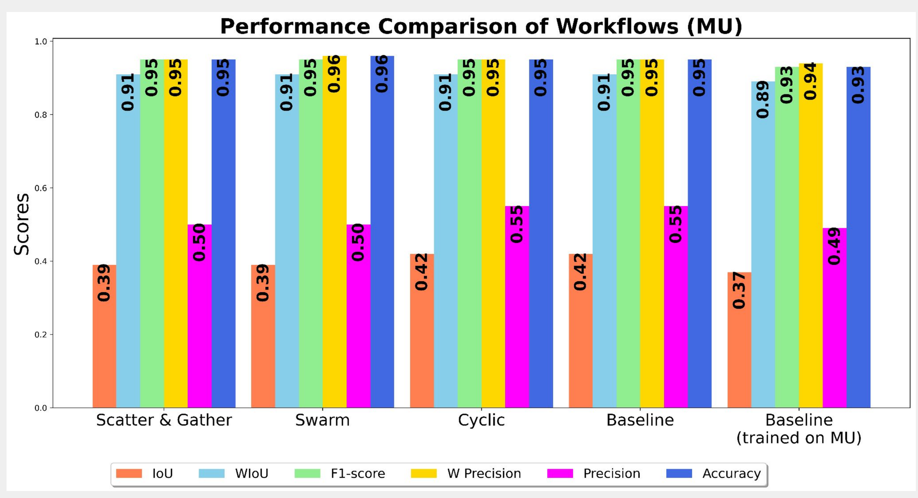


- **FL workflows** achieved performance comparable to the baseline model.
  - IoU values, while slightly lower, remained competitive across all workflows.
  - F1-scores closely aligned with baseline model results.
  - W Precision and Precision scores maintained consistency with the baseline, indicating similar accuracy levels.
  - Accuracy metrics demonstrated comparable performance between the FL workflow and the baseline model.
- **Scatter & Gather** exhibited similar learning performance to **Swarm**.
- **Swarm and Scatter & Gather** should be compared in terms of speed, communication overhead by moving from simulation to real-world deployment.

Model Performance Across Locations

- FL methods shows comparable performance across all locations compared to the baseline.
- Despite the KA dataset being nearly four times smaller than the MU dataset, training both FL and baseline on all datasets improves the model's performance on KA.
- Swarm Learning matches baseline performance on KA (smaller dataset).
- Cyclic Learning performs comparably to baseline on MU (larger dataset).





Outlooks

- **Transition from Simulation to Real World:**
  - Start the server on the AI4EOSC platform and deploy clients on various systems with varying latency.
  - Considerations
    - **Security and Privacy:** Ensure robust measures to protect data.
    - **Consistent Environment for All Clients:** Use Docker to maintain uniform environments across clients.
- **Aggregation Algorithms:** Implement and compare various aggregation algorithms to optimize the FL model for efficiency and accuracy.
- **Scalability and Robustness:**
  - Compare simulation results with real-world deployment in terms of speed, overhead, and accuracy.
  - Evaluate FL system performance under varying conditions, including network latency, device heterogeneity, and data quality.

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[8] AI4EOSC Documentation https://docs.ai4os.eu/

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