Meta Learning-based Few-Shot Learning: Remote Sensing

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Table of Contents

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Motivation

- Remote sensing data is abundant, but labeled data is scarce
- Traditional deep learning needs large datasets → not practical
- Few-Shot Learning allows learning from just a few labeled examples
- Quickly adapts to new terrains or satellite images with little need for manual labeling.

Literature Review

Paper Title	Authors	Work Done	Limitations
Learning to Compare: Relation Network for Few Shot Learning	Flood Sung et al.	Proposed Relation Network (RN) to learn deep similarity metrics using CNNs for few-/zero-shot tasks.	Limited to standard datasets; struggles with similar classes.
Meta-learning Approaches for Few-Shot Learning: A Survey	Hassan Gharoun et al.	Categorizes meta learning into metric, memory, and optimizer based; compares pros and cons.	No detailed implementation; lacks domain transfer evaluation.
EuroSAT: A Novel Dataset and Deep Learning Benchmark	Patrick Helber et al.	Created EuroSAT with 27,000 Sentinel-2 images in 10 land classes; tested CNN models.	Europe-specific, only 10 classes, no atmospheric correction.
AID: A Benchmark for Aerial Scene Classification	Gui-Song Xia et al.	Released AID dataset with 10,000 multi-source images across 30 scene types.	Class imbalance and resolution variance; synthetic imagery used.

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Utility of Remote Sensing

Environmental Monitoring

Picks up deforestation, monitors loss of biodiversity, tracks forest cover and wetlands.

Disaster Management

Real-time satellite imaging assists in early warning, damage assessment, and search and rescue coordination.

Precision Farming

Maximizes irrigation, fertilizer application, and crop health monitoring using multispectral imaging.

Infrastructure Development

Detects urban growth patterns, land use changes, and assists in smart city planning.

Military Applications

Used for border monitoring, terrain analysis, and mission planning in inaccessible regions.

Meta Learning

“Learning to Learn”

Meta-learning is a technique where the model learns how to learn new tasks quickly and efficiently using experience from many similar tasks.

Few Shot Learning

“Learning with few examples”

Few-Shot Learning (FSL) is a machine learning approach where a model learns new tasks using only a few labeled examples per class (e.g., 1-shot, 5-shot).

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Utility of Few Shot Learning

Reduces need for large labeled datasets

Ideal for domains like remote sensing, medical imaging, defense

Fast learning & adaptation

Learn new classes with just 1–5 examples

Works in real-world low-data scenarios

Useful for rare events, new land types, or unseen environments

Enhances model generalization

Adapts to new tasks with minimal retraining

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Approach

Phase 1: Implementing Metric Based Model

- Implement a metric-based few shot learning model using Relation Networks (RNs).
- Train using episodic learning on benchmark satellite datasets under various settings.
- Evaluate the model on metrics like Accuracy and F1 score.

Phase 2: Analyzing Catastrophic Forgetting

- Sequentially train RN across tasks to simulate continual learning.
- Measure knowledge retention to study forgetting behavior.
- Helps understand when and how forgetting occurs during task transitions.

Phase 3: Enhancing with Memory Modules

- Planning to integrate memory-based model like Memory-Augmented Neural Networks (MANN) etc.
- Focused on long-term knowledge retention.
- Aims to improve learning across multiple evolving tasks.

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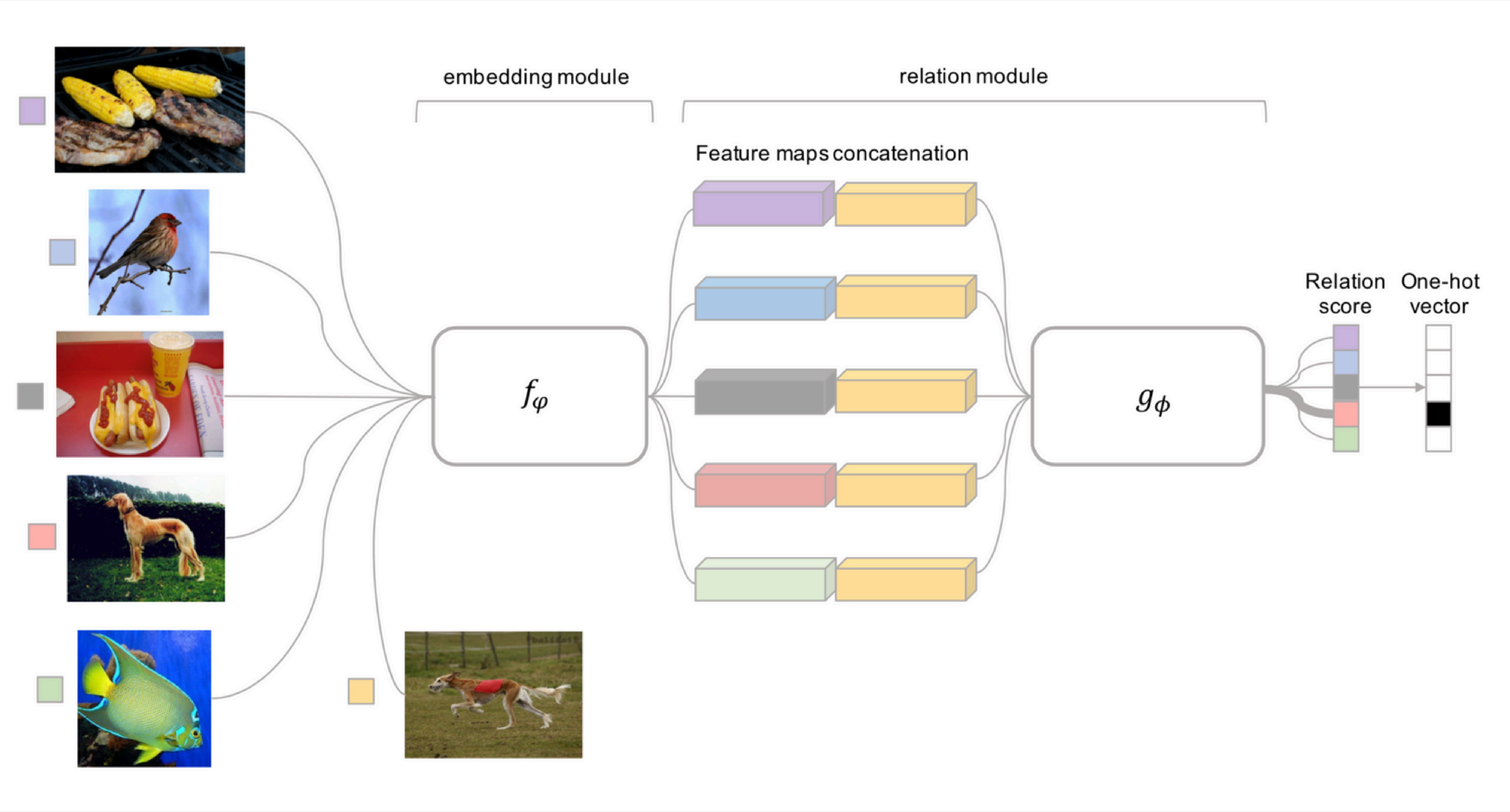
Relation Network



A Relation Network (RN) is a deep learning model that learns relationships between objects or images by comparing them in pairs.

Few-Shot Setup C-way K-shot:

•C classes/episode, K samples/class.

• Support set: C × K labeled images.

• Query set: Unlabeled examples to classify.

Model Components

1. Embedding Module fϕ
   - CNN converts each image into a shared feature space.

2. Pairwise Comparison
   - For query xi , compare with all support xj .
   - Concatenate: $C(f_\phi(x_i), f_\phi(x_j))$

3. Relation Module gϕ
   - Small CNN/MLP outputs $r_{i,j} \in [0, 1]$
   - One score per class; higher = more similar.

4. Training (Episodic)
   - Sample C classes, K support, and queries.
   - For each query:
     -Compare with each support → get ri,j .
     -Predict class with max ri,j

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Loss Function:

Mean Squared Error (MSE) between predicted relation scores and ground-truth match indicators:

$$\mathcal{L} = \sum_{i=1}^{m} \sum_{j=1}^{n} (r_{i,j} - \mathbf{1}(y_i = y_j))^2$$

Goal: High ri,j for correct pairs, low otherwise.

Optimization: $\phi, \varphi \leftarrow \arg\min_{\phi,\varphi} \mathcal{L}$

Why It Works

- Learns to compare, not memorize.
- The model learns a task-specific non-linear similarity function, making it more flexible than fixed metrics like Euclidean or cosine.
- Embedding and relation functions are learned jointly.
- Generalizes across unseen classes.

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Catastrophic Forgetting

Catastrophic forgetting occurs when a model forgets previously learned tasks after training on new tasks — especially common in neural networks and meta-learning.

Why it happens?

- When the model updates its weights for a new task, it overwrites what it learned from the old tasks
- Happens in sequential learning or continual learning settings

How to Prevent It?

- Use memory-based methods (like MANN)
- Meta-learning techniques like Relational Networks, which compare rather than memorize

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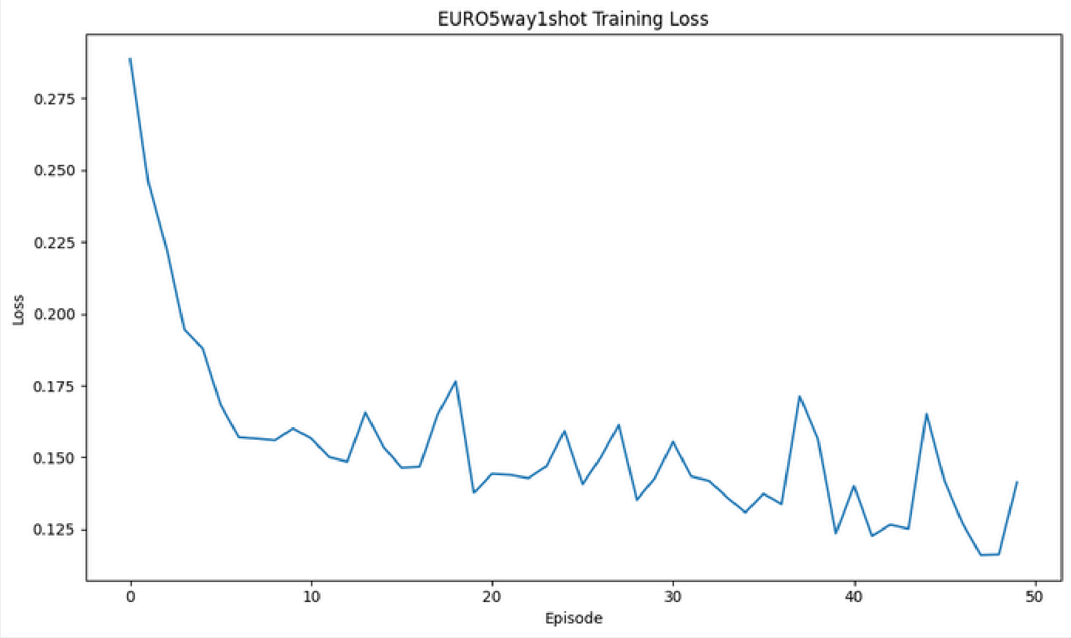
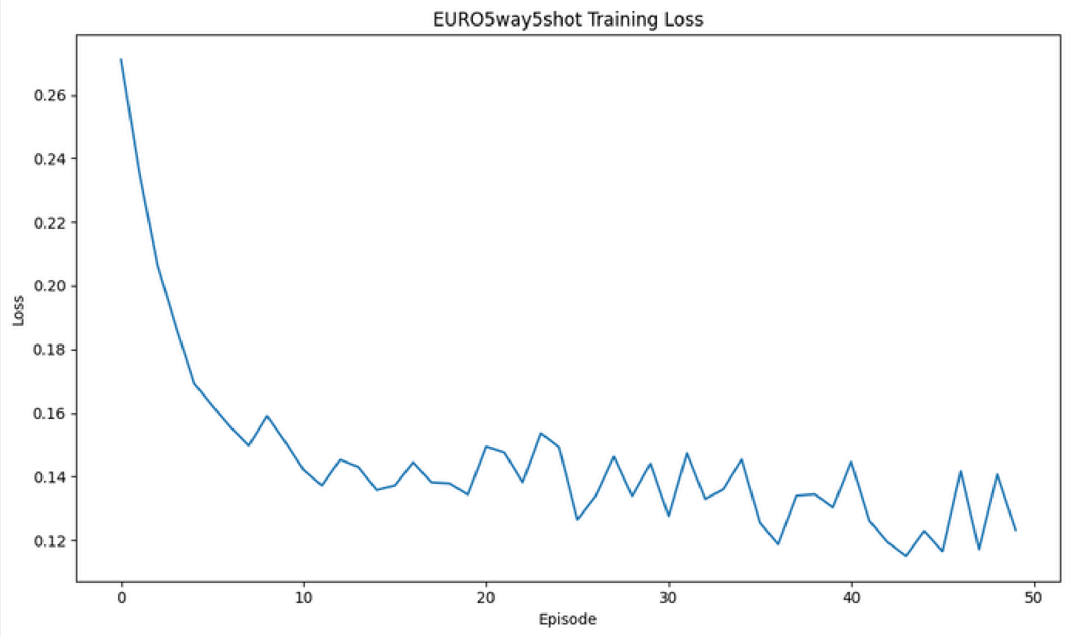
Result

EuroSAT Dataset

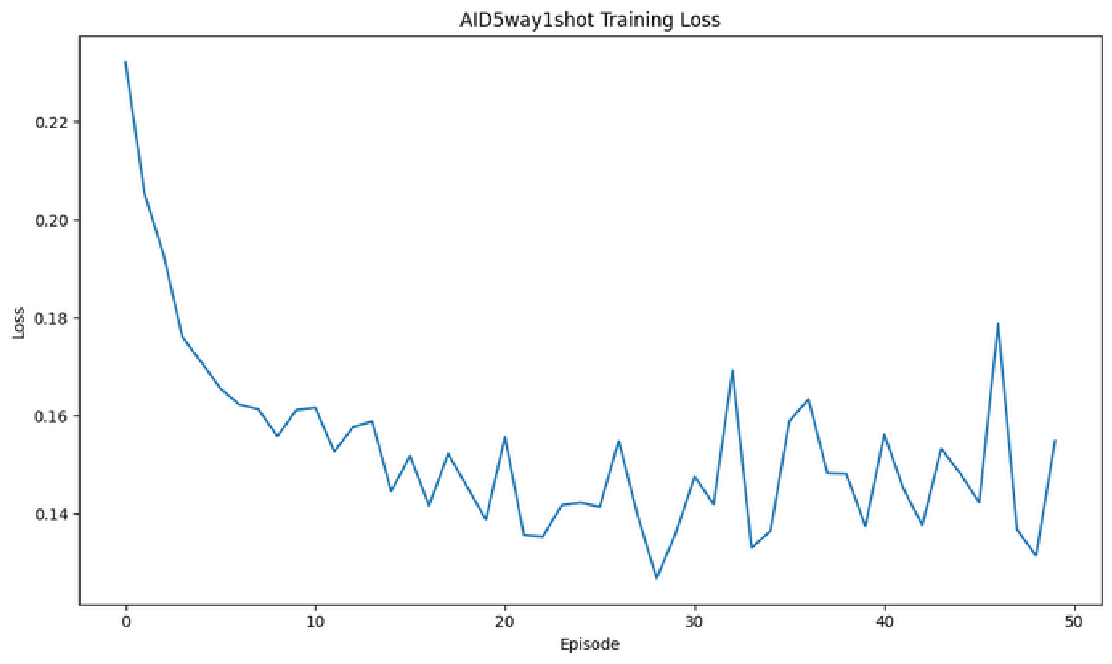


5way1shot

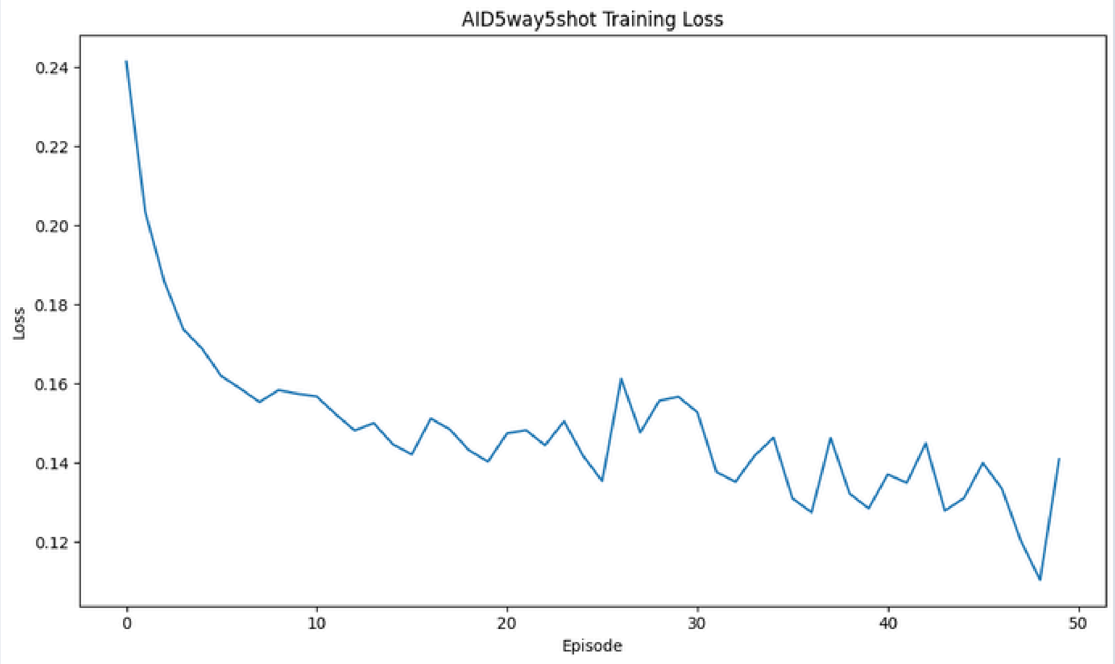


5way5shot

AID Dataset

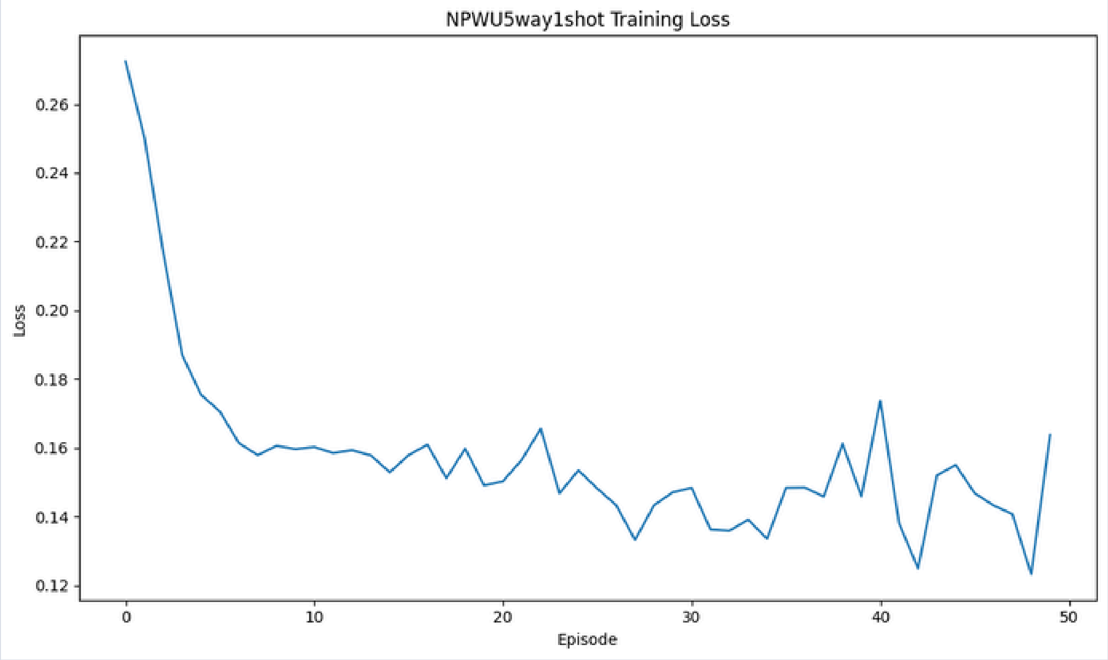


5way1shot

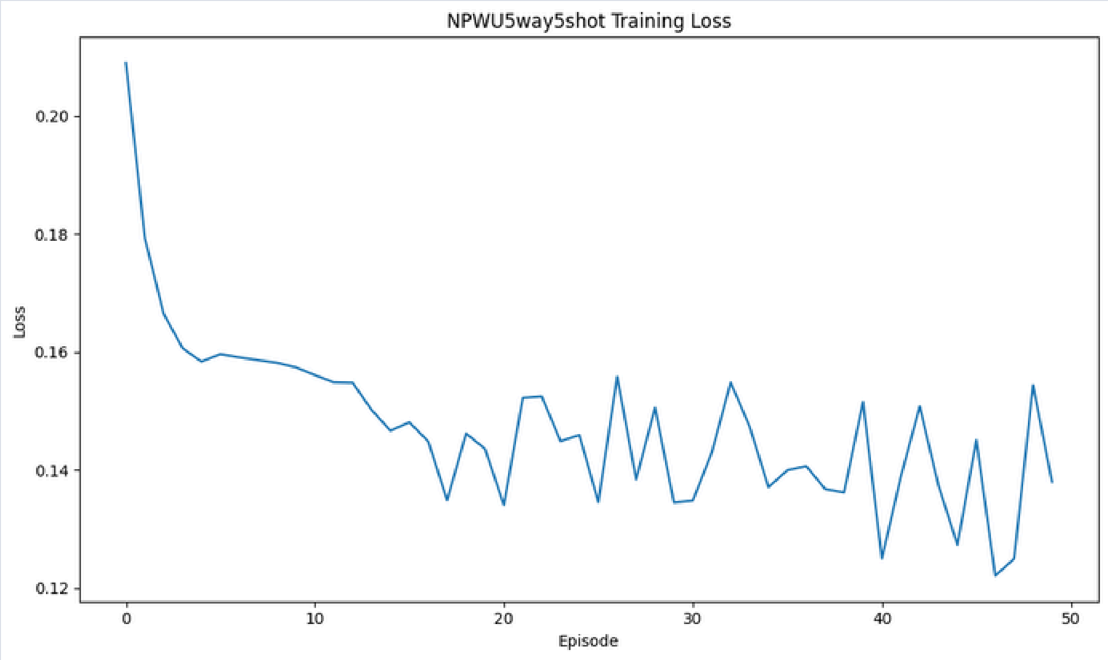


5way5shot

NPWU Dataset



5way1shot



5way5shot

Final Result

Dataset	1-Shot	2-Shot	3-Shot	4-Shot	5-Shot
NPWU	0.3747	0.4227	0.3360	0.4587	0.3907
EURO	0.4160	0.5013	0.4147	0.5293	0.5120
AID	0.4682	0.4244	0.5279	0.5380	0.5064

Report:

Project Report Github Link

Code:

Code Github Link

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References:

1] F. Sung, Y. Yang, L. Zhang, T. Xiang, P. H. Torr, and T. M. Hospedales, “Learning to compare: Relation network for few-shot learning,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 1199–1208, 2018.

[2] H. Gharoun, F. Momenifar, F. Chen, and A. H. Gandomi, “Meta-learning approaches for few-shot learning: A survey of recent advances,” ACM Computing Surveys, vol. 56, no. 12, pp. 1–41, 2024.

[3] P. Helber, B. Bischke, A. Dengel, and D. Borth, “Introducing eurosat: A novel dataset and deep learning benchmark for land use and land cover classification,” in IGARSS 2018-2018 IEEE international geoscience and remote sensing symposium, pp. 204–207, IEEE, 2018.

[4] G.-S. Xia, J. Hu, F. Hu, B. Shi, X. Bai, Y. Zhong, L. Zhang, and X. Lu, “Aid: A benchmark data set for performance evaluation of aerial scene classification,” IEEE Transactions on Geoscience and Remote Sensing, vol. 55, no. 7, pp. 3965–3981, 2017.

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