Meta Learning-based Few-Shot Learning: Remote Sensing

Priyanshu Gupta - 22UCS155
Shashwat Agarwal - 22UEC123
Shantanu Gupta - 22UCC094

The LNM Institute of Information Technology, Jaipur
Supervisor: Dr. Lal Upendra Pratap Singh
CSE Department

November 20, 2025

Table of Contents

LNMIIT
The LNM Institute of Information Technology

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.

LNMIIT
The LNM Institute of Information Technology

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.

LNMIIT
The LNM Institute of Information Technology

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.

LNMIIT
The LNM Institute of Information Technology

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).

LNMIIT
The LNM Institute of Information Technology

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.

Phase 2: Analyzing Catastrophic Forgetting

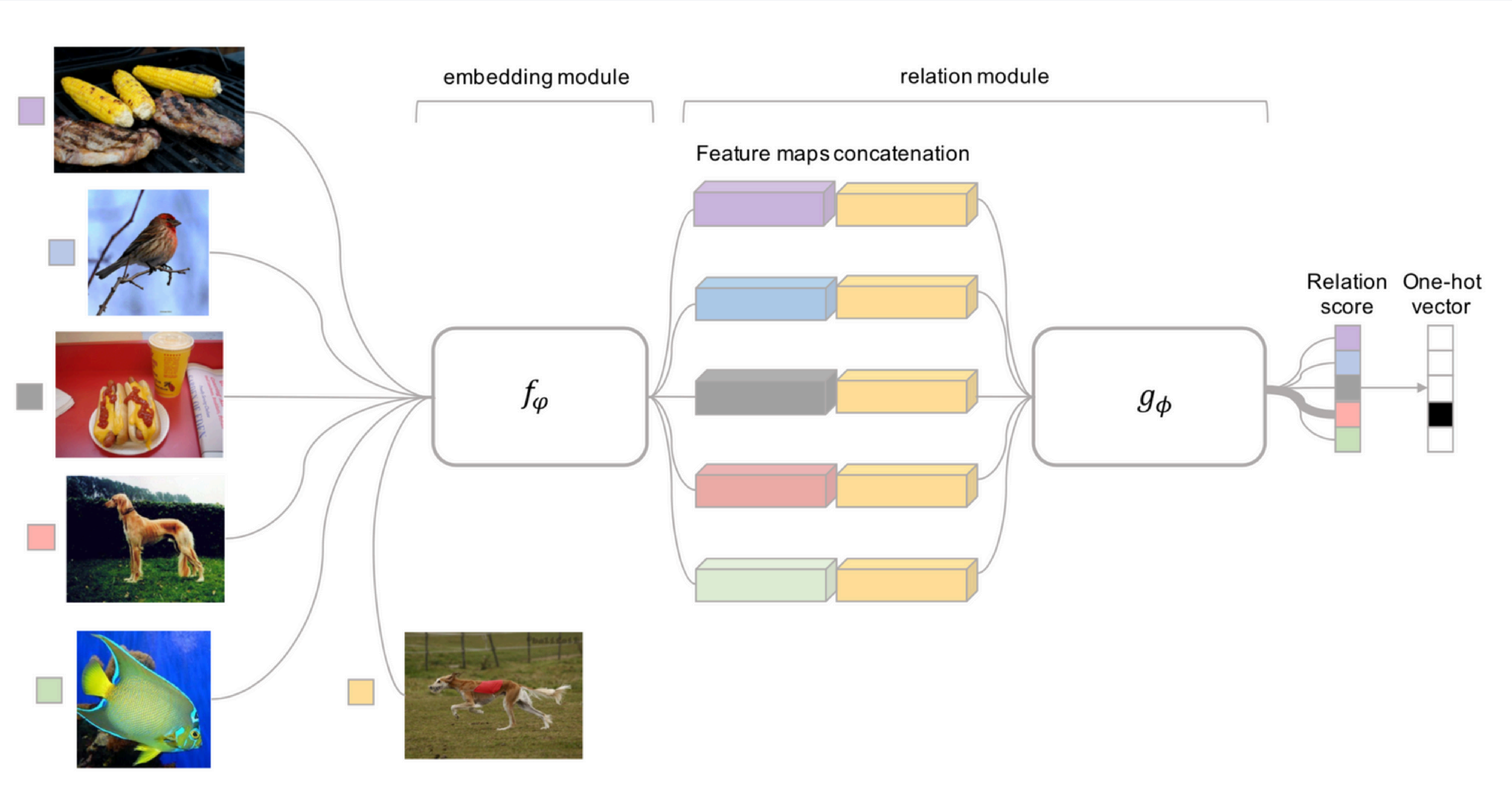
- Sequentially train RN across tasks to simulate continual learning.
- Measure knowledge retention to study forgetting behavior.
- Helps understand when and how forgetting occurs during task transitions.

Phase 3: Unified Multi-Domain Meta-Learning

- Simultaneous multi-domain training with balanced episode sampling.
- Use Attention-based Relation Networks + pretrained EfficientNet-B0 backbone.
- Apply curriculum learning (5-shot → 3-shot → 1-shot)

LNMIIT
The LNM Institute of Information Technology

Relation Network



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

LNMIIT
The LNM Institute of Information Technology

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

The LNM Institute of Information Technology

Loss Function:

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

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

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

Optimization: Adam Optimizer

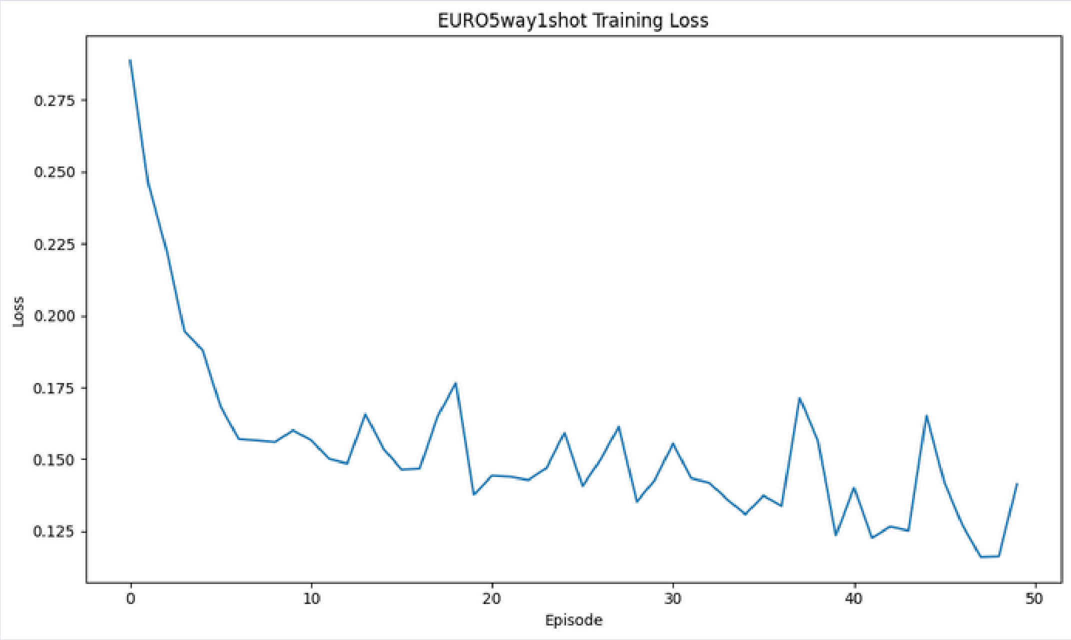
Why It Works

- 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.

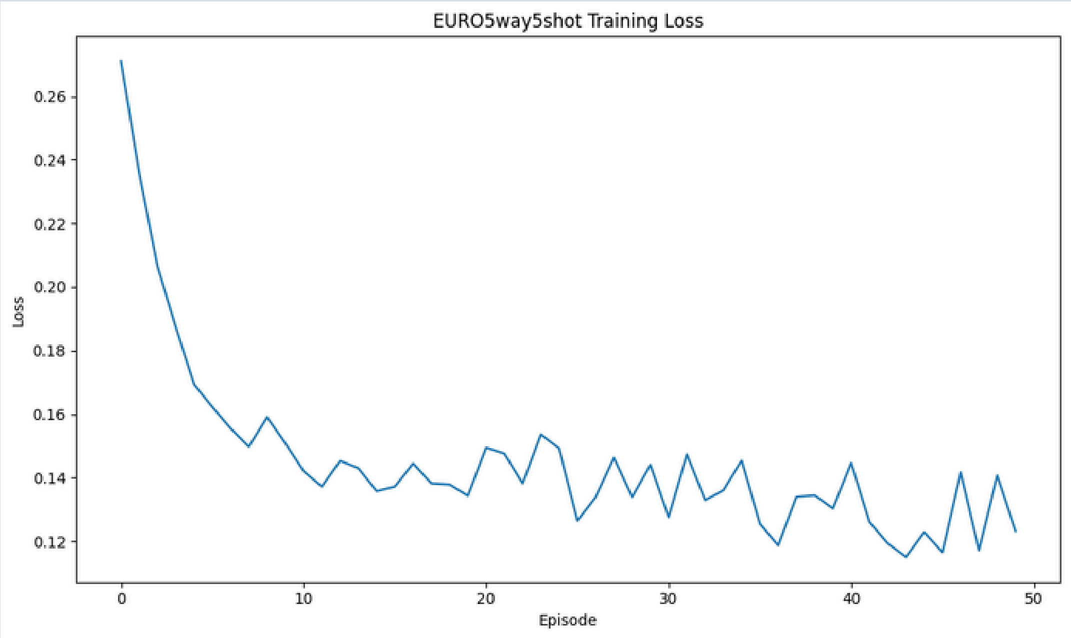
LNMIIT
The LNM Institute of Information Technology

Result

EuroSAT Dataset

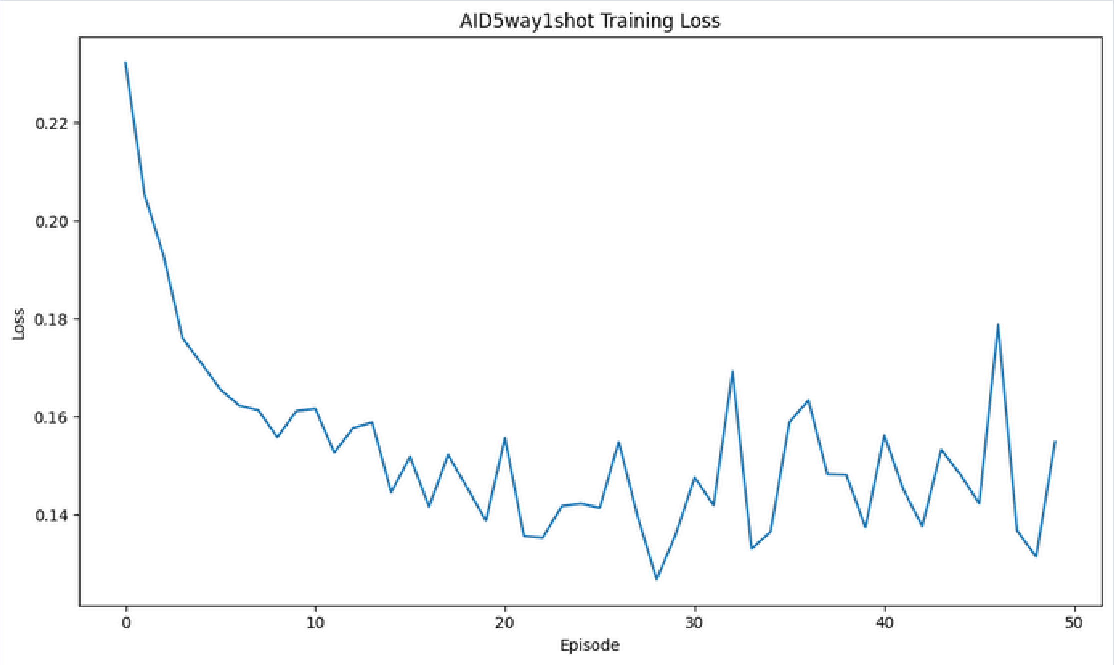


5way1shot



5way5shot

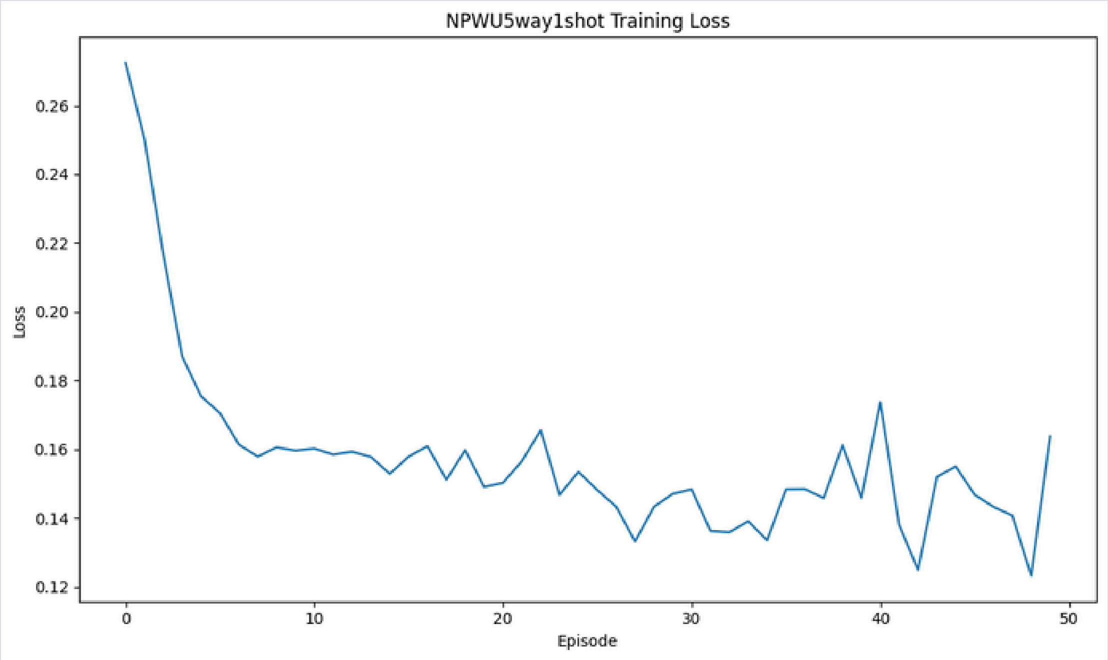
AID Dataset



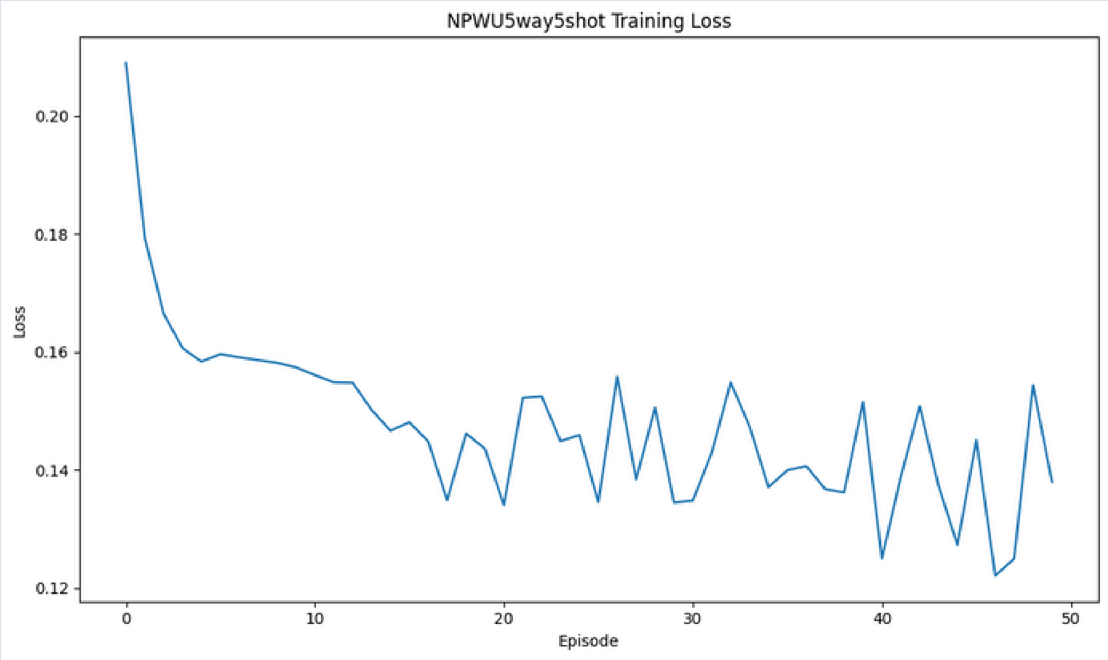
5way1shot

5way5shot

NPWU Dataset

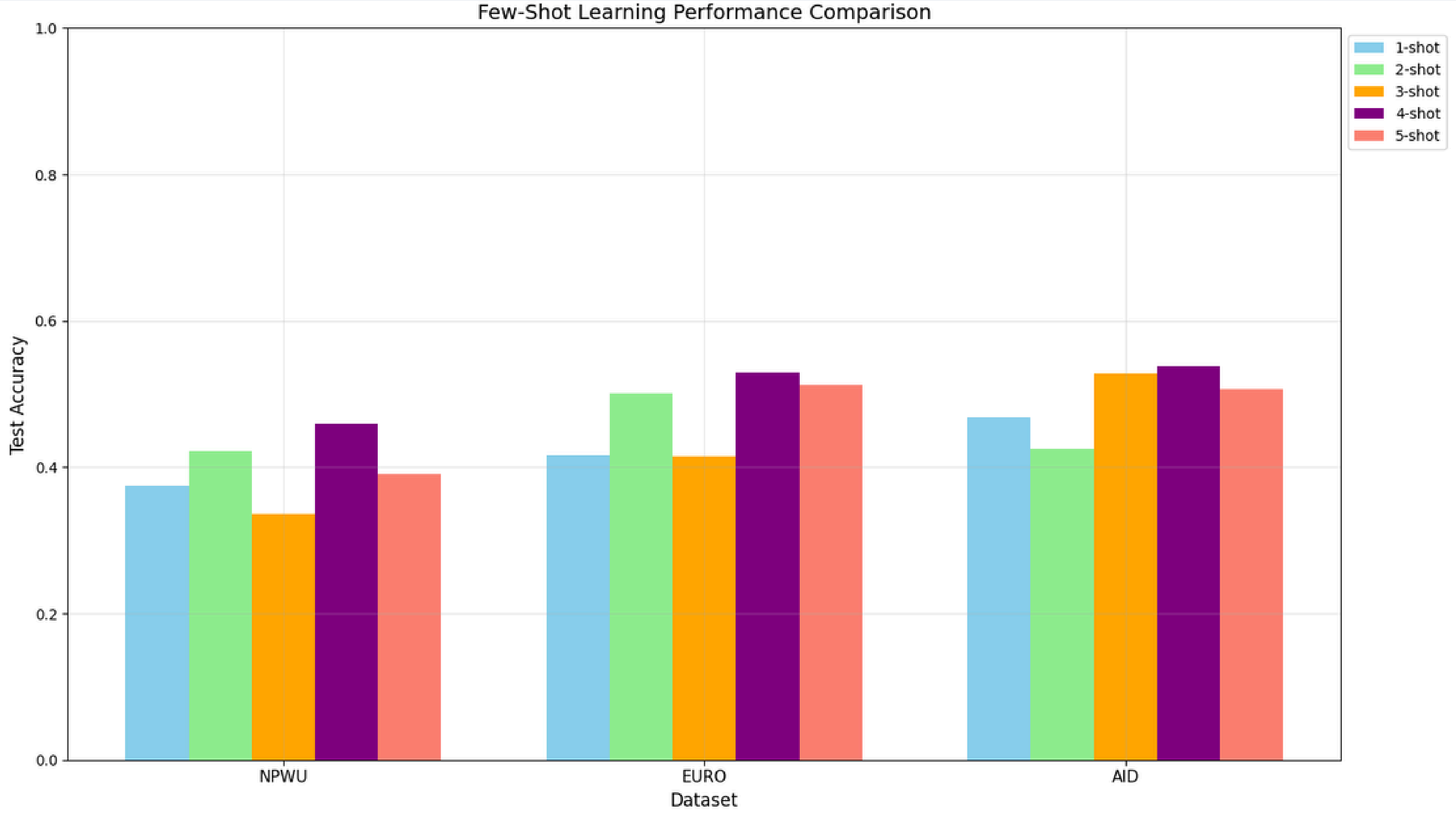


5way1shot



5way5shot

Phase 1 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

LNMIIT
The LNM Institute of
Information Technology

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?

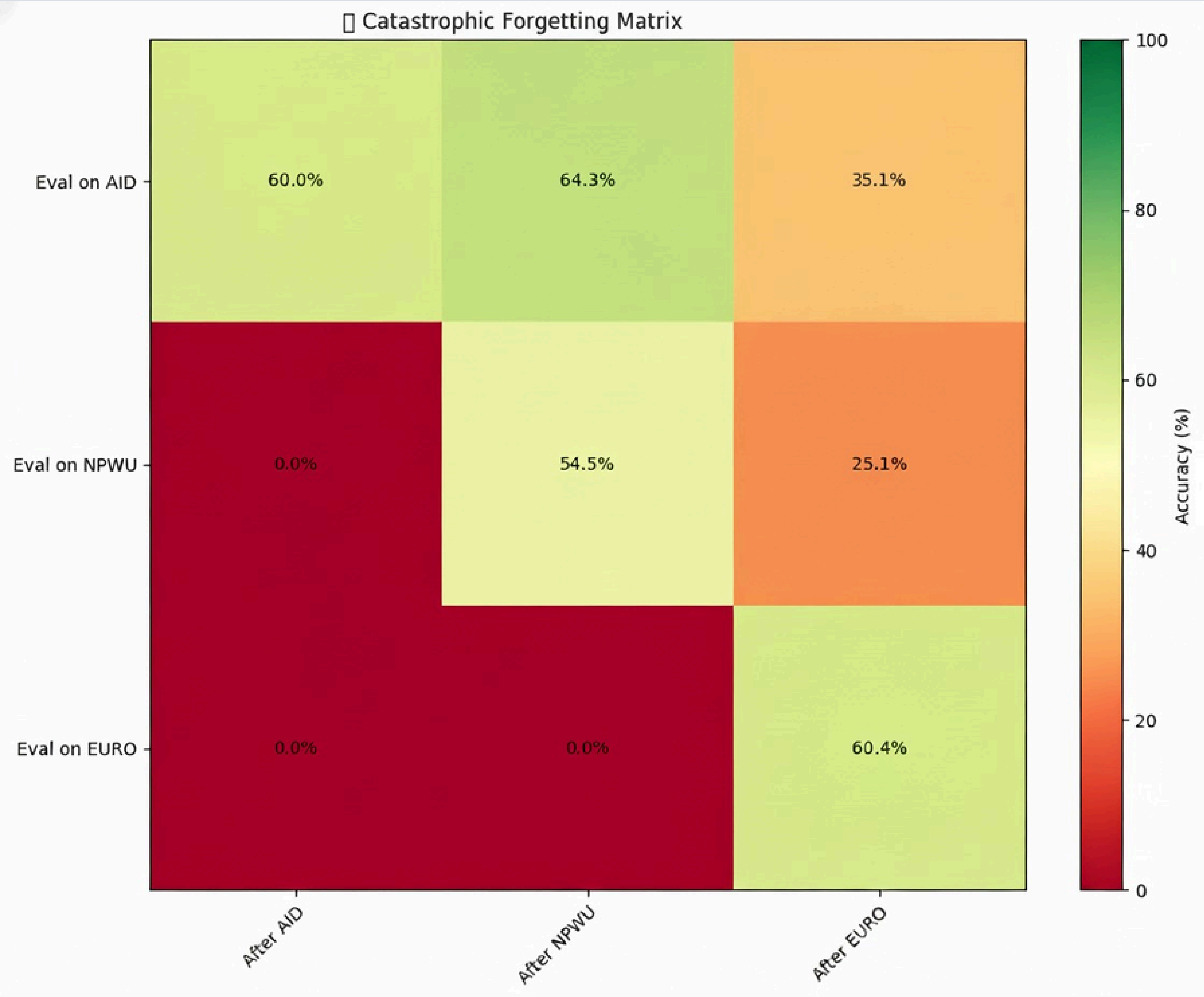
- When the model updates its weights for a new task, it overwrites what it learned from the old tasks
- Happens in sequential learning or continual learning settings

How to Prevent It?

- Unified Multi-Domain Training
- Attention-Enhanced Feature Learning (EfficientNet-B0 + Attention RN)
- Curriculum Learning + Adaptive Sampling

LNMIIT
The LNM Institute of Information Technology

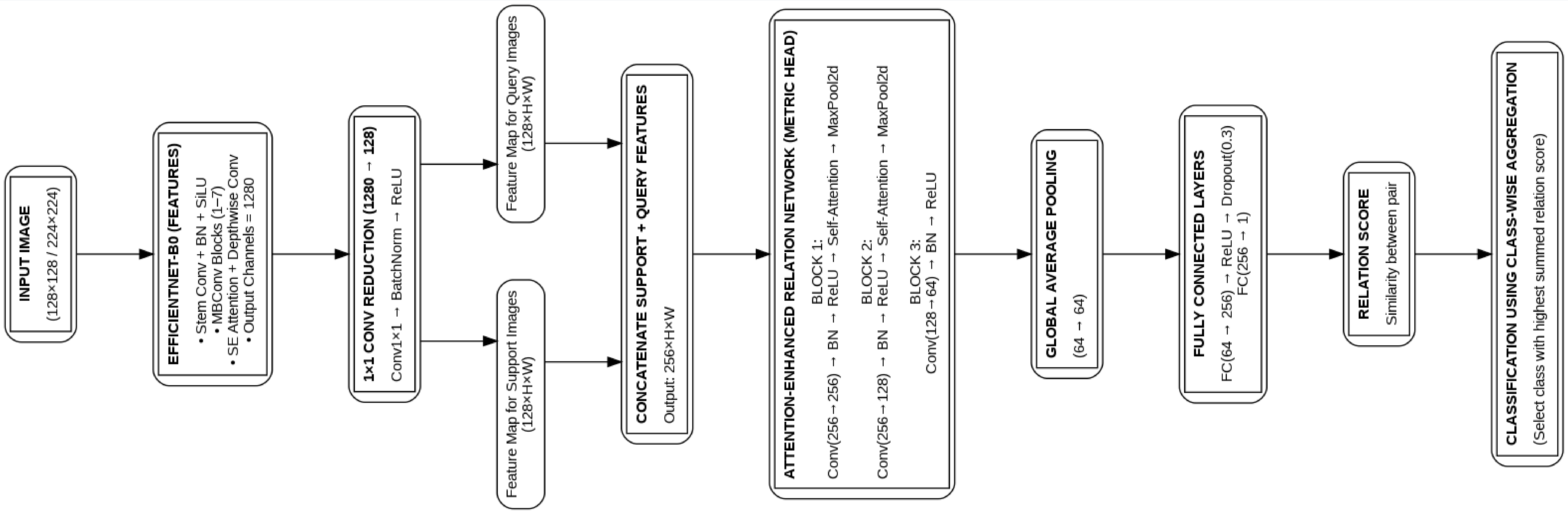
Analysis Of Catastrophic forgetting



	AID	NPWU	EuroSAT
Initial	59.97	54.55	60.40
Final	35.14	25.12	60.40
Forgetting	24.83	29.43	0

LNMIIT
The LNM Institute of Information Technology

Model Architecture



Unified Multi Domain Training

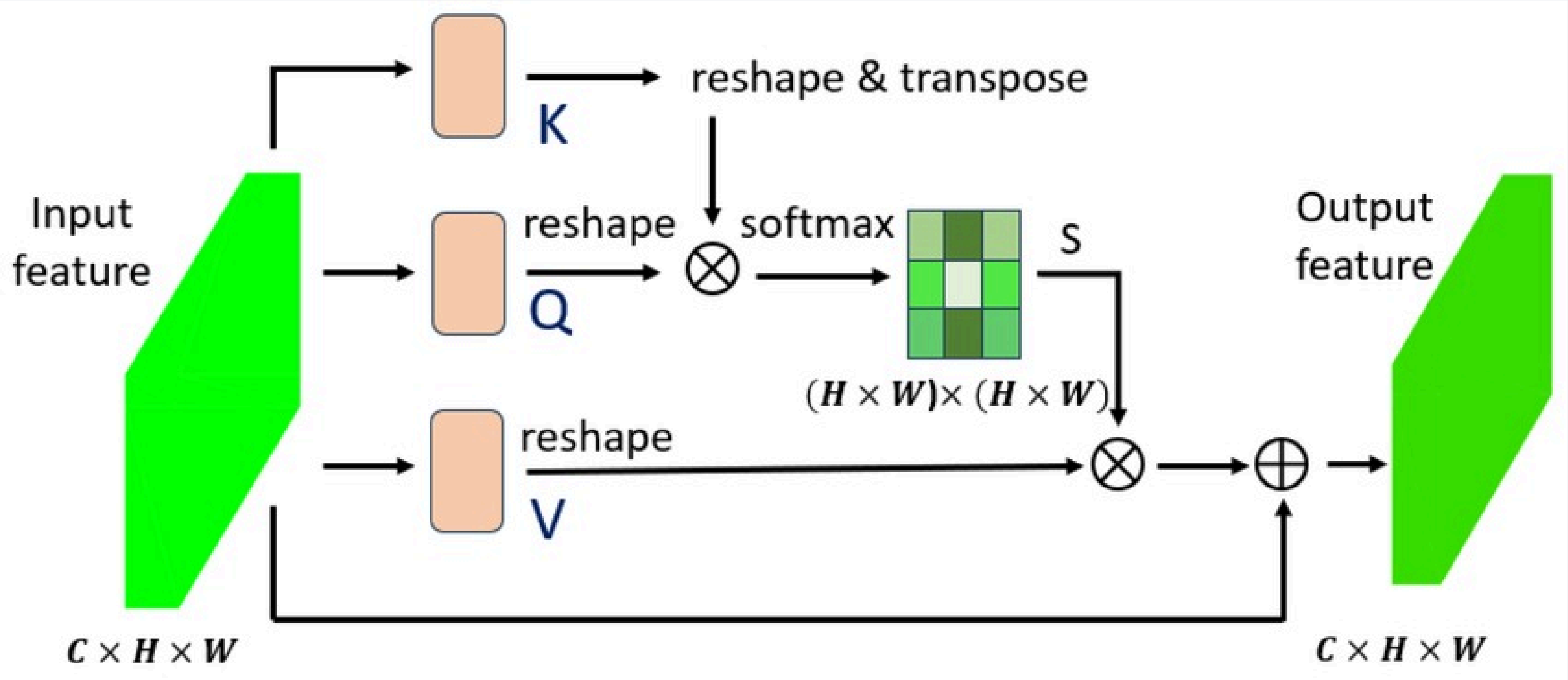
- We train on all datasets together using round-robin episode sampling:
  Episode 1 → AID
  Episode 2 → NWPU
  Episode 3 → EuroSAT
- Continuous domains prevent weight drift.
- Generalization improves

EfficientNet-B0 Shared Feature Extractor

- Pretrained on 1.2M ImageNet images
- Strong, stable features : needs smaller updates
- Adapter (1280→128 channels) keeps training light
- Reduces overwriting and makes features more universal

LNMIIT
The LNM Institute of Information Technology

Attention-Enhanced Relation Network



Self-attention inside the relation network helps the model:

- Focus on task-relevant regions
- Ignore dataset-specific noise
- Learn cross-dataset structure
- Result → Stable representations → Less forgetting

Curriculum Learning (5 → 3 → 1 Shot)

- Early (easy): 5-shot tasks stabilize learning
- Mid (medium): 3-shot improves generalization
- Late (hard): 1-shot makes the model robust
- Smooth progression avoids sudden distribution shifts → prevents forgetting

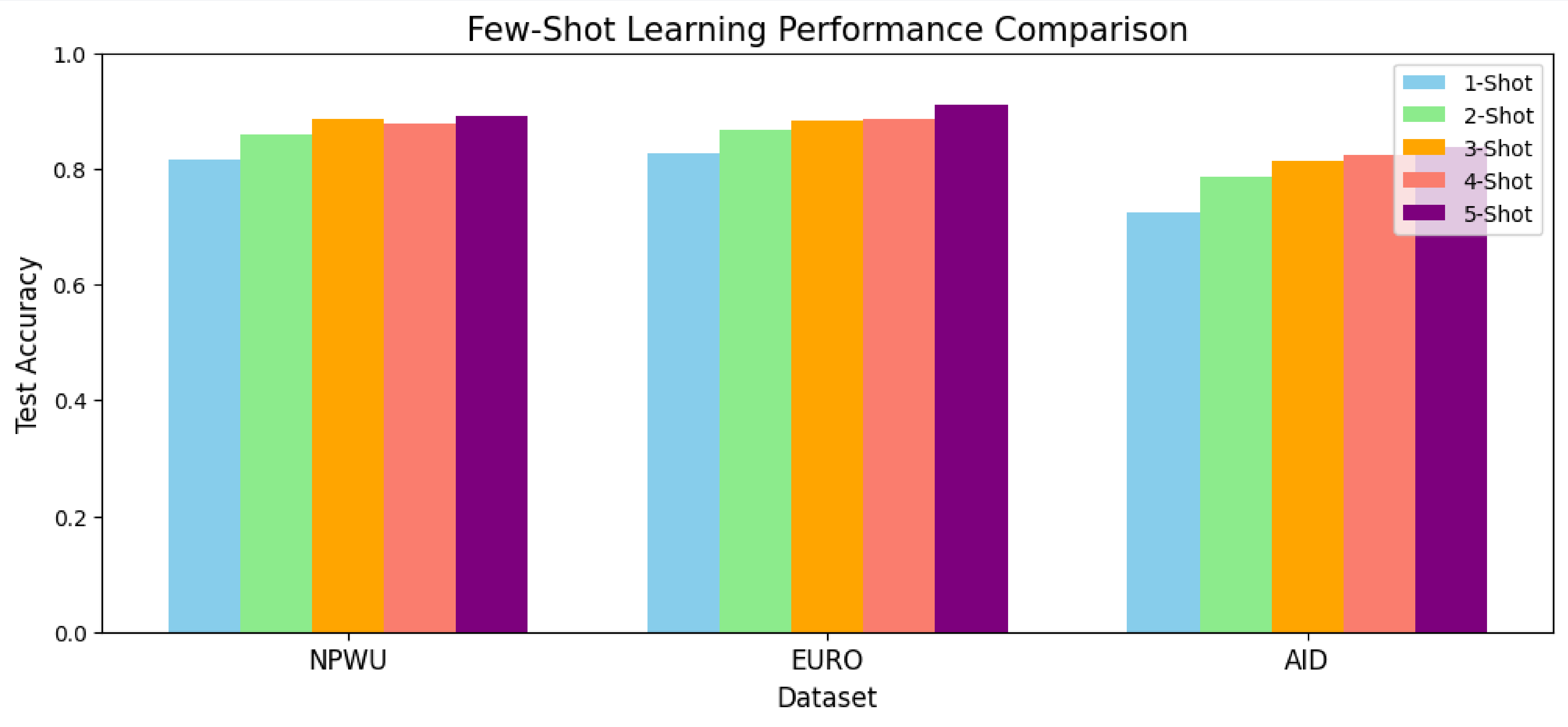
$$k = \begin{cases} 5, & 0 \leq \text{episode} < 8000 \\ 3, & 8000 \leq \text{episode} < 16000 \\ 1, & 16000 \leq \text{episode} \leq 25000. \end{cases}$$

Adaptive Query Sizing

- Automatically reduces query size for small classes
- Uses sampling-with-replacement when needed
- Ensures all classes are used, even tiny ones
- Prevents forgetting rare classes

LNMIIT
The LNM Institute of Information Technology

Final Result



	Dataset	1-Shot	2-Shot	3-Shot	4-Shot	5-Shot
0	NPWU	0.8168	0.8580	0.8863	0.8784	0.8903
1	EURO	0.8262	0.8665	0.8831	0.8871	0.9105
2	AID	0.7250	0.7865	0.8138	0.8250	0.8363

LNMIIT
The LNM Institute of
Information Technology

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.

LNMIIT
The LNM Institute of Information Technology