Pre-trained Deep Learning Networks for Analyzing Hyperspectral Image Data

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1 . Exploring Cross-Domain Pretrained Model for Hyperspectral Image Classification

Goal : Enable **better generalization** in hyperspectral image classification using **pretraining** across **multiple HSI datasets/domains**, even when sensors and spectral bands differ.

Multi-Domain Pretraining Phase

- Train a CNN **simultaneously** on multiple HSI datasets.
- Use **domain-specific input and output layers**, but **share middle layers** to learn **domain-invariant features**.
- These shared layers extract common **spatial-spectral representations**

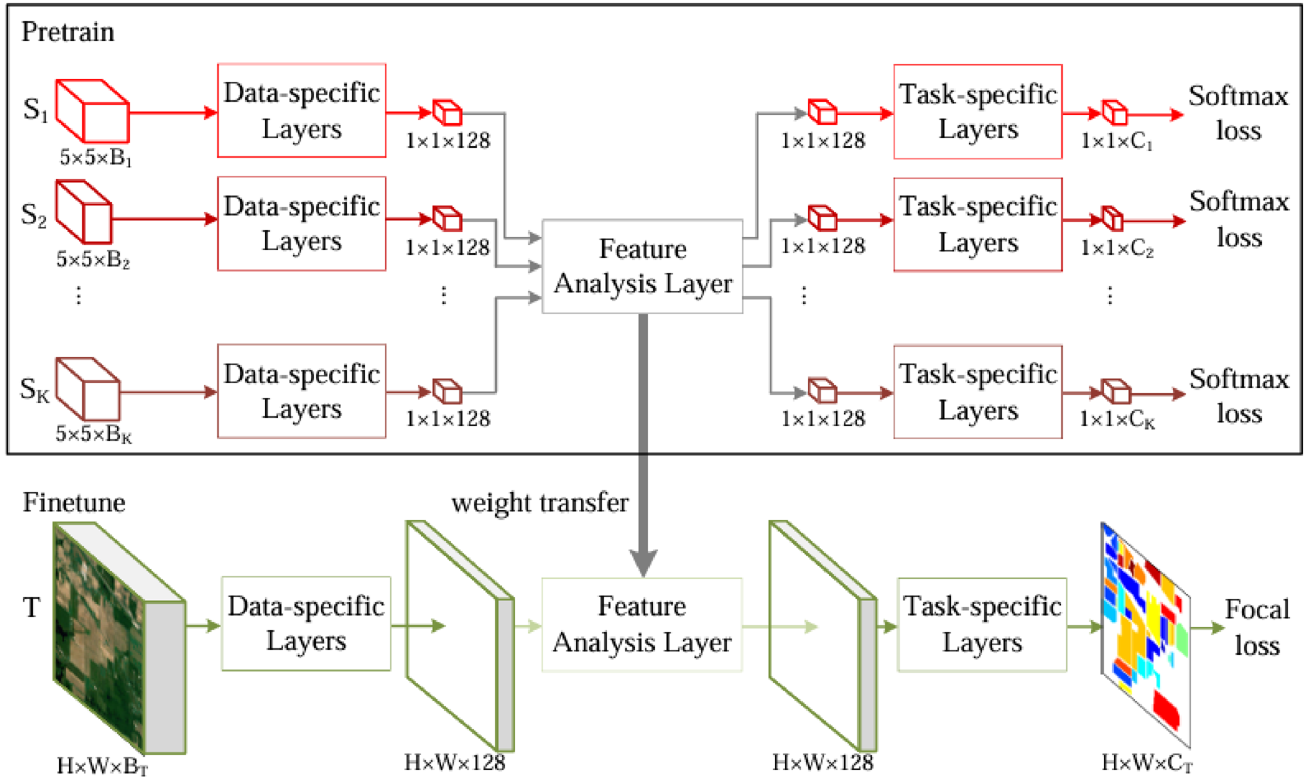
Fine-Tuning Phase

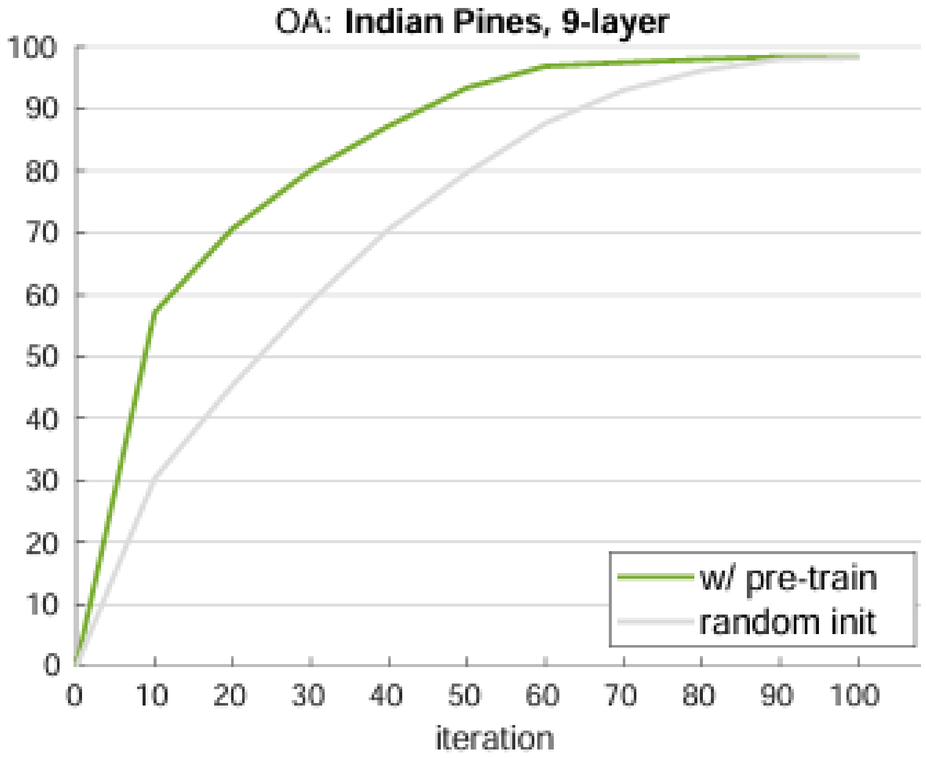
- For a new target dataset, initialize:
    - A **new inlet** for the input spectral characteristics.
    - A **new outlet** for classification.
    - Reuse pretrained **shared middle layers**.

Fine-tune:

- Shared layers: continue learning general features.
- Inlet and outlet layers: adapted to the specific domain.

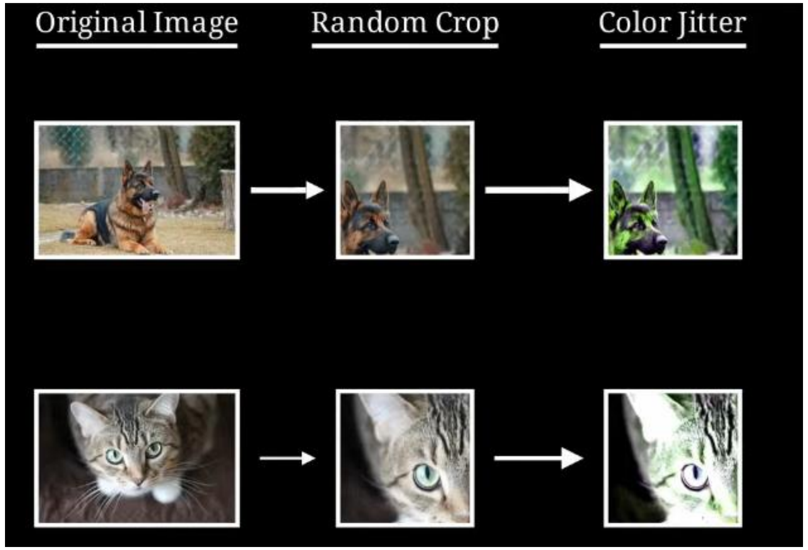
https://arxiv.org/pdf/2204.03144

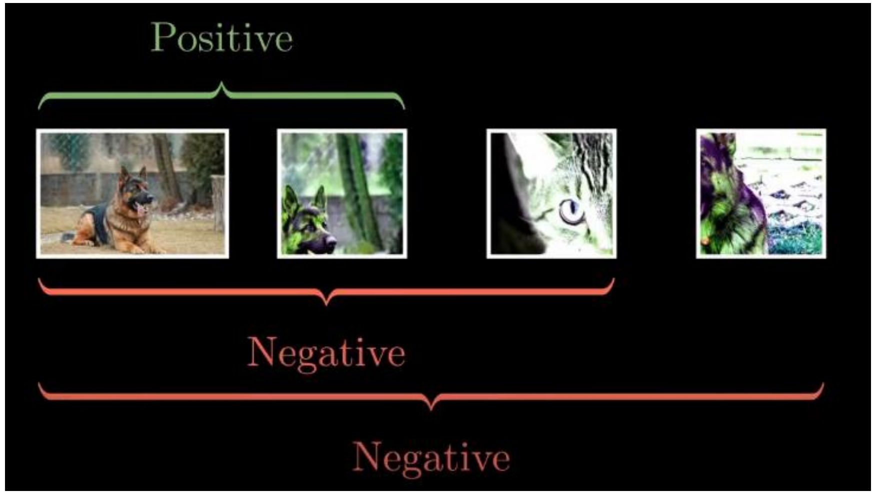

Pretrain
S1
5×5×B1
S2
5×5×B2
SK
5×5×BK
Data-specific Layers
1×1×128
Feature Analysis Layer
Task-specific Layers
1×1×C1
1×1×C2
1×1×CK
Softmax loss
Finetune
weight transfer
T
H×W×BT
H×W×128
H×W×CT
Focal loss

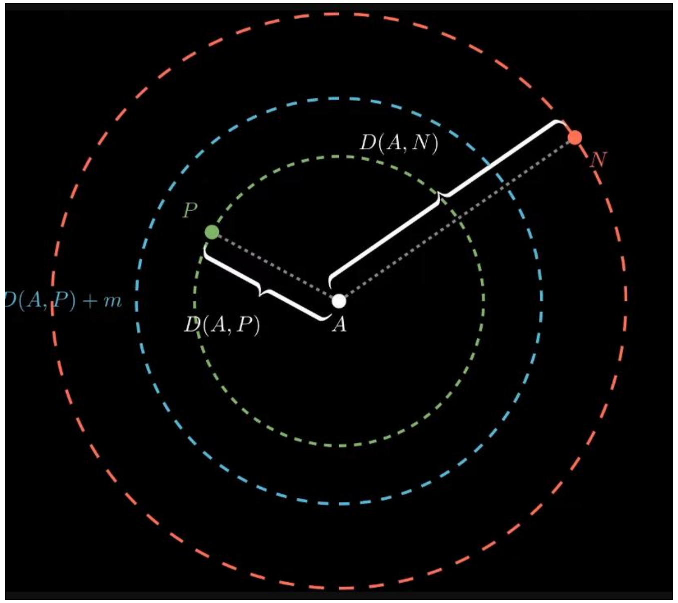

OA: Indian Pines, 9-layer
w/ pre-train
random init
iteration
0
10
20
30
40
50
60
70
80
90
100

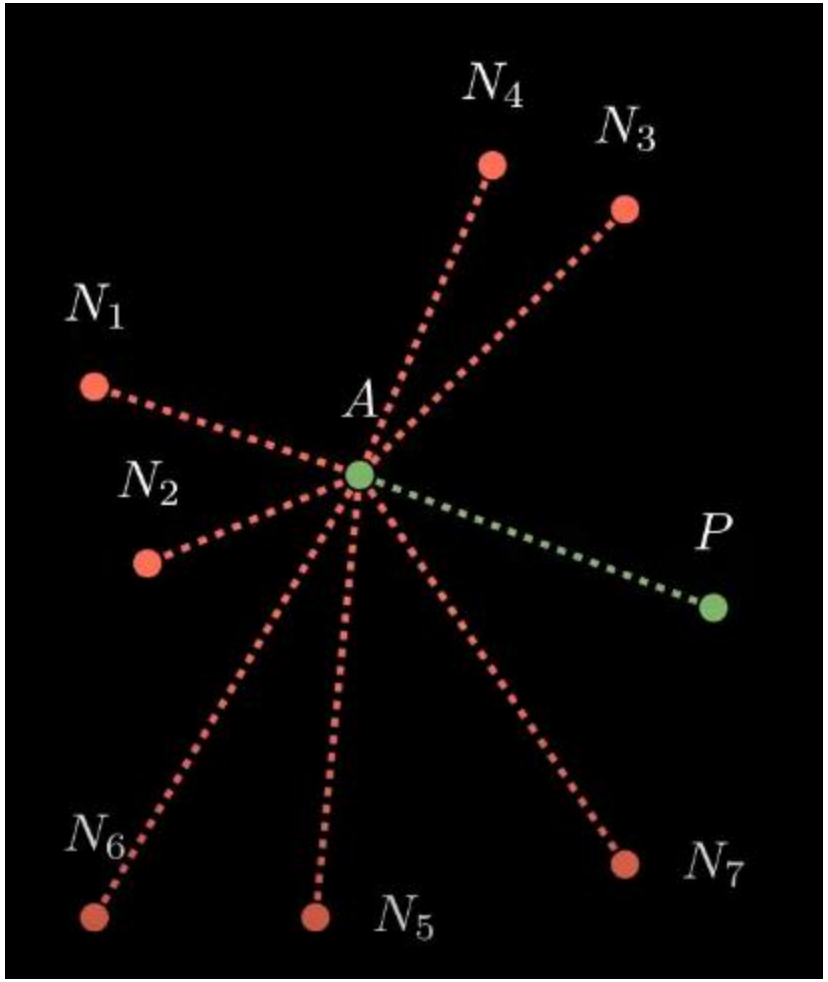
2. A Simple Framework for Contrastive Learning of Visual Representations

SimCLR is a self-supervised learning framework that learns visual features without labels using contrastive learning.

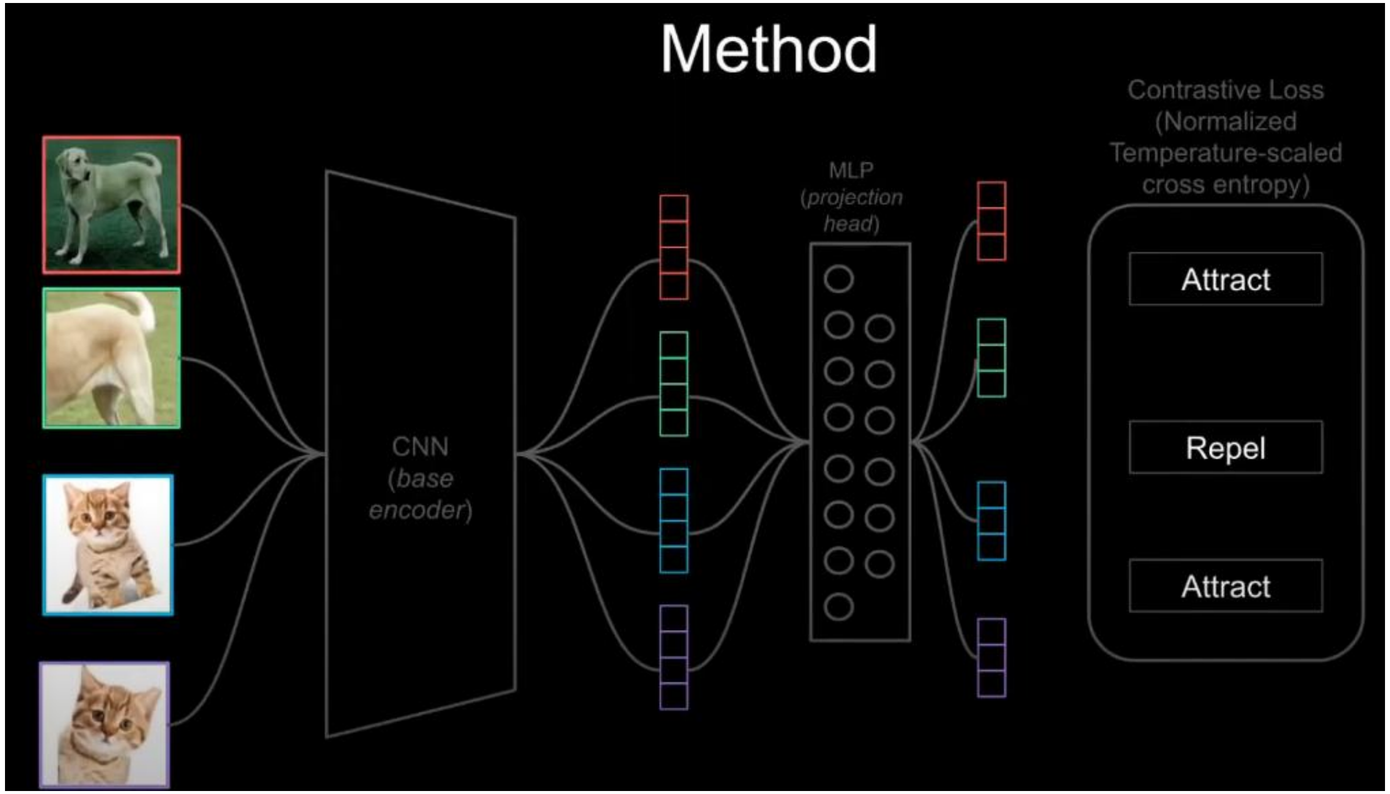


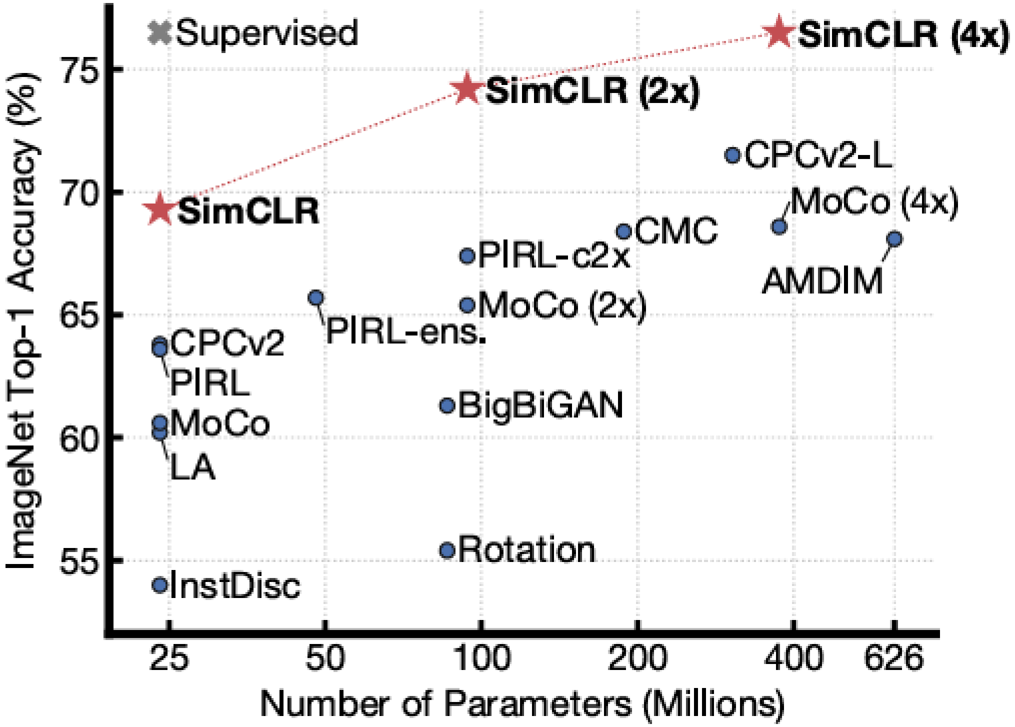






[arXiv:2002.05709](https://arxiv.org/abs/2002.05709)


Method
CNN
(base
encoder)
MLP
(projection
head)
Contrastive Loss
(Normalized
Temperature-scaled
cross entropy)
Attract
Repel
Attract


Supervised
SimCLR (4x)
SimCLR (2x)
SimCLR
CPCv2-L
MoCo (4x)
AMDIM
CMC
PIRL-c2x
MoCo (2x)
PIRL-ens.
CPCv2
PIRL
BigBiGAN
MoCo
LA
Rotation
InstDisc
ImageNet Top-1 Accuracy (%)
75
70
65
60
55
25
50
100
200
400
626
Number of Parameters (Millions)

3. SELF-SUPERVISED CONTRASTIVE LEARNING FOR CROSS-DOMAIN HYPERSPECTRAL IMAGE REPRESENTATION

Goal: The paper introduces a **cross-domain CNN-based contrastive learning framework** to learn **domain-invariant hyperspectral representations** without any labels. It builds on prior cross-domain CNN work but integrates **contrastive self-supervision**

Domain-Specific Encoder (enc_i)

- Each hyperspectral domain (individual image) has its own encoder to handle varying spectral characteristics.

Shared Cross-Domain Network (CD-CNN)

- Core network shared across all domains for learning joint representations.

No Output Heads in Pretraining Stage

- Since it's self-supervised, task-specific (classification) heads are omitted during representation learning.

Contrastive Module

- For every spatial patch, select neighboring spectral pixels as positive pairs (same material) and pixels from other domains/images as negatives.
- Applies contrastive loss to learn clustering across domains.

https://arxiv.org/pdf/2202.03968

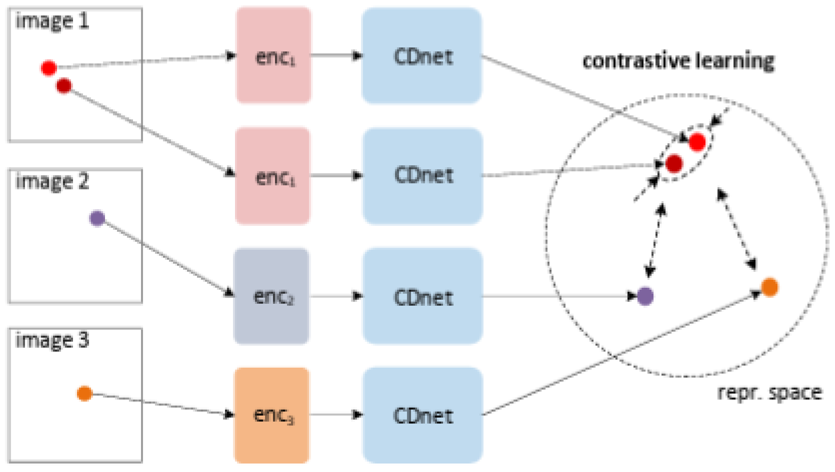
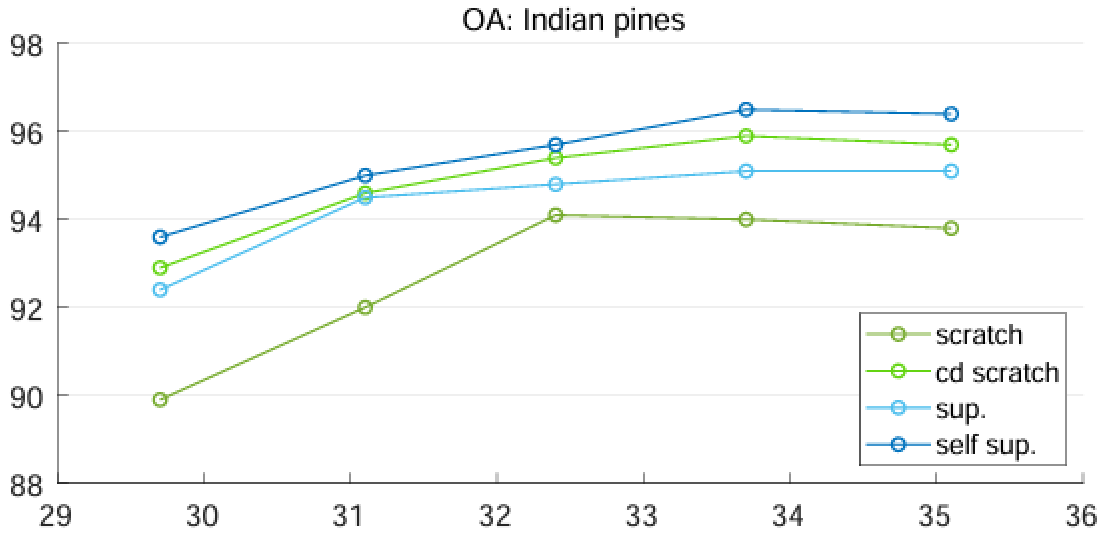


image 1
image 2
image 3
enc1
enc1
enc2
enc3
CDnet
CDnet
CDnet
CDnet
contrastive learning
repr. space



OA: Indian pines
98
96
94
92
90
88
29
30
31
32
33
34
35
36
scratch
cd scratch
sup.
self sup.

4. Building Cross-Domain Mapping Chains From Multi-CycleGAN for Hyperspectral Image Classification

Goal : Tackle **cross-domain hyperspectral image (HSI) classification** when you have **limited labeled samples in the target domain** and want to leverage labeled data from a **different sensor/source domain**

1. **Input and Initial Encoding**
You start with an image (x_T) from the **target domain**.
It's processed by an **encoder (E_T)**, which extracts and flattens the image into a latent **feature vector**

- First, {f}T is sent through a generator (G{TS}) to simulate what it would look like in the source domain
- Then, this feature is evaluated by the source discriminator (D_S) to ensure it looks realistic in S.
- Use Multi-CycleGAN to translate all source domain data to the spectral style of your target domain.
- Result: You can now apply a pretrained model as if all data came from the same sensor.

https://ieeexplore.ieee.org/document/10604917

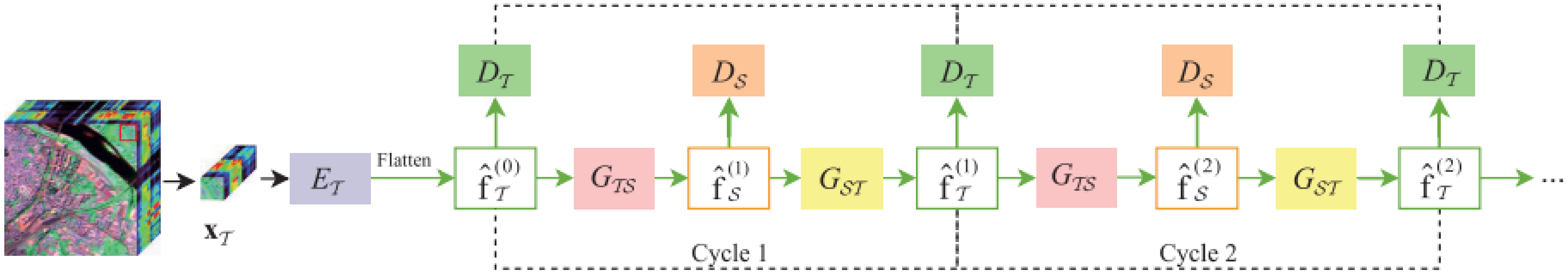


Fig. 4. Target chain unfolded through cycles in our proposed CDMC. The features generated by each cycle are fed into the next cycle. Note that the proposed CDMC also includes a source chain. To obtain a view of the source chain, swap $\mathcal{T}$ and $\mathcal{S}$, and replace $\hat{\mathbf{f}}$ with $\widetilde{\mathbf{f}}$.

Project Phase	Jun-25		Jul-25				Aug-25				Sep-25				Oct-25				Nov-25				Dec	
	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4	W1	W2
Literature review																								
Research Paper Gathering																								
Summarizing LR																								
Thesis Proposal																								
Deciding Implementation																								
Implementation																								
Test and Finalize																								
Evaluation of Performance																								
Report Writing																								
Proof Reading/ Changes																								
Review and Submission																								

References

1. H. Lee, S. Eum and H. Kwon, "Exploring Cross-Domain Pretrained Model for Hyperspectral Image Classification," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-12, 2022, Art no. 5526812, doi: 10.1109/TGRS.2022.3165441.
keywords: {Hyperspectral imaging;Training;Task analysis;Data models;Convolutional neural networks;Data analysis;Analytical models;Cross domain;hyperspectral image classification;pretrain-finetune strategy},

2. arXiv:2002.05709 **[cs.LG]**

3. H. Lee and H. Kwon, "Self-Supervised Contrastive Learning for Cross-Domain Hyperspectral Image Representation," ICASSP 2022 - 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Singapore, Singapore, 2022, pp. 3239-3243, doi: 10.1109/ICASSP43922.2022.9747010. keywords: {Training;Representation learning;Conferences;Transfer learning;Semantics;Signal processing;Image representation;Self-supervised learning;Contrastive learning;Cross-domain;Hyperspectral image classification;Transfer learning},

4. M. Ye, Z. Meng and Y. Qian, "Building Cross-Domain Mapping Chains From Multi-CycleGAN for Hyperspectral Image Classification," in IEEE Transactions on Geoscience and Remote Sensing, vol. 62, pp. 1-17, 2024, Art no. 5524117, doi: 10.1109/TGRS.2024.3431460.
keywords: {Adversarial machine learning;Transfer learning;Generators;Task analysis;Knowledge transfer;Accuracy;Adaptation models;Adversarial learning;cross-domain hyperspectral image (HSI) classification;Cross-Domain Mapping Chain (CDMC);heterogeneous transfer learning},

Thesis Proposal

- Preliminary title
- Background and context
- Problem and research topic
- State of the art
- Goals, theses, questions
- Benefit, relevance, originality
- Methodology
- Project plan
- Requirements

Thank you