

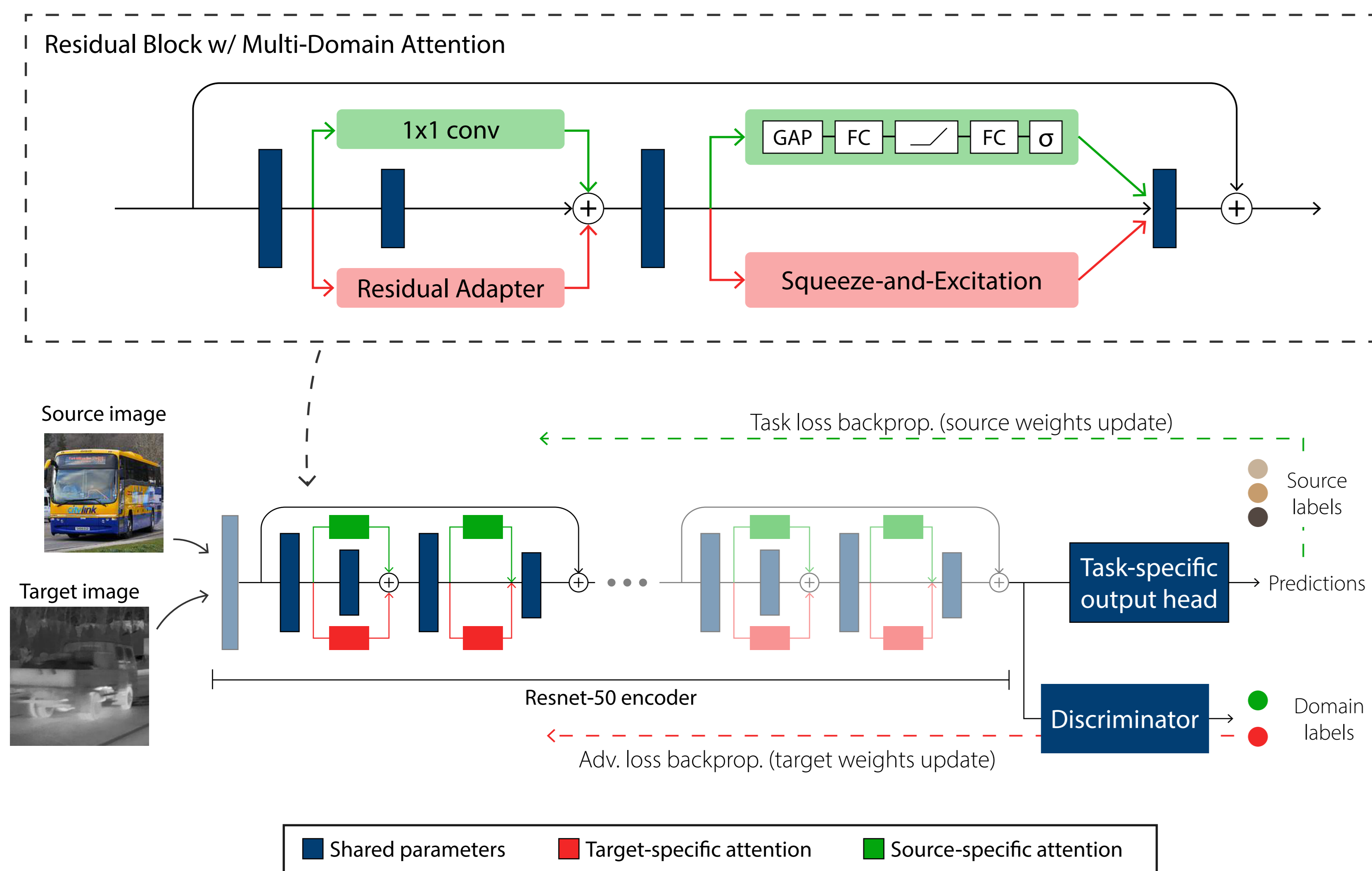
Background

- Lack of large, annotated thermal datasets prevent adoption of deep learning algorithms for nighttime robotic operations.
- Current unsupervised domain adaptation (UDA) methods align images/features across domains but struggle with cross-modal data where not all features transfer.
- We use shared CNN encoders with domain-specific attention modules that mitigate forced transfer by attending to domain-invariant and domain-specific features.

Multi-Domain Attention Network Architecture

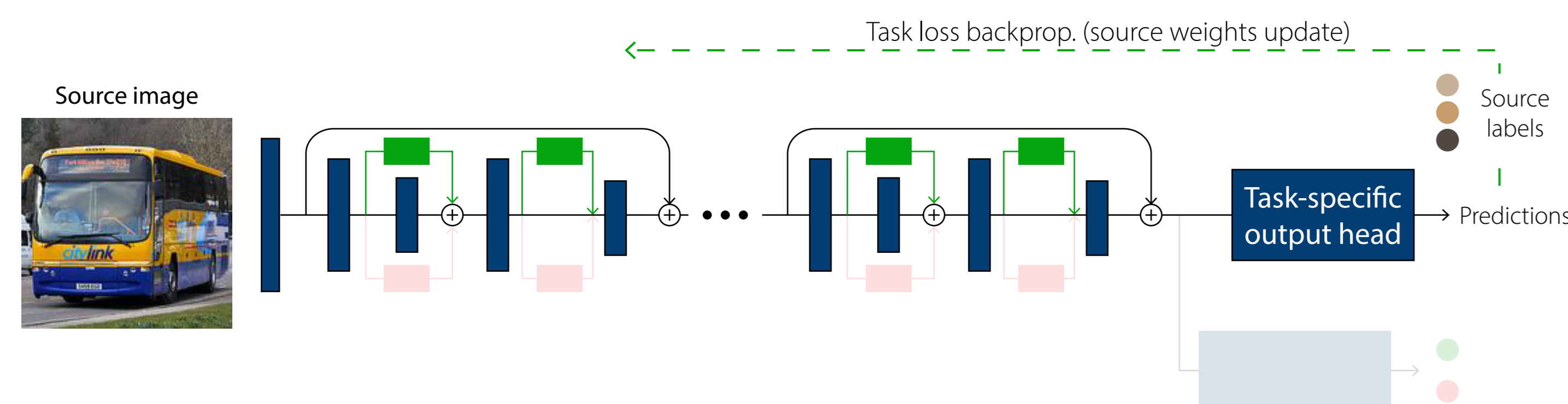
We insert source- and target-domain residual adapters and squeeze-and-excitation blocks into basic CNN blocks to enable RGB-T DA. This requires:

- Source (RGB) images use only shared and source weights.
- Target (thermal) images use only shared and target weights.

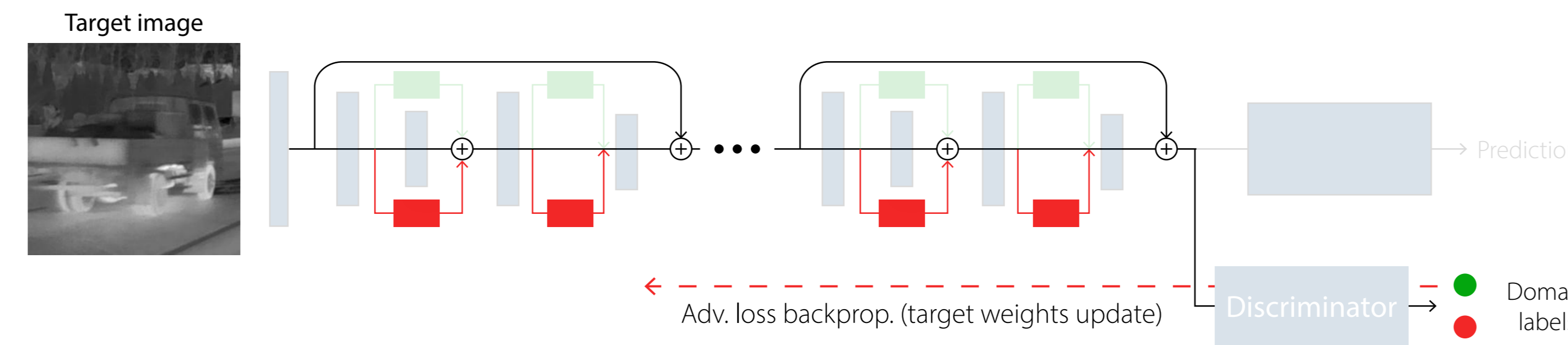


Unsupervised Training Algorithm

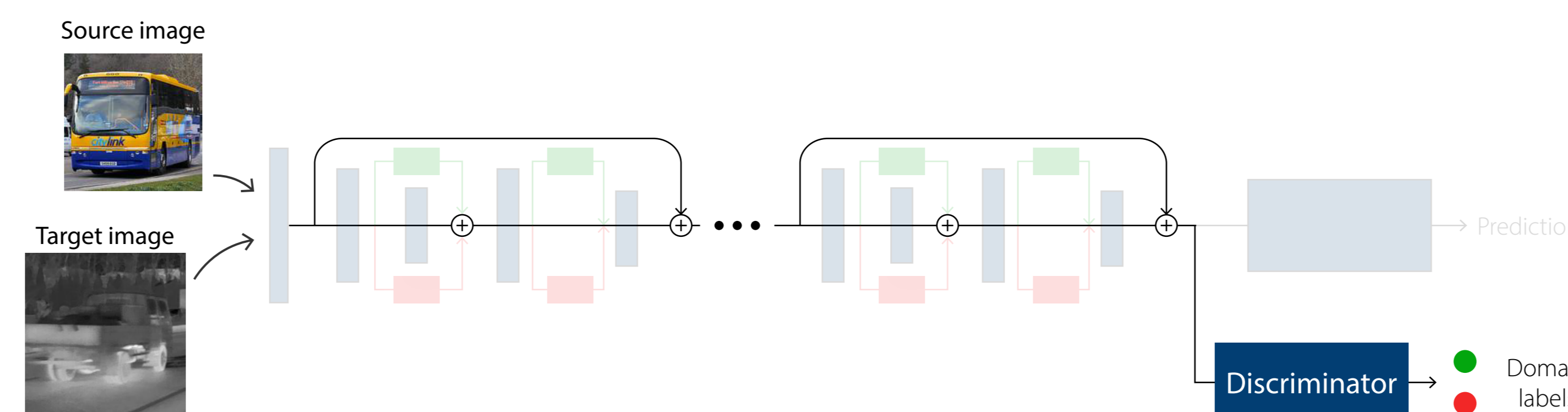
Step 1: Update shared and source weights with source task loss



Step 2: Update target weights via adversarial target domain confusion loss using a fixed discriminator



Step 3: Fix encoder and update domain discriminator. Repeat steps 1-3 until converged.



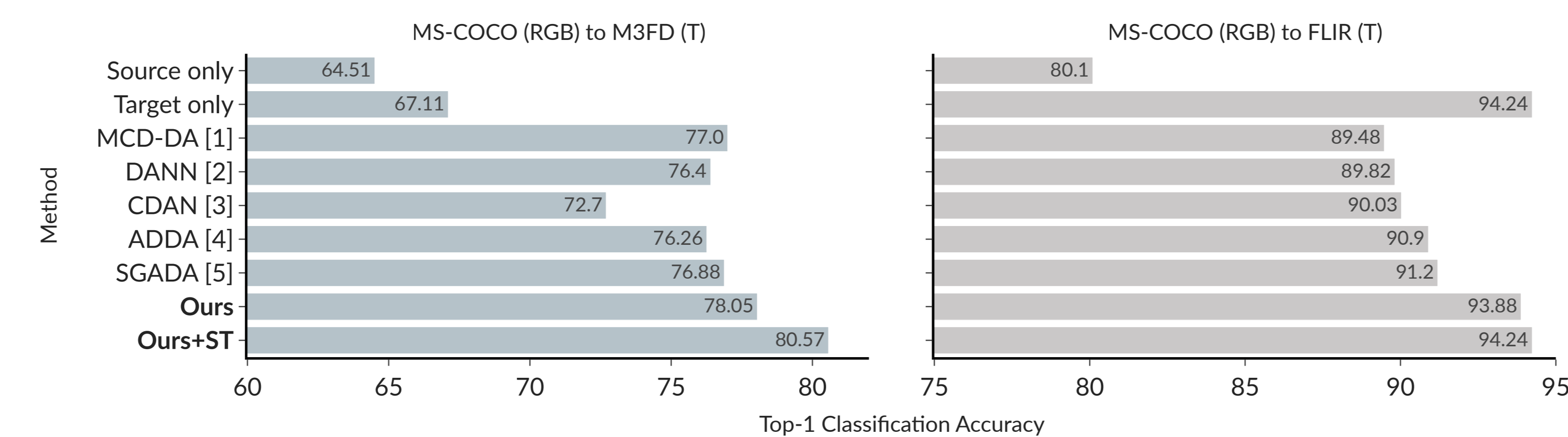
Step 4 (optional): Self-train on target domain data

- Finetune target weights using pseudolabels of target samples.
- Good pseudolabel = confused discriminator + high confidence.

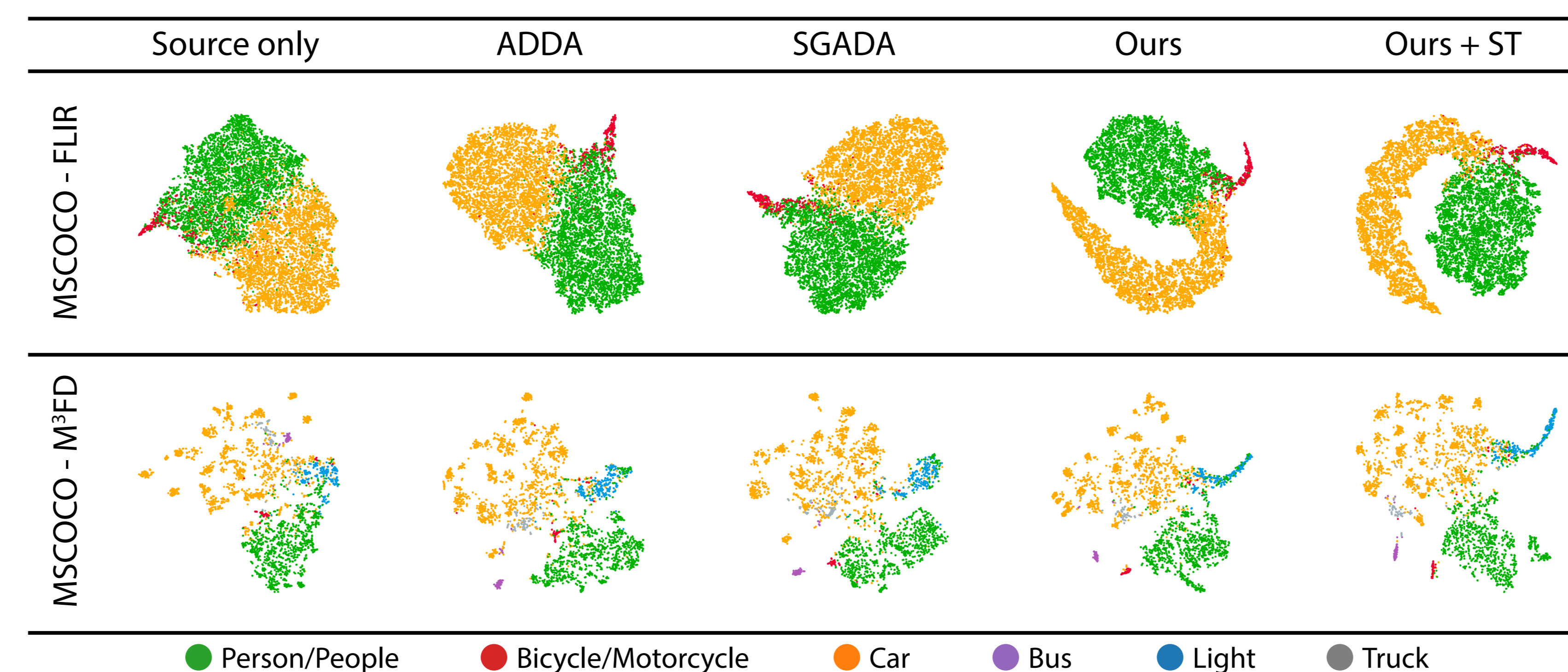
Results: Unsupervised Thermal Image Classification

We benchmark our method on image classification, using bounding box crops from object detection datasets.

- Source data: RGB images from MSCOCO
- Target data: Thermal images from (1) FLIR and (2) M³FD datasets



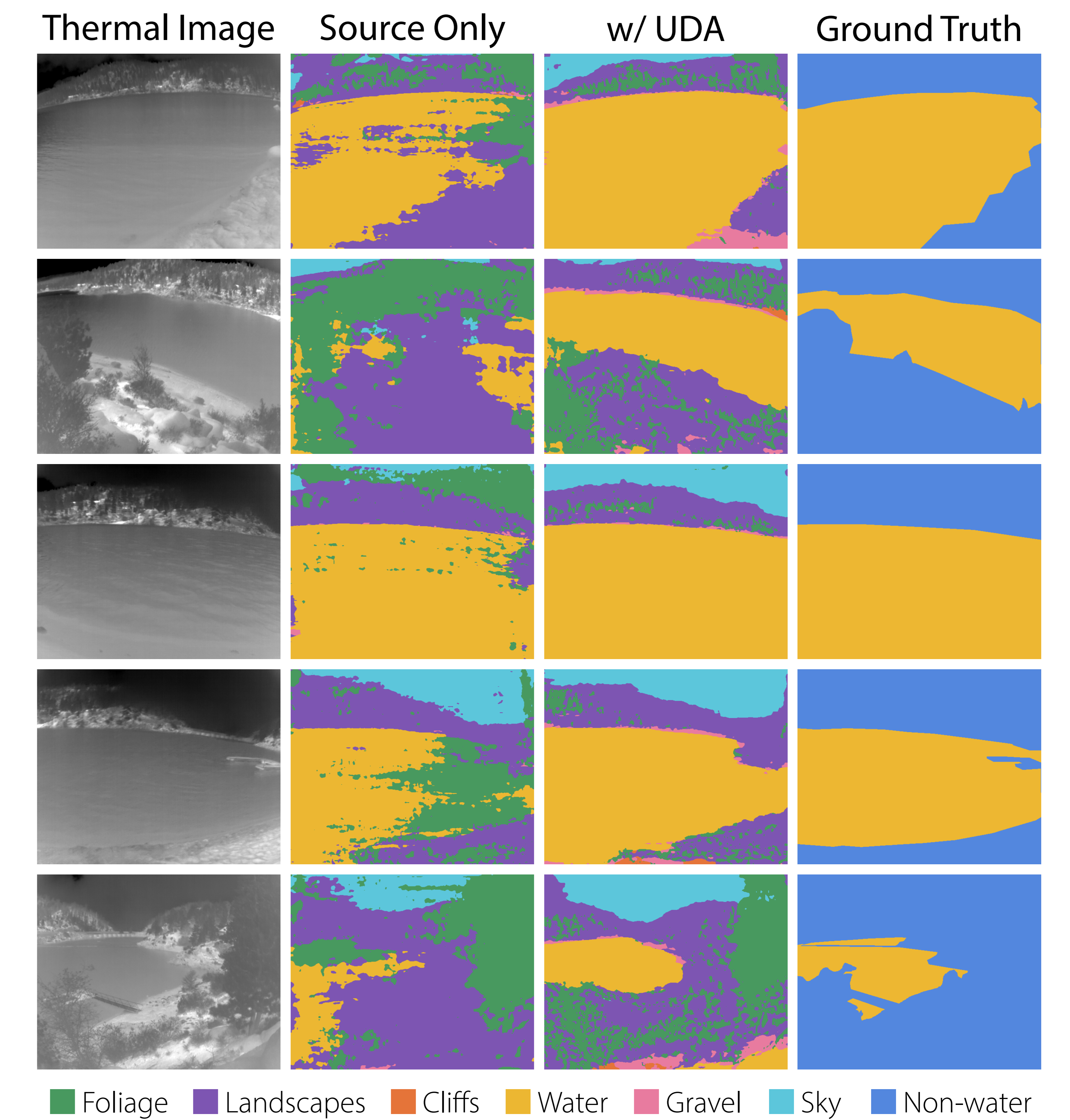
T-SNE analysis shows improved class distinction in target test samples.



Results: Unsupervised Thermal Water Segmentation

We train a DeepLabV3+ network to perform thermal water segmentation in order to assist nighttime littoral robotic operations.

- Source data: Synthetic grayscale images of rivers/lakes from Microsoft AirSim.
- Target data: Thermal lake images captured at Big Bear Lake, California



Conclusions

- RGB-T UDA using modular multi-domain attention and adversarial training.
- Outperformed other RGB-T DA methods in two classification benchmarks.
- Easily extends to other networks and tasks, like semantic segmentation.

References

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