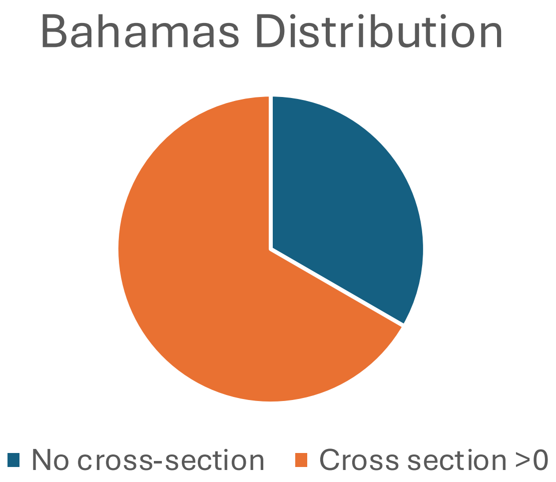
Dark Matter
Update: 24/06/2025

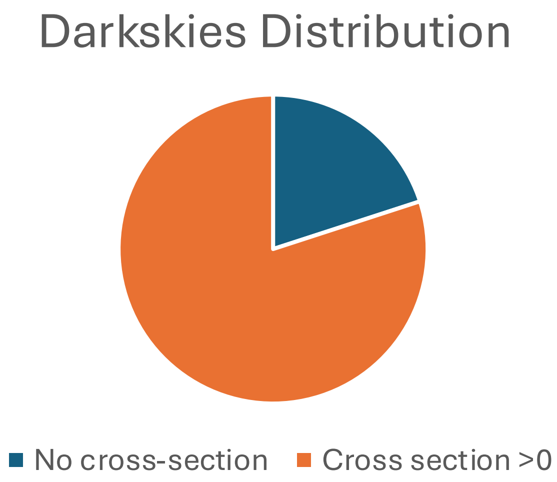
A Systematic Study of Models, Augmentations, and Adaptation Techniques

Brief overview:

- **Problem:** Significant performance gap between source and target domains
- **Approach:** Systematic evaluation of models, augmentations, loss weighting, and adaptation methods
- **Goal:** Bridge the domain gap and improve target domain performance

Data used for experiments



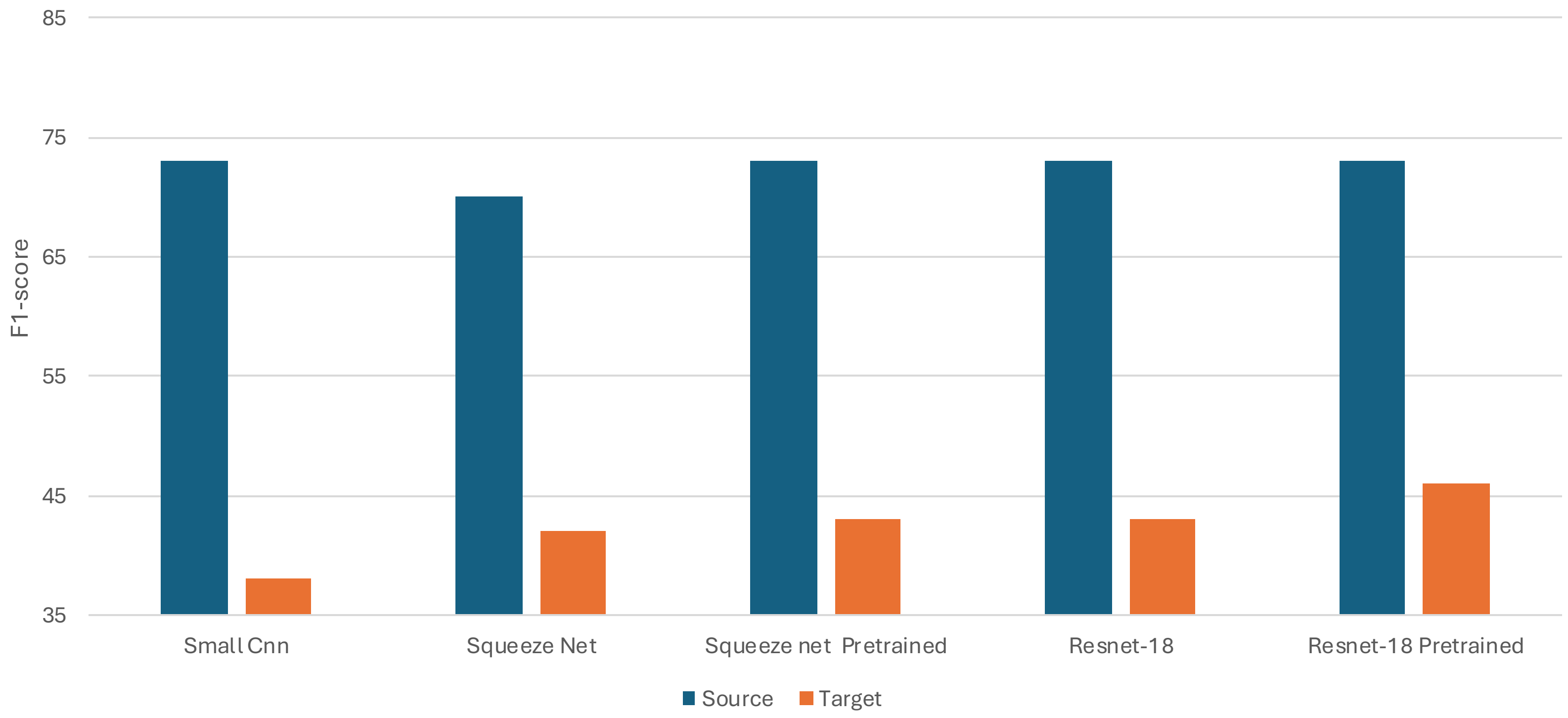


Cross-section:
- 0.0
- 0.1
- 0.3

Cross-section:
- 0.0
- 0.01
- 0.05
- 0.10
- 0.20

The Domain Gap

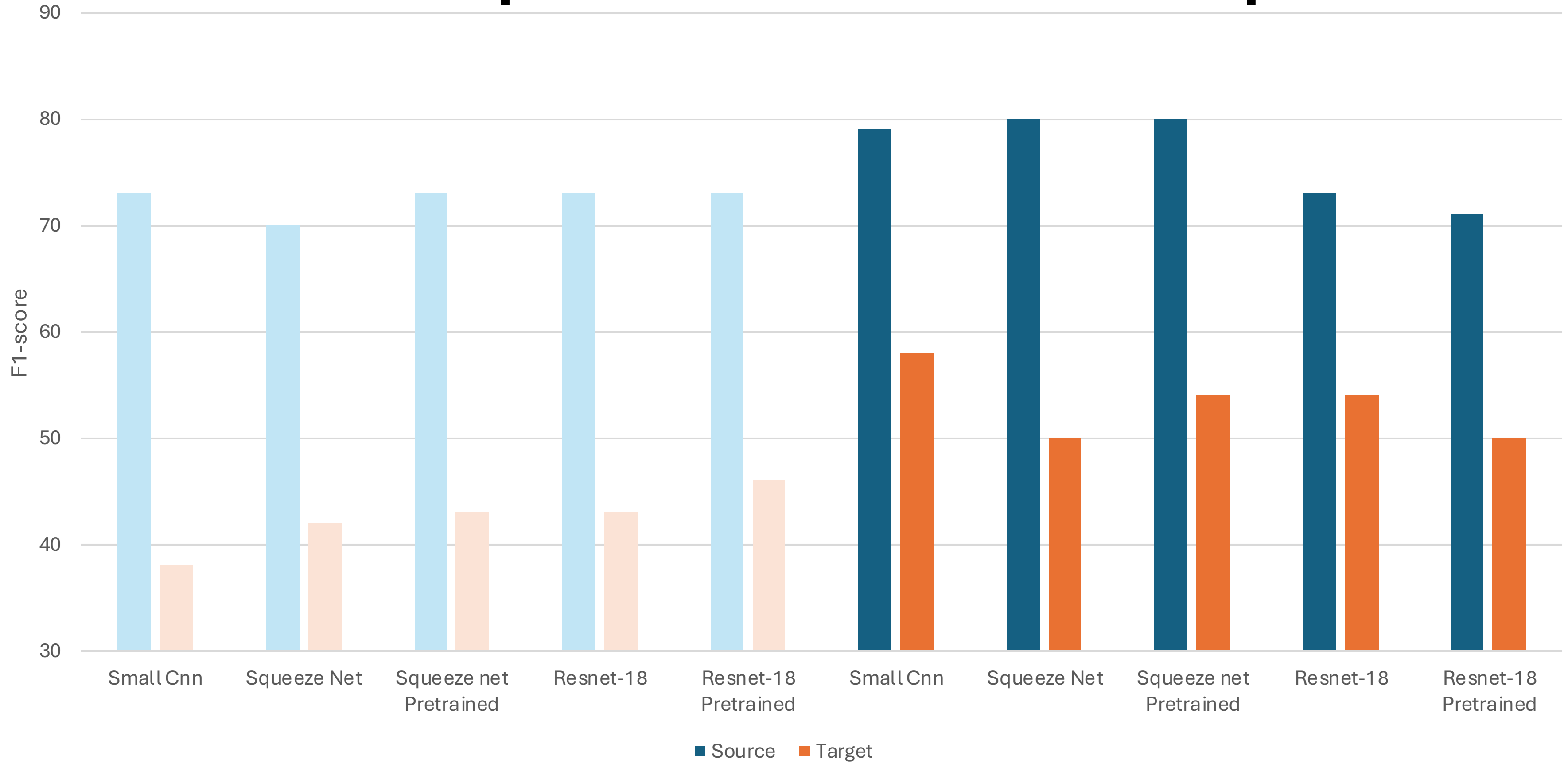
Baseline Performance Comparison



Key Insight: Substantial performance degradation across all models when moving from source to target domain

Impact of Data Augmentation

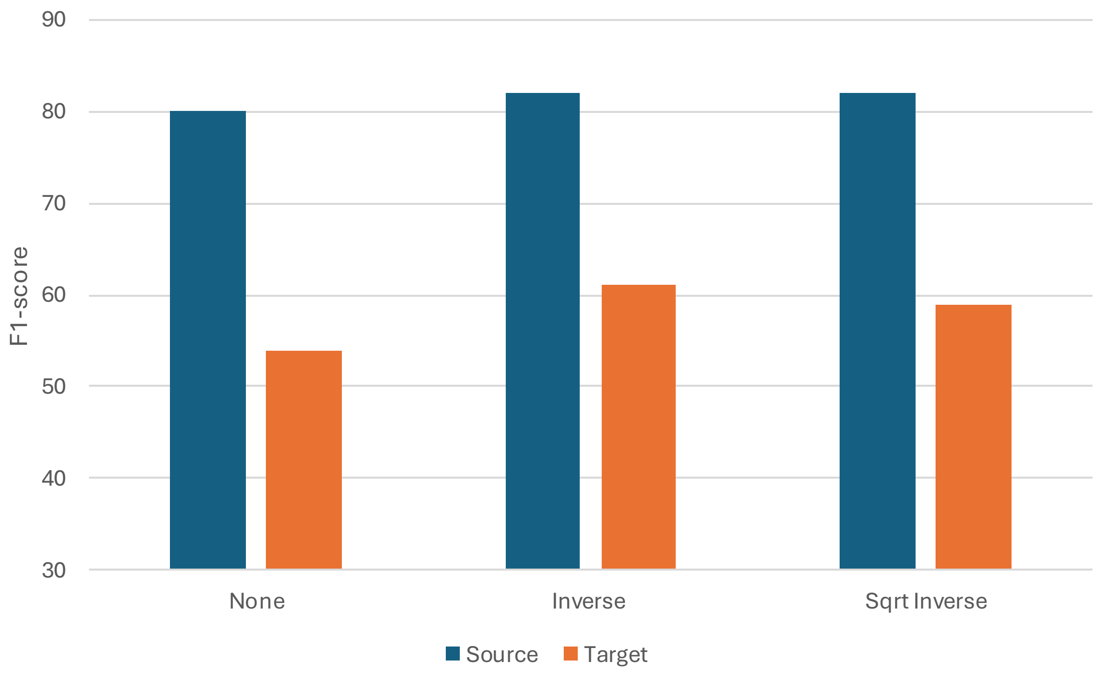
Vertical/Horizontal Flip vs. Random Center Crop



Key Insight: Random center crop augmentation provides substantial improvements

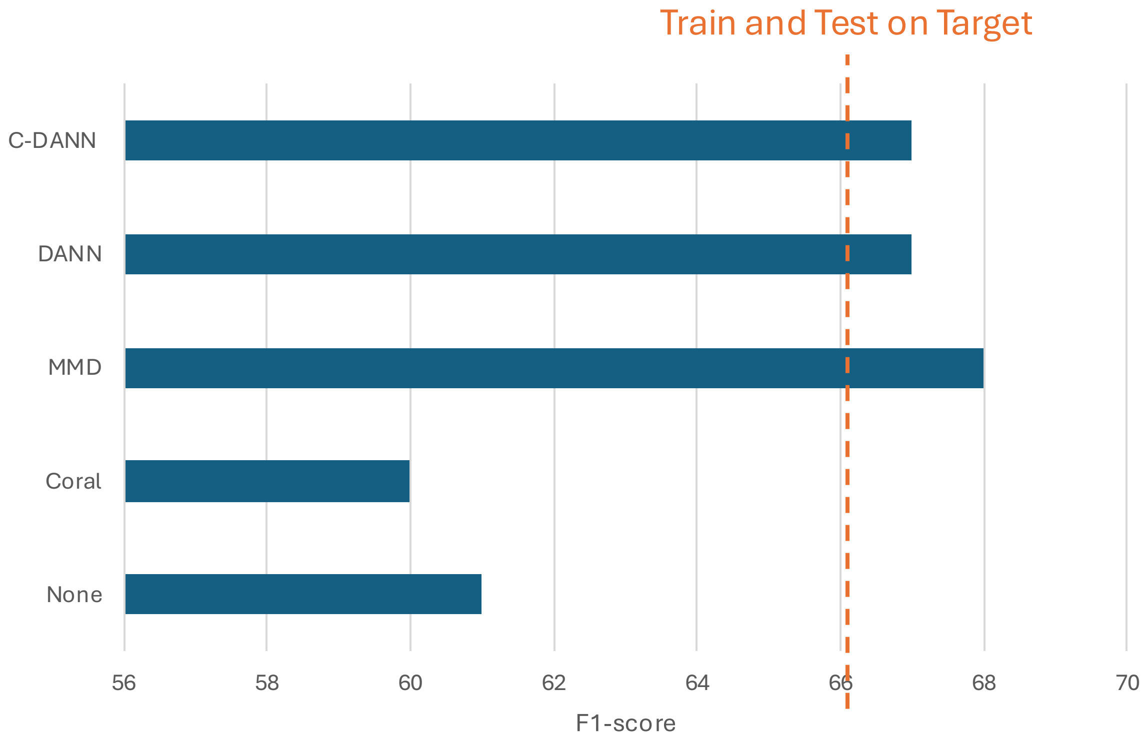
Loss Weighting Strategies

Different Loss Weights



Key Insight: Inverse loss weighting achieves best target performance (61%) while maintaining strong source performance

Comparing Domain Adaptation Techniques



Key Insight: MMD achieves highest target performance (68%), showing 7% improvement over baseline.

Cross-Section Predictions Analysis

Source

Cross-section	Nb Samples	True Class	Class 0 Pred	Class 1 Pred
0.00	1079	0	**84.6%**	15.4%
0.10	518	1	31.7%	**68.3%**
0.30	561	1	11.6%	**88.4**

Target

Cross-section	Nb Samples	True Class	Class 0 Pred	Class 1 Pred
0.00	599	0	**67.8%**	32.2%
0.01	141	1	61.7%	**38.3%**
0.05	158	1	34.8%	**65.2%**
0.10	152	1	19.21%	**80.9%**
0.20	148	1	13.5%	**86.5%**

Mixup strategies

Source Only

	Target F1-score
None	61
Random	59
Same Index	63

C-DANN

	Target F1-score
None	67
Random	66
Same Index	68