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# Paired Neural Networks for Hyperspectral Target Detection

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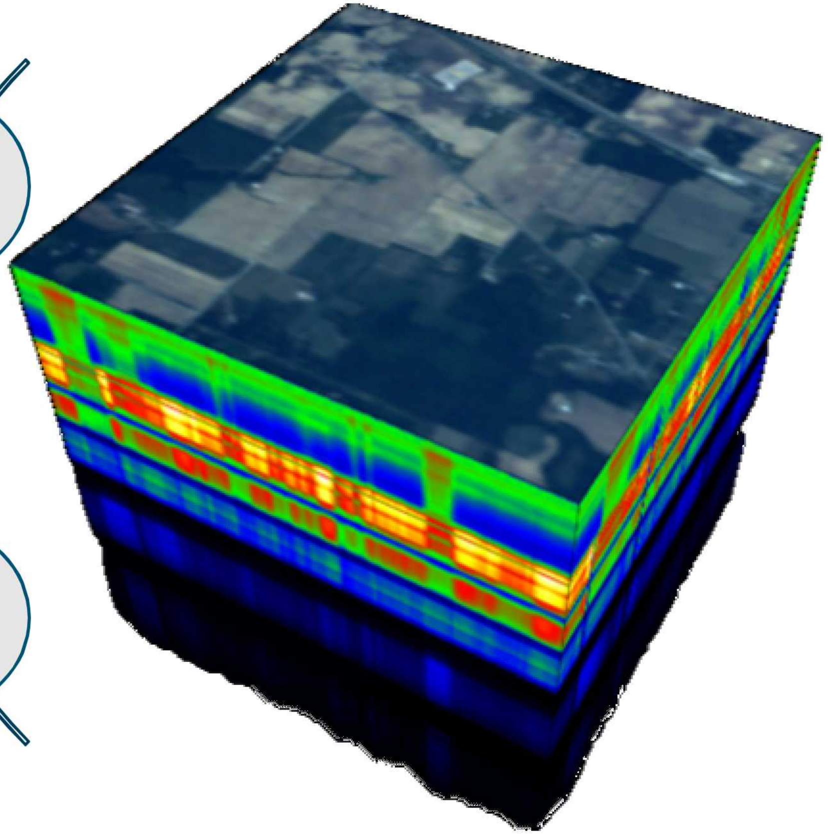
# Hyperspectral Target Detection

## Hyperspectral Imagery

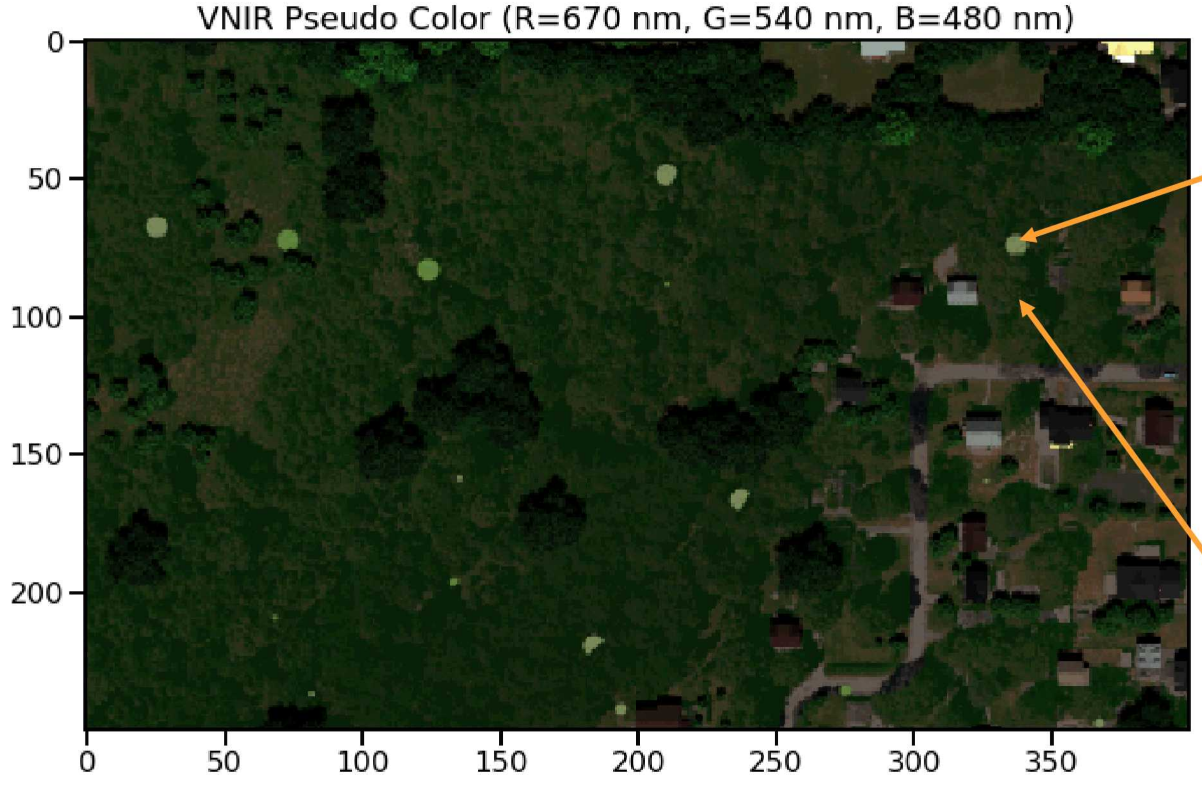
- Powerful material discriminant
- High dimensionality
- High co-linearity between bands

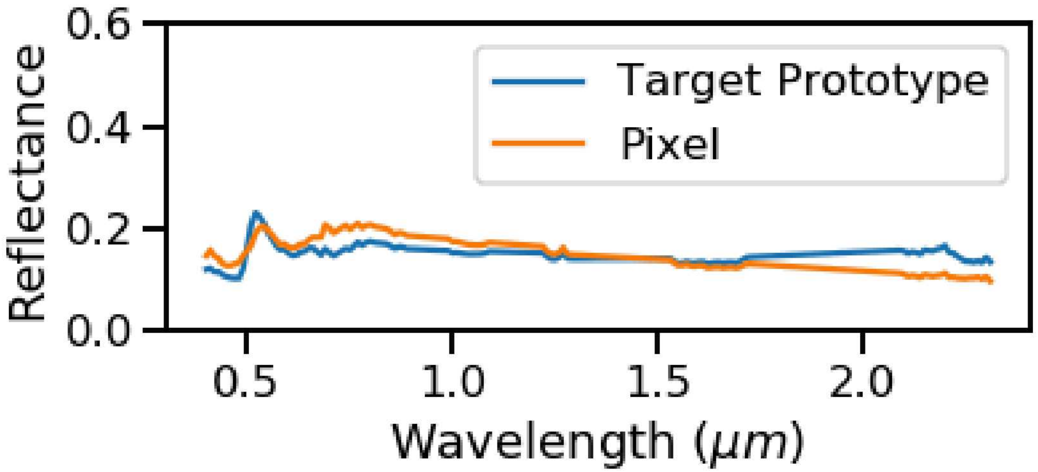


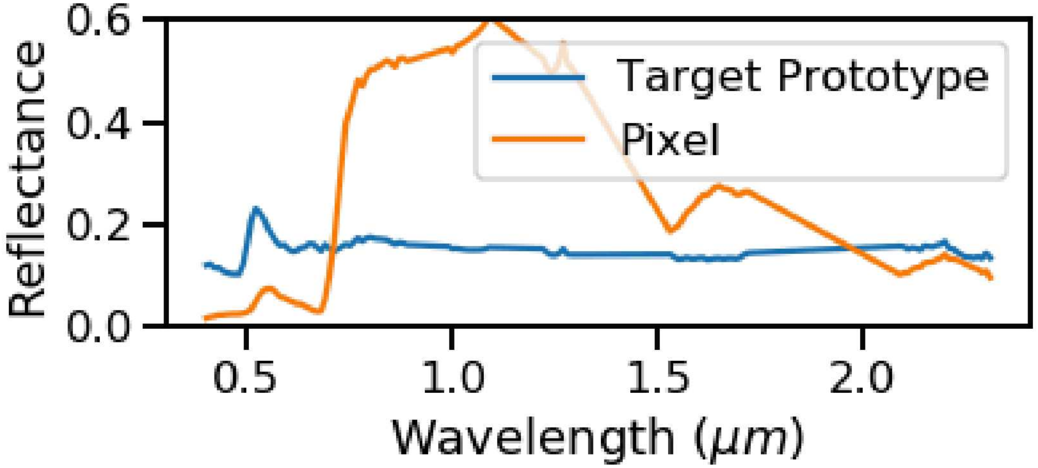
## Target Detection

- Explicit appearance model
- Rare - few target pixels per image
- Sub-pixel - low fill fraction

# Classical Statistical Detectors

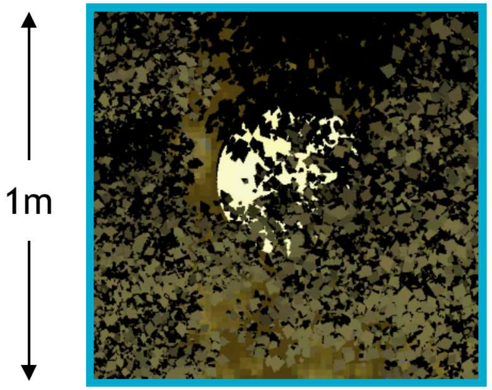


# Adaptive Cosine Estimator

Single Pixel




Target fill fraction

Background spectra

$$x \approx a\, s + v, \qquad \text{if } 0 < a \ll 1$$

Measured spectra

Target spectra

For Gaussian Target and Clutter with shared covariance, ACE detector is uniformly most powerful.

$$y_{ACE} = \frac{s^T C_b^{-1} x}{\sqrt{s^T C_b^{-1} s}\sqrt{x^T C_b^{-1} x}}$$

# The Expanding Library Problem

When are ACE assumptions poor?

- Complex target morphology
- Off-nadir collection geometry and illumination
- Errors in reflectan
- Transmissive targe
- Non-linear mixing

**Idea:** What if we could design a function that mitigates these effects for target detection?

$$x' = h_\theta(x)$$

Solution: measure target in many conditions!

$s_0$

$s_1$

$s_2$

⋮

$s_n$

# Contrastive Loss

The distance between a target prototype spectra and pixel spectra:

$$D_\theta = \|h_\theta(p_t) - h_\theta(x_i)\|_2$$

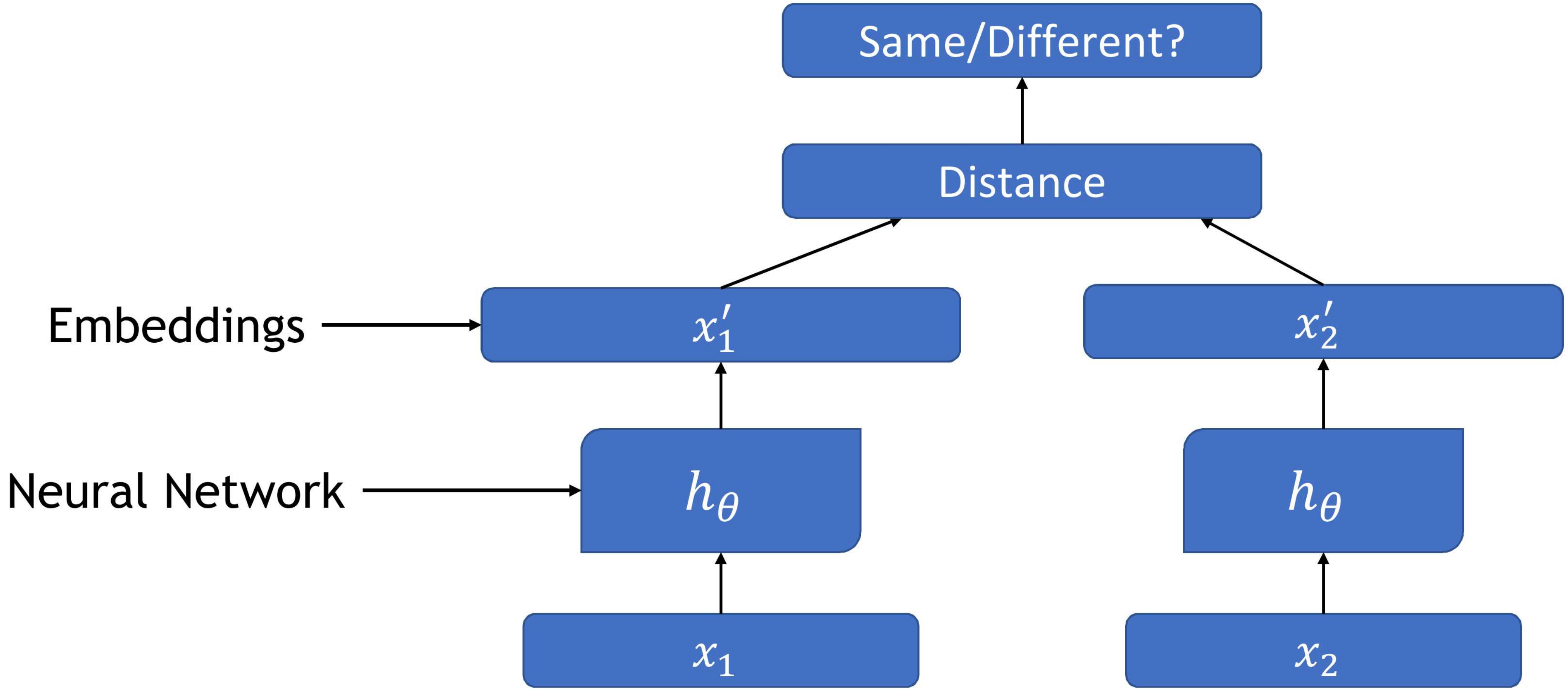
We desire:

- Small $D_\theta$ when $x_i$ contains target $t$
- Large $D_\theta$ when $x_i$ does not contain target $t$

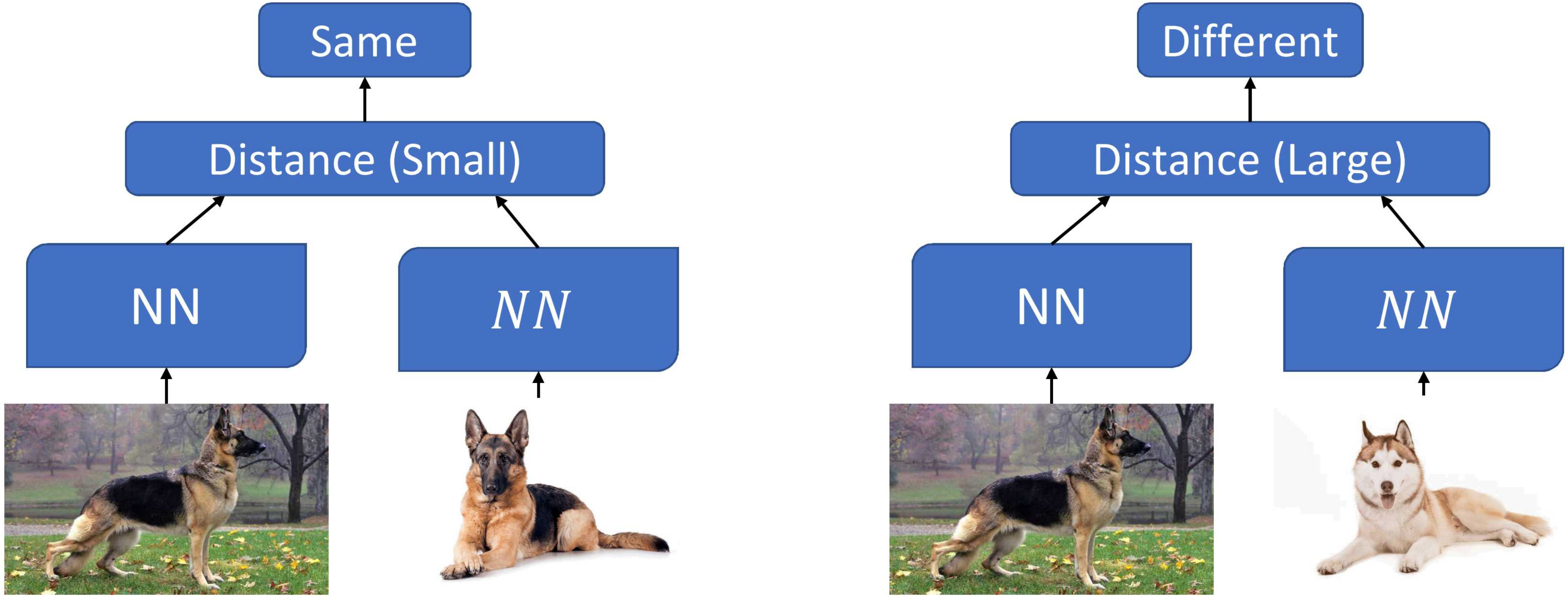
We can evaluate the goodness of a particular $h_\theta$ with the **contrastive loss**

$$\mathcal{L} = y\frac{1}{2}D_\theta^2 + (1 - y)\frac{1}{2}\{\max(0, m - D_\theta)\}^2$$

# Paired Neural Networks



# Paired Neural Networks



# Paired Neural Networks for Hyperspectral Target Detection

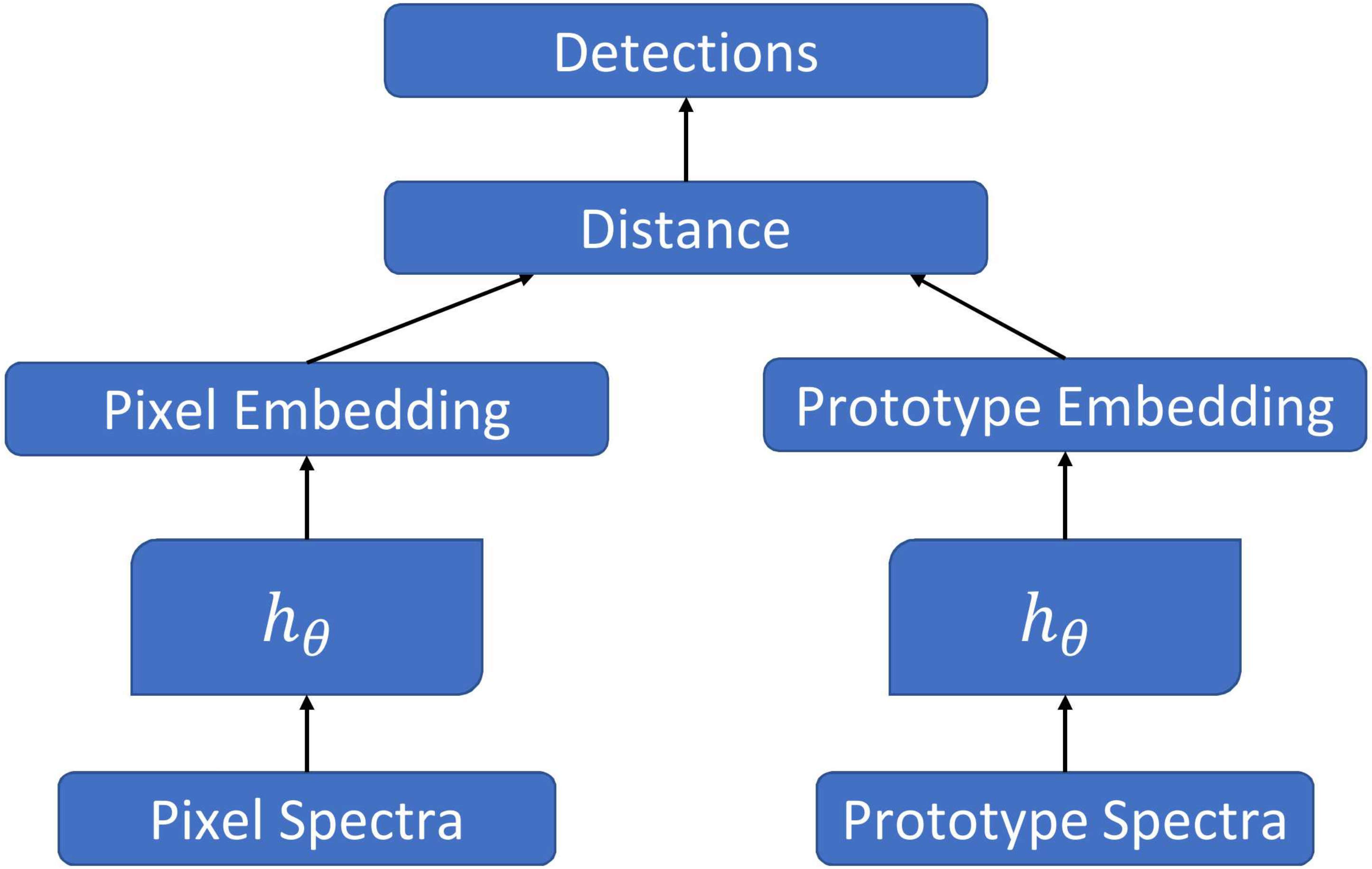
Training set consists of:

- (pixel spectra, target spectra, target/non-target)

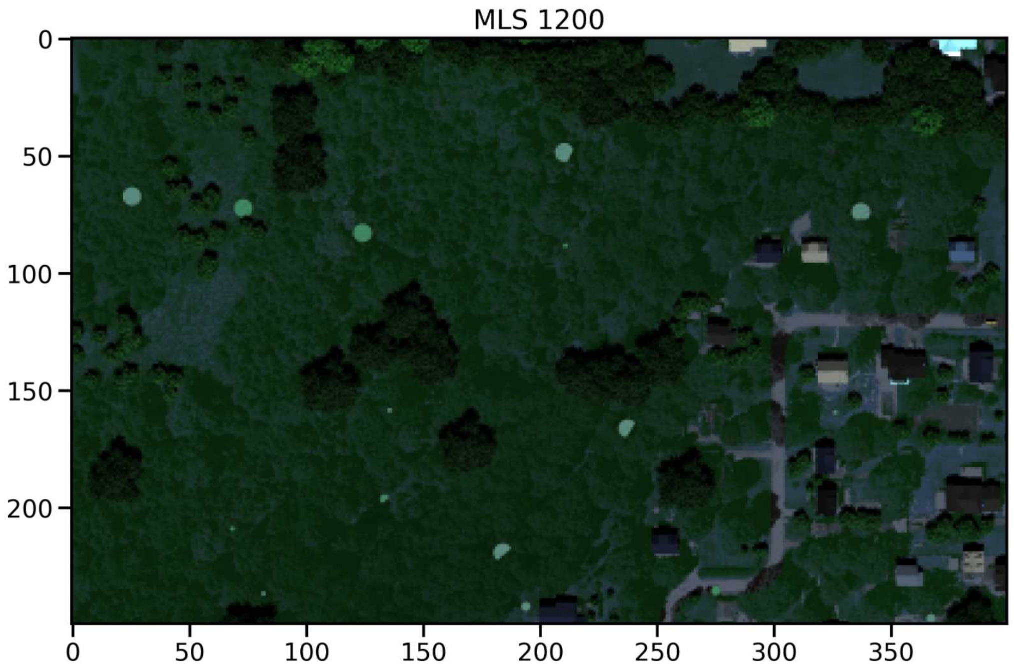
New target materials can be detected during inference!

Converting distance to similarity (target score):

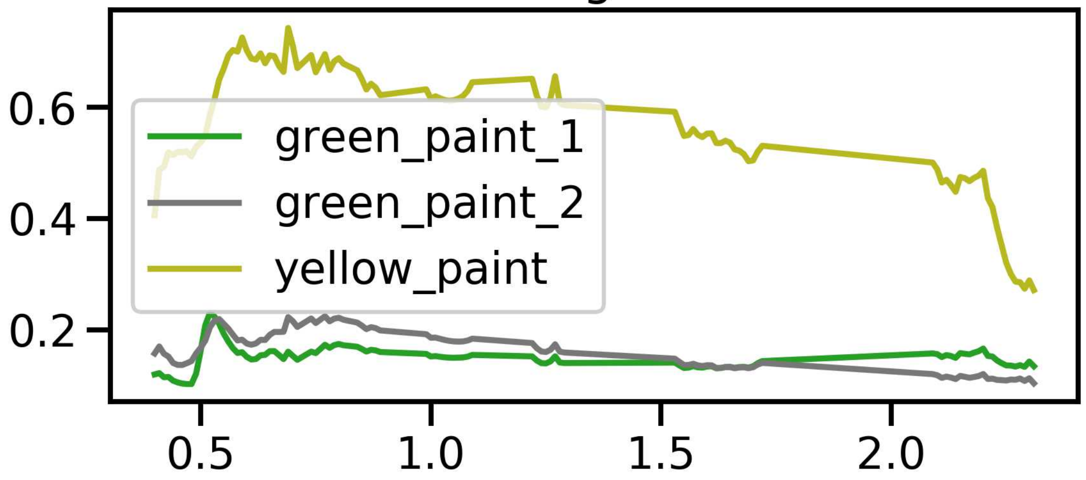
$$S_\theta = \frac{1}{1+D_\theta}$$

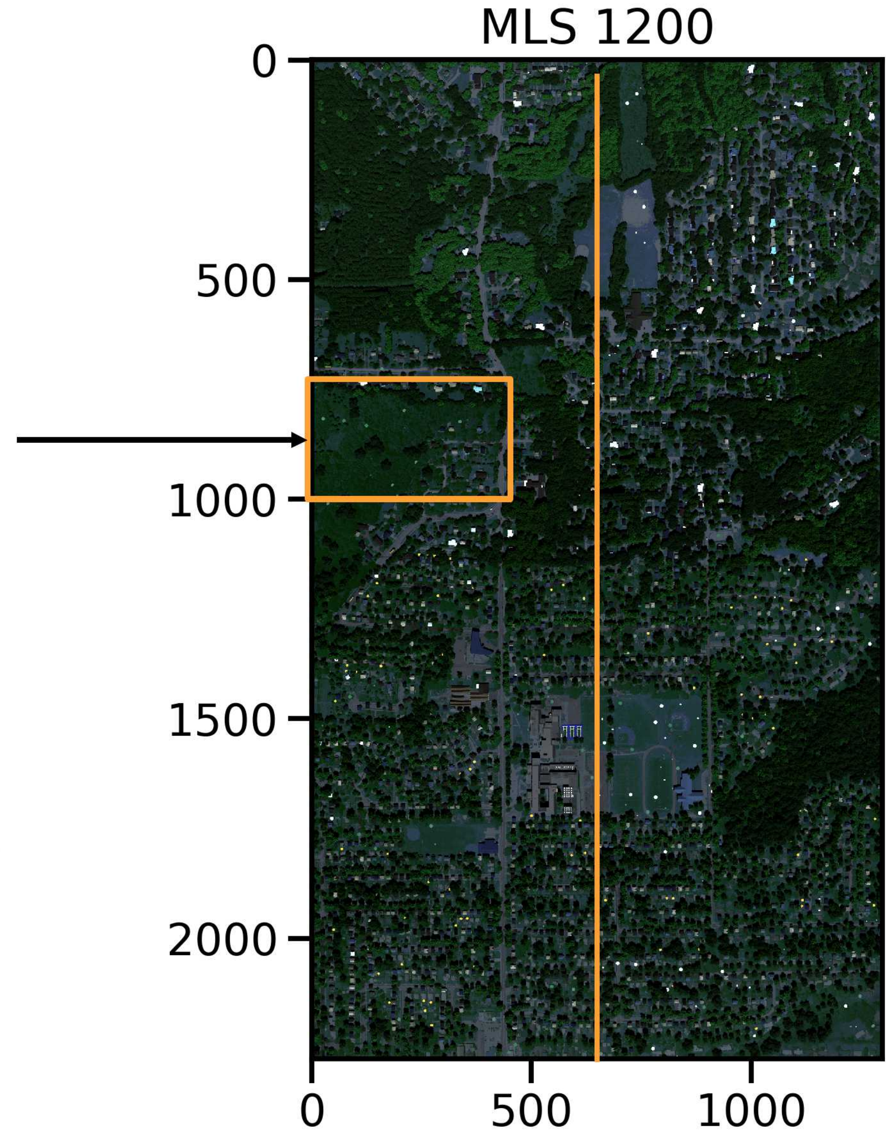


# Megascene Experiment



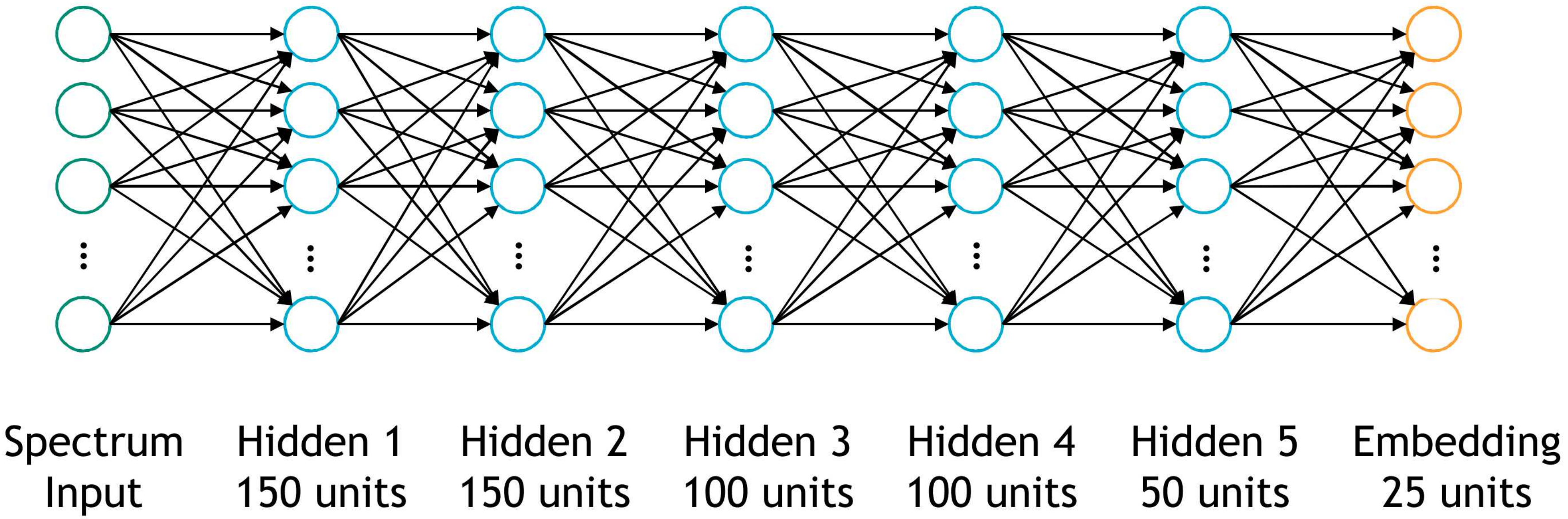

Inserted Target Materials




VNIR Pseudo Color
(R=670 nm, G=540 nm, B=480 nm)

# Megascene Experiment




Up to 3,000 positive pairs per material

Resample pairs every 100 epochs

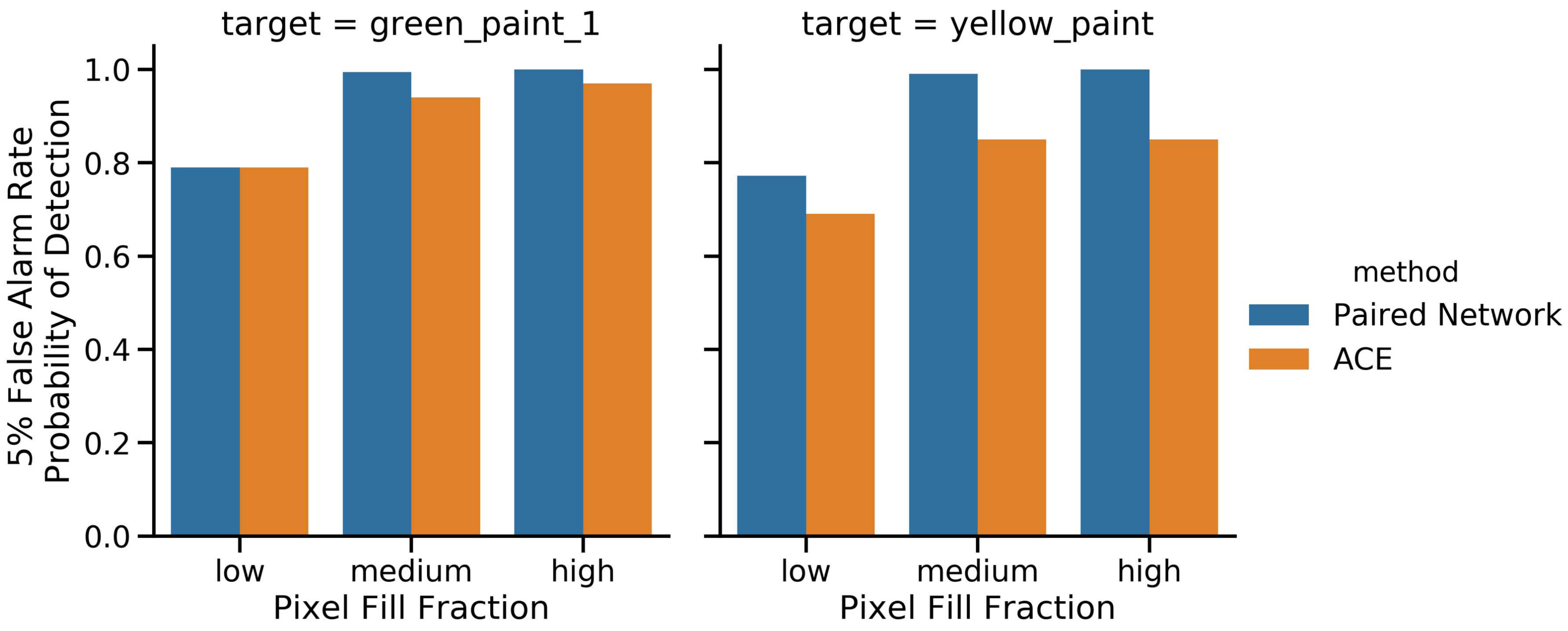
10,000 epochs

ReLU activations

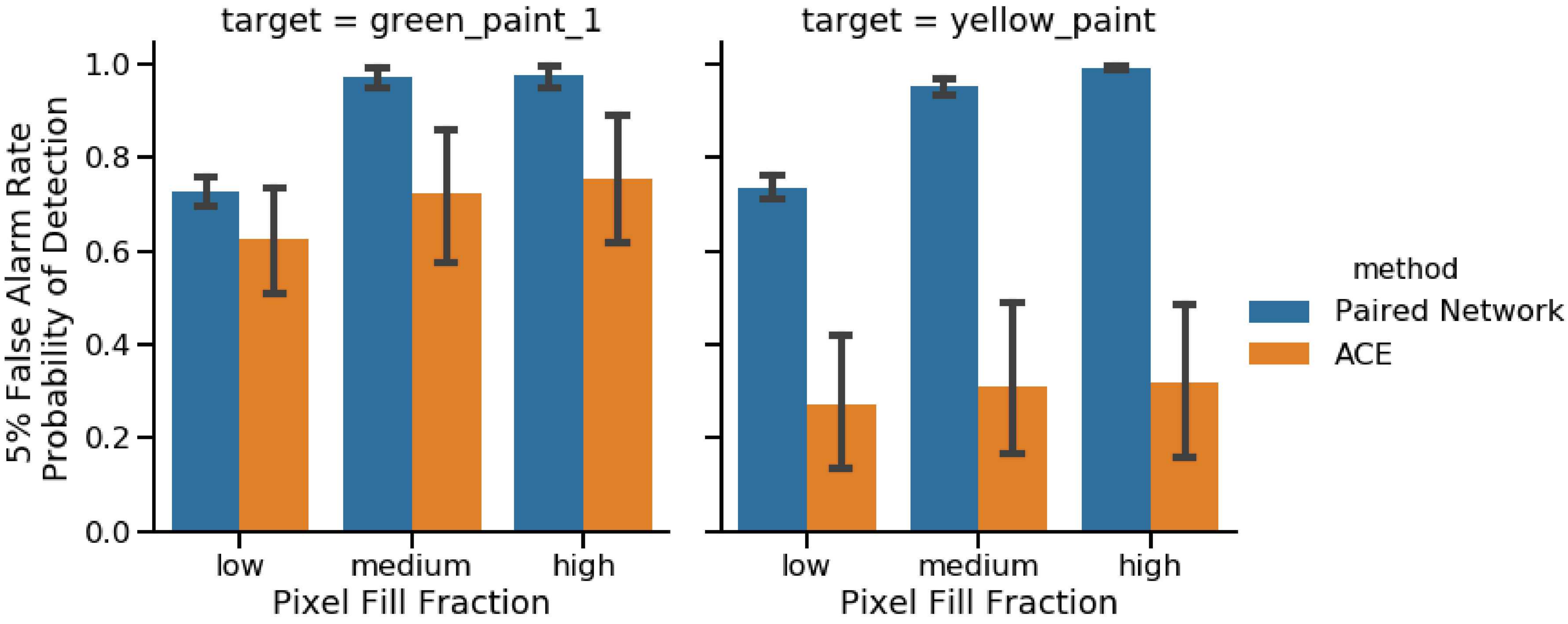
Adam optimizer

Contrastive margin 175

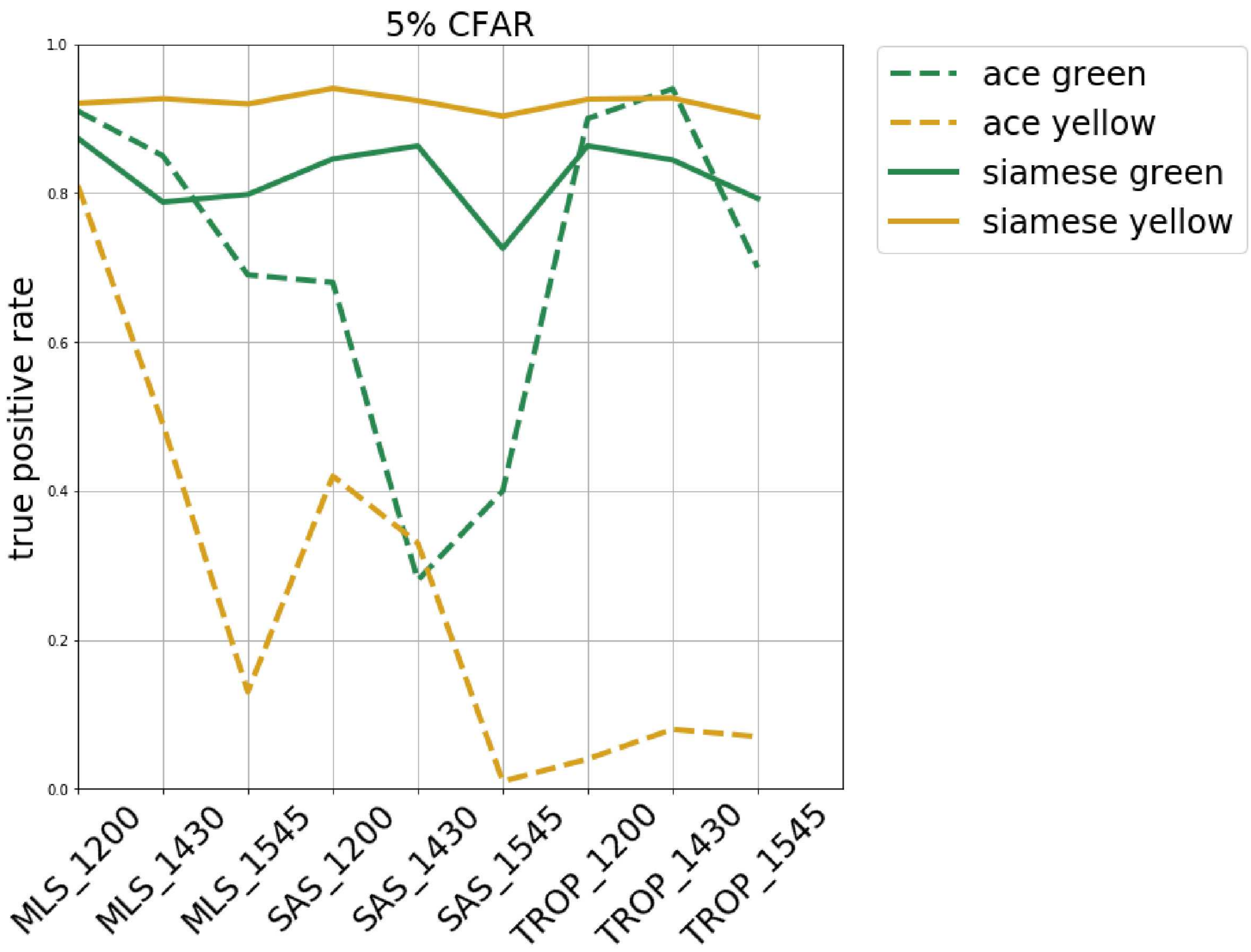
# MLS 1200 CFAR Results



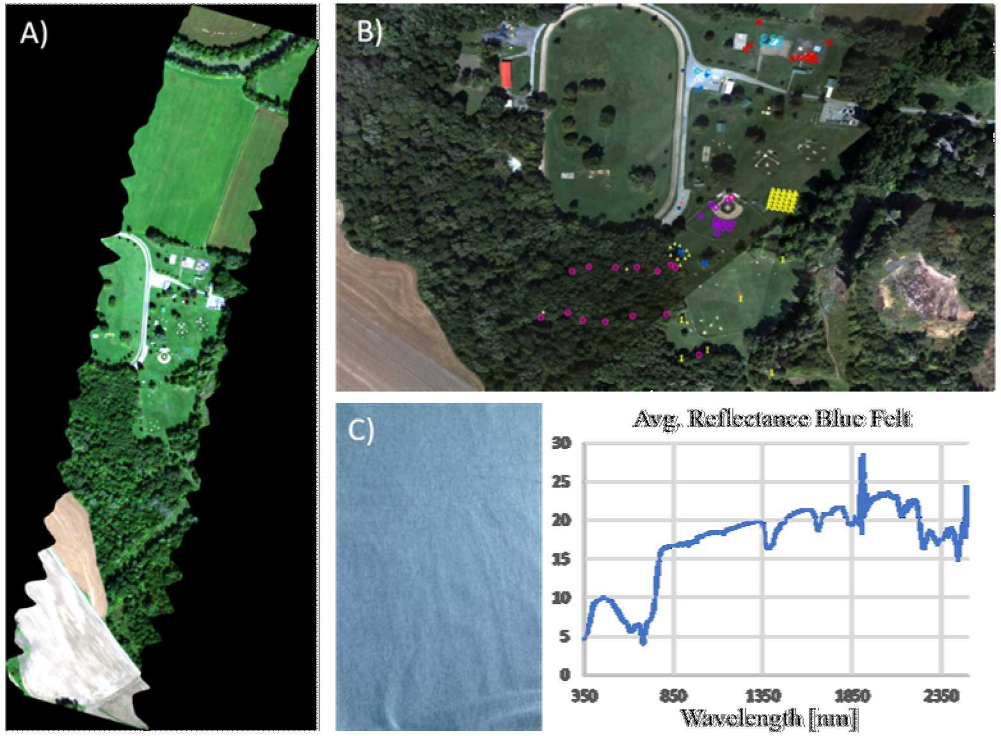
# CFAR Results

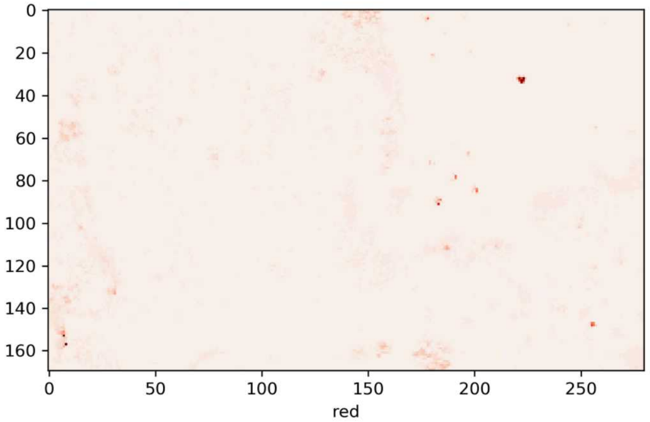


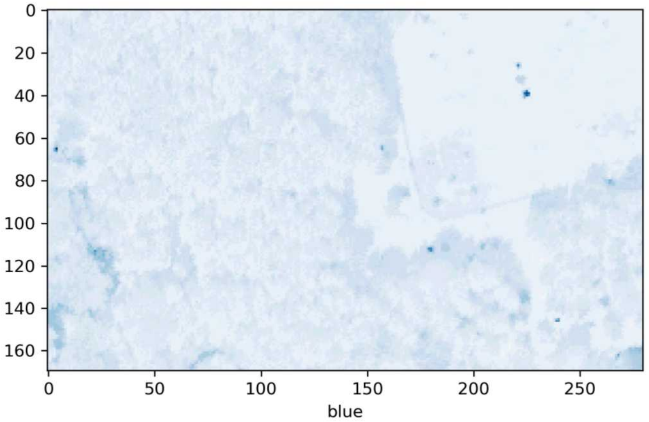
# CFAR Results – By Scene

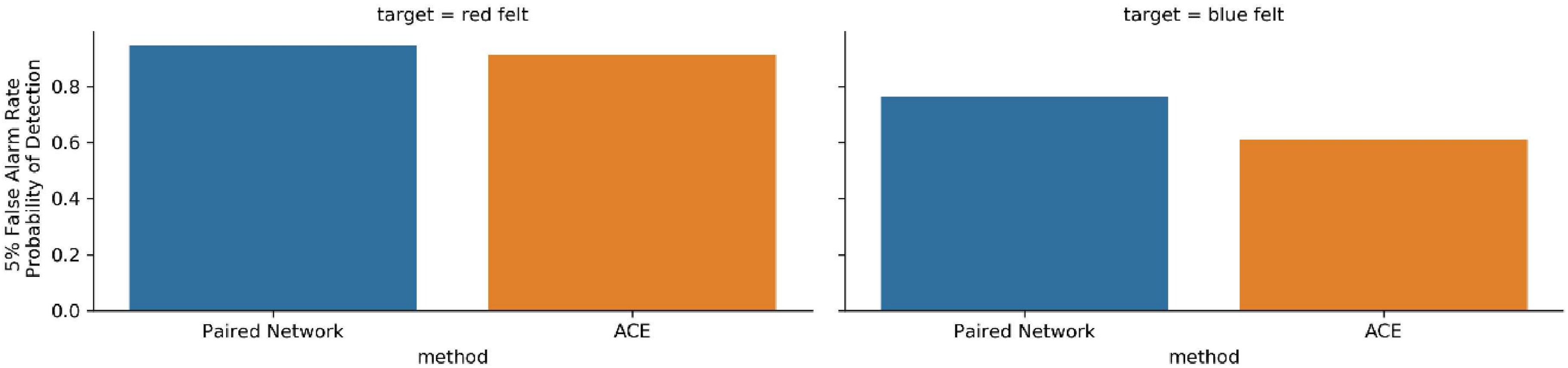


# Performance on SHARE2012

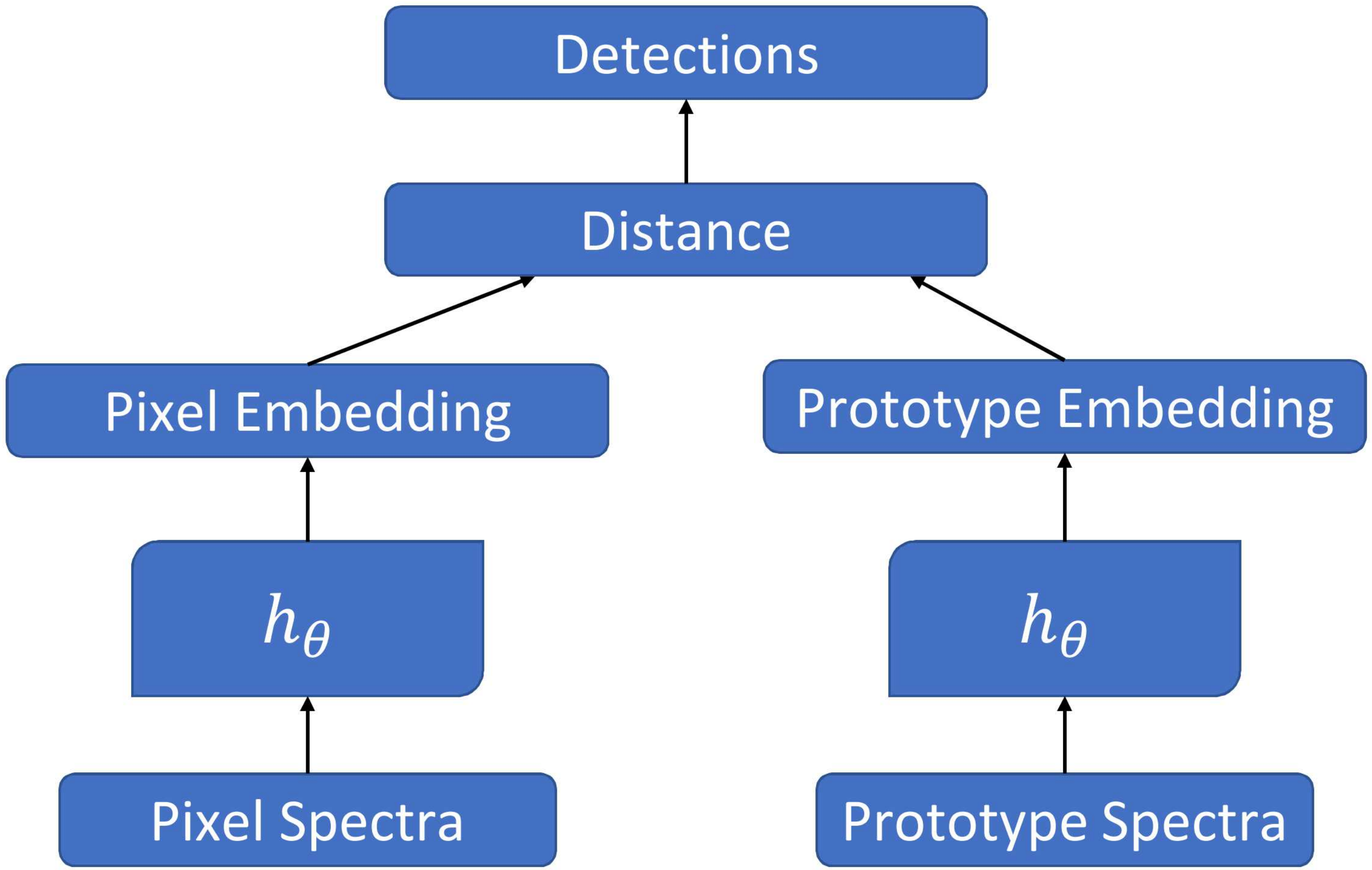


# Discussion


Detections
Distance
Pixel Embedding
Prototype Embedding
$h_\theta$
$h_\theta$
Pixel Spectra
Prototype Spectra

Thank you for your attention!

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# Indian Pines Experiments

## Data

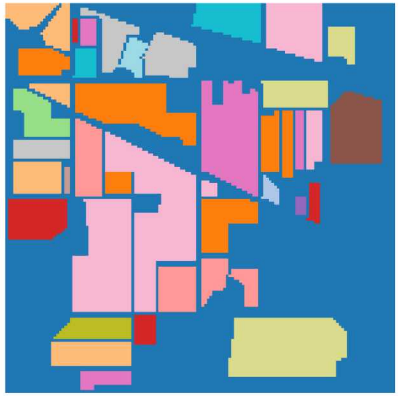
- Corn-notill as “target” class
- 60% train/20% val/20% test
- 10 same/different pairs per pixel in the train set

## Model

- 5 layer, fully connected
- ReLU activation
- Contrastive margin 2
- Adam optimizer
- 100 epochs

Scene

Class Labels



Target Labels