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# Hyperspectral Image Target Detection Using Deep Ensembles for Robust Uncertainty Quantification

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# Presentation Outline

- Hyperspectral Image (HSI) Target Detection
- Deep Learning for HSI Target Detection
- Uncertainty Quantification Using Deep Ensembles
- Experiments
  - Dataset
  - Implementation
  - Results and Comparison with Bayesian Neural Networks (BNNs)
- Conclusion

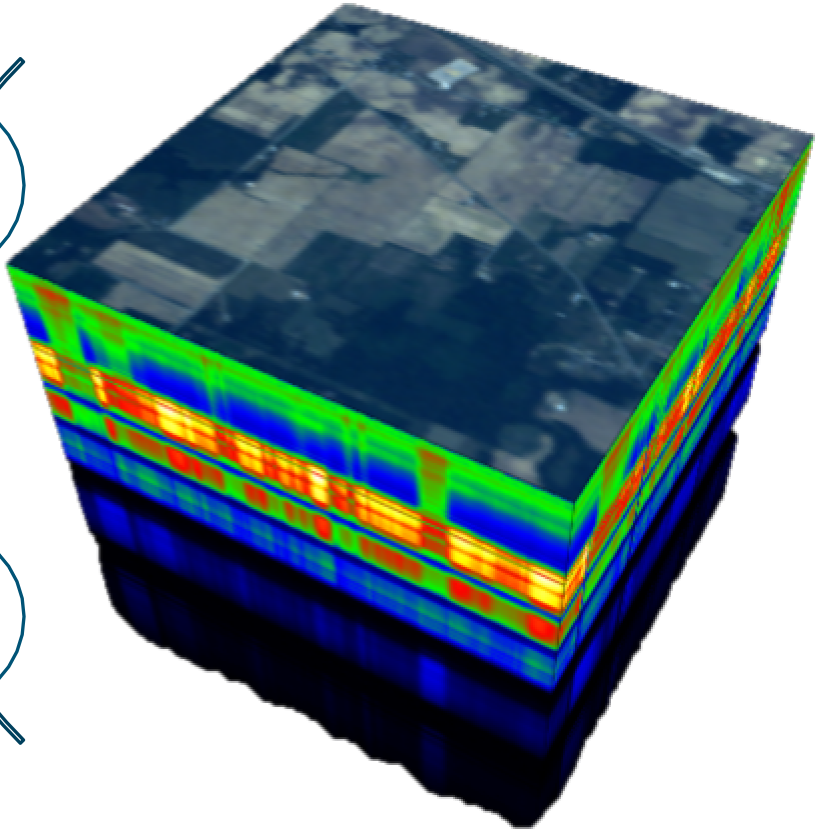
# Hyperspectral Image (HSI) Target Detection

## Hyperspectral Imagery

Strong material discriminant captured in spectral bands

High dimensionality

High co-linearity between spectral bands



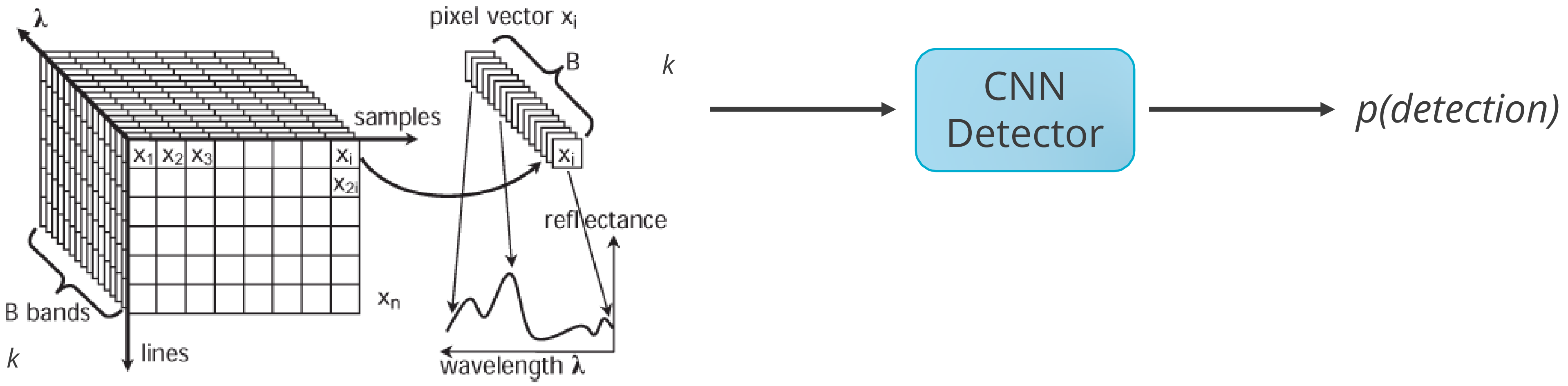
## Target Detection

Identification of one (or more) target material(s)

Class Imbalance - few target pixels per image

Low target abundance levels

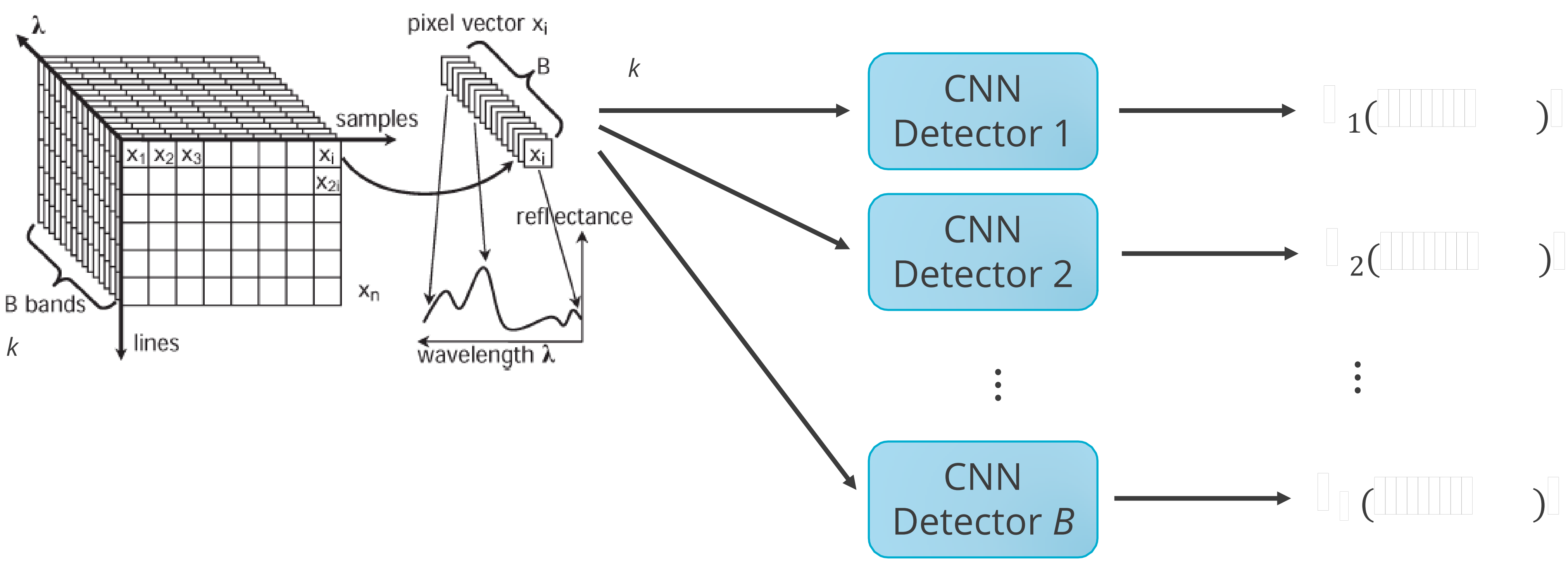
# Deep Learning for Hyperspectral Image (HSI) Target Detection




- CNN-based detectors have been found to be robust predictors for HSI target detection
- However, standard DL models produce point estimates at test time with no associated measure of uncertainty
- *Uncertainty quantification* (UQ) is vital in national security problems – especially on sub-filled pixels in which target abundance level is very little but we still need to be confident in its detection
- Note that 'probabilistic interpretation' of output models is not a good measure of confidence due to adversarial samples, wrong prediction with high p(detection), inability to detect trace materials, etc.
- We build upon the success of CNNs for HSI target detection by incorporating them into a UQ framework

Image modified from https://www.researchgate.net/figure/Hyperspectral-image-cube-and-a-typical-SRC-of-a-pixel-1_fig1_261500739

# Uncertainty Quantification Using Deep Ensembles




- Use an ensemble of identical CNNs to generate a distribution of predictions – then, use this distribution to characterize the (un)certainty associated with the model's prediction

- Train each detector using the same training data but with different random initializations – this creates diverse models
  - Also incorporate adversarial training to improve detection performance

# Uncertainty Quantification Using Deep Ensembles

Metrics of Interest

- The probability of detection: $\mathrm{p}(detection) = \frac{1}{\mathrm{B}} \sum_{i=1}^{B} p_i(detection)$

- Detection performance: area under the ROC curve (AUC)

- Confidence interval (CI): $p(detection) \pm z_\alpha \frac{s_i}{\sqrt{B}}$
  - $s_i$ - standard deviation of prediction over ensemble
  - $z_\alpha$ - $\left(1 - \frac{\alpha}{2}\right)$ quantile of Gaussian distribution

- High confidence (HC) set
  - Setting $\alpha = 0.2$, each sample for which (i) at least an 80% chance of containing the target, or (ii) at most a 20% chance of containing the target, is added to the HC set

- Probability of detection (PD) at a constant false alarm rate (CFAR)

# Experiments – Dataset

Employed Dataset: Megascene

- HSI scenes from upstate New York
- Targets: Green paint (manually inserted) with abundance varying between 0 – 100%

Three considered atmospheric scenes

1. Mid-latitude summer (MLS)
2. Sub-arctic summer (SAS)
3. Tropical (TROP)

Three considered times of day

1. 1200
2. 1430
3. 1545

Training scene: MLS 1200

# Experiments – Implementation

Consideration of 2 architectures

- Each architecture operates on the 25 functional principal components of the data as input

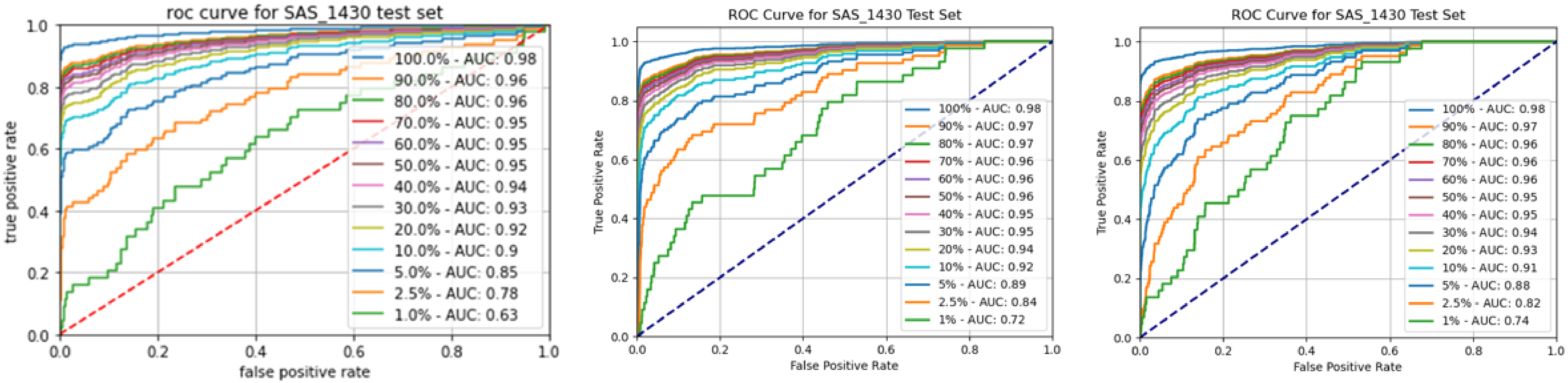
1. Convolutional Neural Network Detector
    - Hidden layer 1 (convolutional ReLU): $64 \times 4 \times 1$
    - Hidden layer 2 (convolutional ReLU): $32 \times 3 \times 1$
    - Hidden layer 3 (Dense ReLU): 128

2. Fully Connected Neural Network Detector
    - Hidden layer 1 (dense sigmoid): 10
    - Hidden layer 2 (dense sigmoid): 10
    - Hidden layer 3 (dense sigmoid): 10

Comparison UQ model: Bayesian Neural Network (BNN) trained using MCMC

- Same architecture as fully connected NN described above with $\mathcal{N}(0, 10)$ priors on all weights

# Experiments – Results



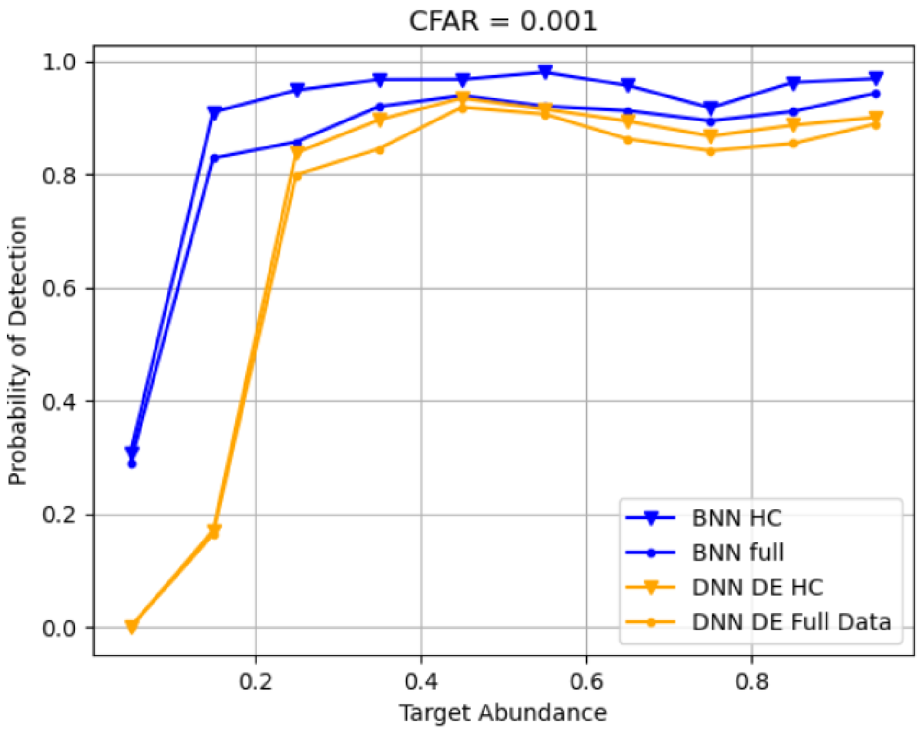

ROC curves for different target abundance levels on BNN (left), DNN DE (middle), and CNN DE (right) on SAS 1430.

# Experiments – Results

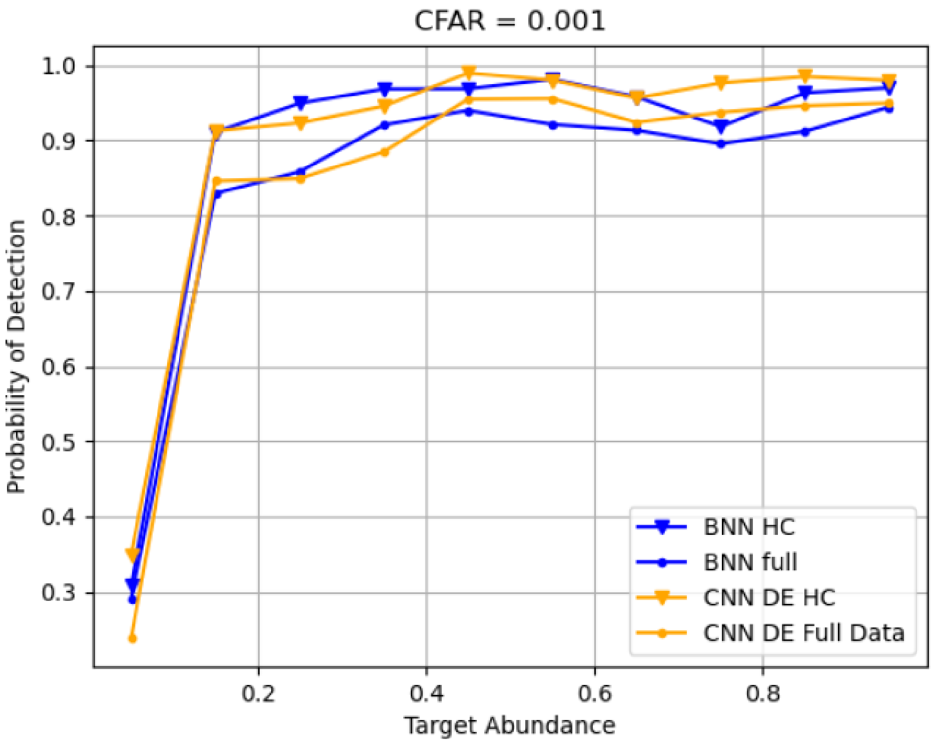
| Scene | BNN | DNN DE | CNN DE |
|---|---|---|---|
| MLS 1200 | 0.81 | 0.99 | 0.91 |
| MLS 1430 | 0.79 | 0.99 | 0.90 |
| MLS 1500 | 0.74 | 0.98 | 0.90 |
| SAS 1200 | 0.66 | 0.99 | 0.90 |
| SAS 1430 | 0.67 | 0.99 | 0.90 |
| SAS 1545 | 0.88 | 0.99 | 0.89 |
| TROP 1200 | 0.51 | 0.97 | 0.91 |
| TROP 1430 | 0.50 | 0.96 | 0.91 |
| TROP 1545 | 0.53 | 0.96 | 0.90 |

Proportion of samples captured in the HC set for each considered model

# Experiments – Results




Comparison between BNN and DNN DE of PD at CFAR = 0.001 (averaged across all nine scenes)




Comparison between BNN and CNN DE of PD at CFAR = 0.001 (averaged across all nine scenes)

# Conclusion

- Deep learning-based HSI target detectors demonstrate robust performance, but standard models lack measurements of uncertainty

- Our deep ensemble framework successfully incorporates the robustness of DL detectors while also providing UQ characteristics

- We showed that our framework serves as a robust detector and provides high probabilities of detection on low CFARs – often desirable for national security problems

Uncertainty quantification is critical in security sensitive deep learning applications