Investigation of Target Detection in Hyperspectral Images for Aided Target Recognition

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Aided Target Recognition (AiTR)

- Aided Target Recognition (AiTR) enhances the human functions of target detection
  - **Preprocess sensor data:** improve machine detection accuracy
  - **Differentiate targets** from background
  - **Visualize sensor data:** human understandability
- Potential Applications:
  - Agriculture: pest detection
  - Environment: land cover changes
  - Military: camouflaged target detection

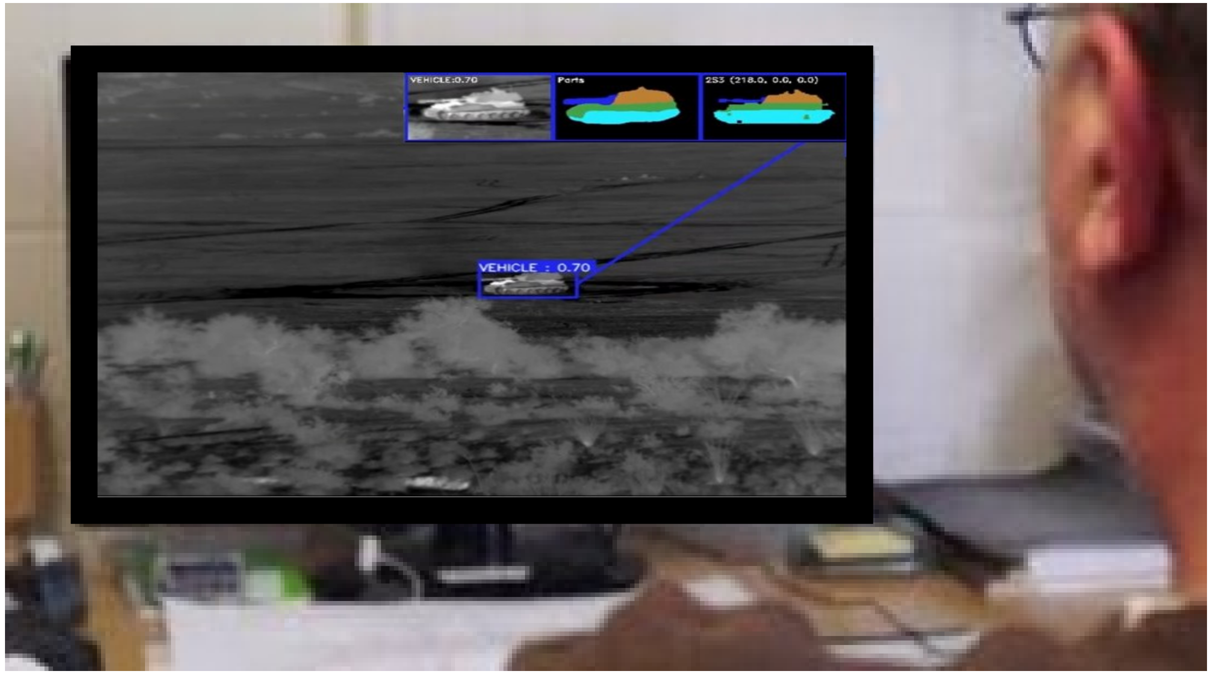


Figure source: Advanced Targeting & Lethality Aided System (ATLAS), https://covar.com/case-study/atlas/

Generic AiTR algorithm system [5]

Input sensor data

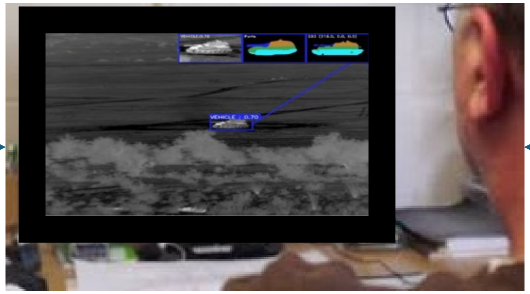
Preprocessing for Machines
- Noise removal
- Light scattering reduction

Detection
- Candidate Regions of Interest Detection
- Anomaly Detection

Extraction
- Feature Extraction
- Spectral features
- Spatial features

Identification
- Object Detection
- Classification
- Identification

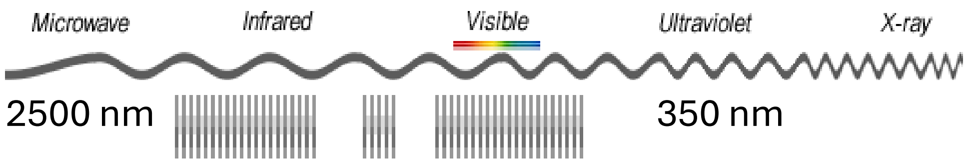
Preprocessing for Humans
- Edge enhancement
- Super-resolution

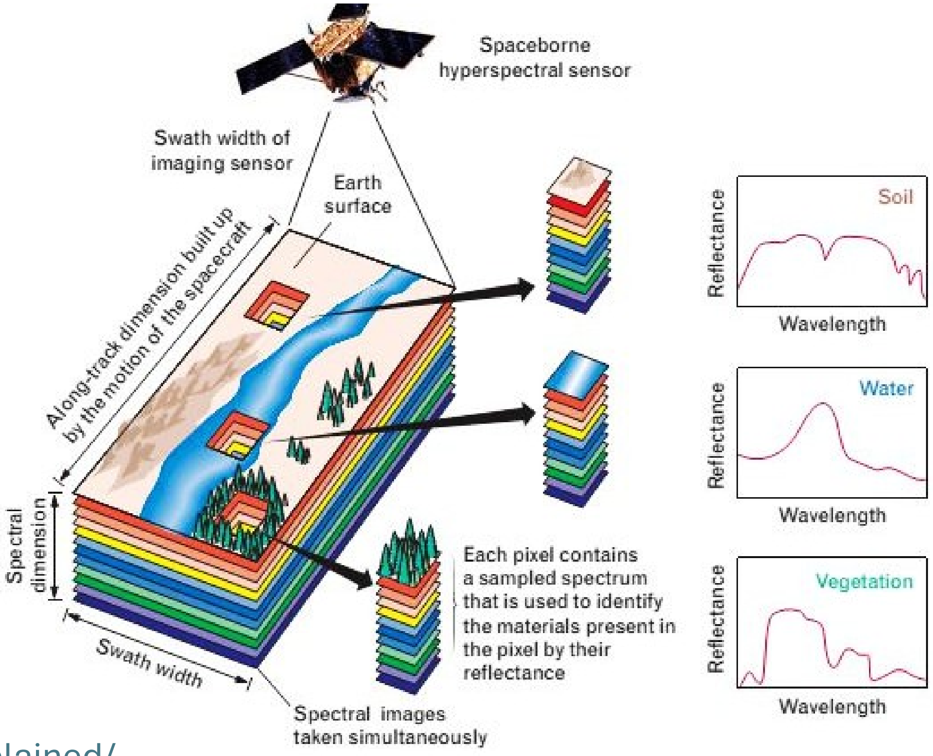


- Low False Alarm Rate (FAR)[2,3] vs High Detection Rate (i.e., recall)[4]
- Aided target detection can prioritize a high detection rate, which may lead to a higher false alarm rate

Hyperspectral (HS) Imaging

- Hyperspectral imagers capture **contiguous electromagnetic bands**
  - **Hundreds of channels**
  - **Additional reflectance information** per pixel[1].
- Different materials reflect light differently
  - A **unique reflectance signature**
  - Helps classify materials
- Recognize and pinpoint any objects that are out of place in the captured scene
  - **Anomaly targets deviate spectrally** from their surroundings





- Figure 1 source: https://gisgeography.com/multispectral-vs-hyperspectral-imagery-explained/
- Figure 2 source: 6

Challenges of AiTR with HS Images

- A hyperspectral imager is **susceptible to environmental** variables
- A hyperspectral imager has **low spatial resolution** at a high altitude
- **Limited** public hyperspectral data and annotated data are even scarcer
- Hundreds of correlated channels put **memory constraints** on fitting deeper networks

Research Goals

- **Preprocess hyperspectral images** to improve machine detection accuracy
- **Preprocess digital images** to enhance human visibility

- Detection: **Detect anomalies** in diverse scenarios with higher accuracy to aid humans
- Identification: **Semantic Segmentation** scenes

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1: **Preprocess hyperspectral images** to improve machine detection accuracy

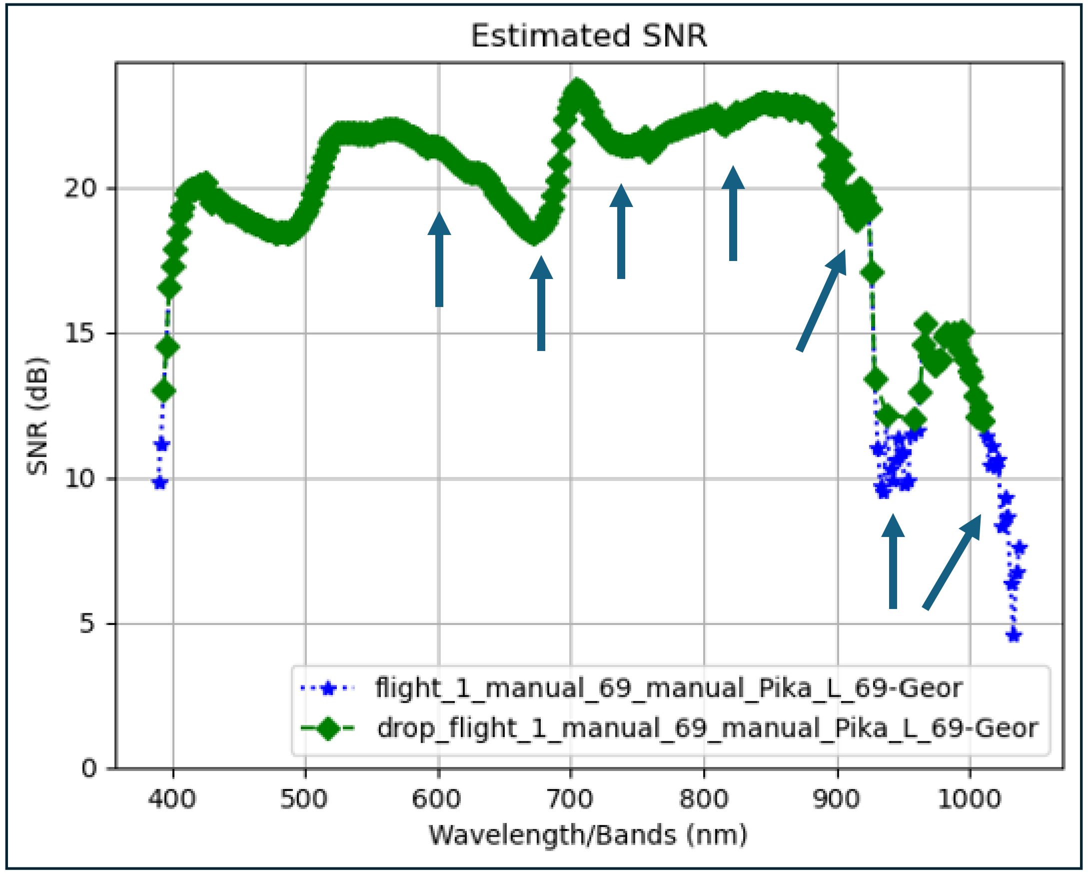
2: **Preprocess digital images** to enhance human visibility

3 Detection: **Detect anomalies** in diverse scenarios with higher accuracy to aid humans

4 Identification: **Semantic Segmentation** scenes

Noisy Band Removal

- Preprocessing: Remove noisy bands below a fixed threshold (5 SNR) or below a certain percentage
- Sensor noise: before 0.40 and after 1.00μm
- Atmospheric water absorptions:
  - Weak: 0.60 and 0.66μm
  - Slightly stronger: 0.73, 0.82, and 0.91μm
  - Strong: 0.94 and 1.14μm
- I will investigate the impact of dropping and recovering some of these bands



- Visual comparison showing quantitative improvement of removing noisy bands from Florida Image 1. The green line shows SNR in [dB] after deleting noisy bands, whereas the blue line shows the dropped channels.

Weaknesses of Existing Preprocessing

- Problems:
  - Data collection and stitching may introduce artifacts and noise
  - Dropping noisy channels may cause loss of data
  - Low performance due to the manual section

- Objectives: improve the performance of machine detection methods by preprocessing
  - Find a systematic way to select preprocessing to get the best results in each scenario

Proposed Research Plan I

- Investigate the use of noise reduction and channel dropping (partially complete[1])
- Investigate edge enhancement (partially complete[1])
- Investigate a systematic way to select preprocessing methods to get the best detection results in each scenario (pending)

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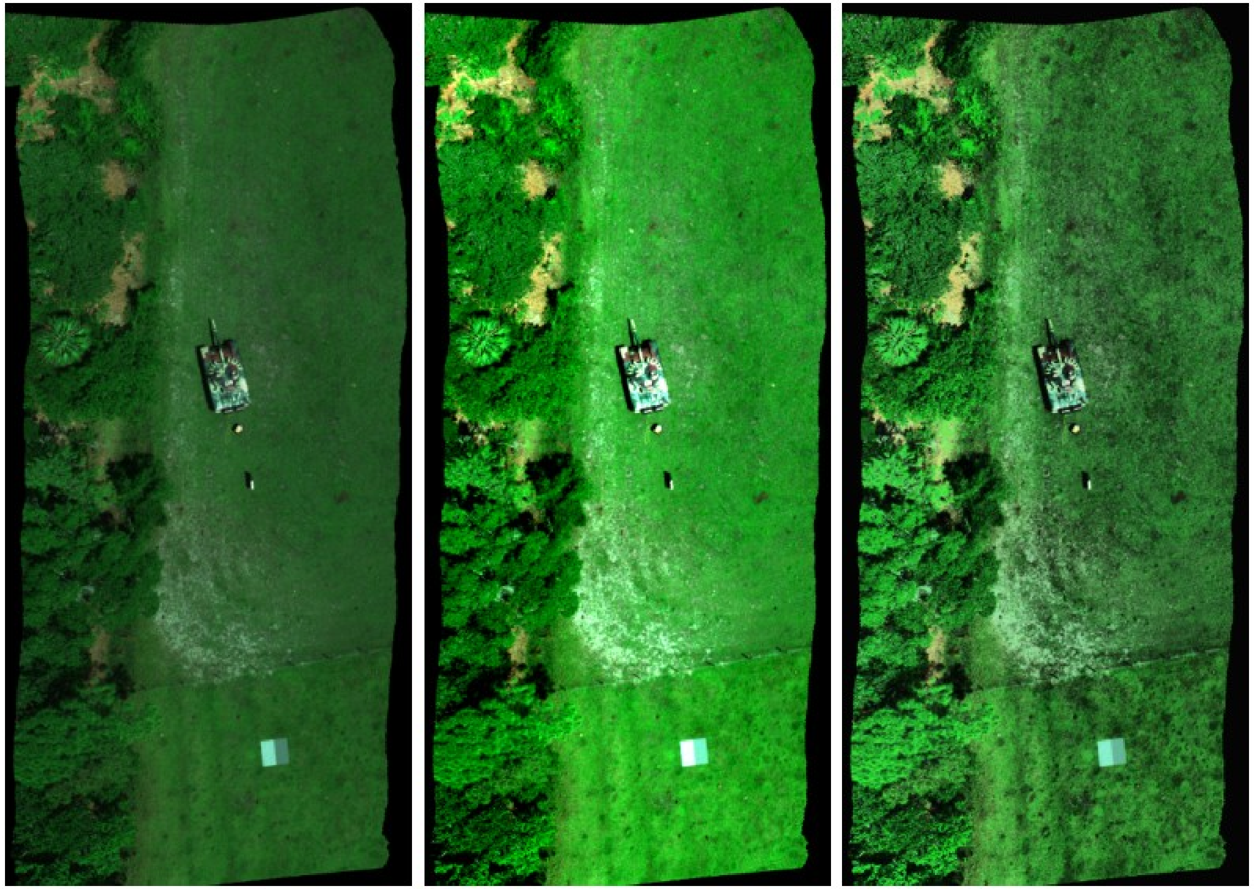
Brightness and contrast in visualization

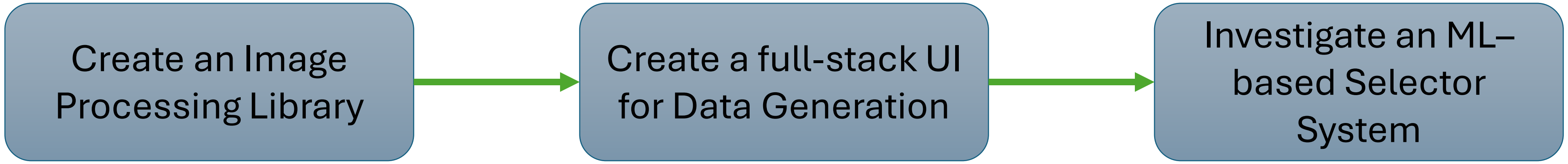


(a) Original (b) Auto brightness adjust (c) HSV CLAHE

- Brightness weights image pixels toward white
- Contrast adjustment remaps image intensity values to the full display range
- Challenge: automatically select any preprocessing method or combination of methods to create task-dependent enhanced digital images

Image Enhancement Methods for Human Understandability

- Preprocess digital images to improve human visibility
  - Single channel: greyscale, NIR
  - Three channel: NIR-RG, RGB
- Collect various image processing algorithms
- Create a new dataset
- Propose a new Algorithm Selector System



Dataset Generation

- A new application will randomly use any preprocessing method or combination of methods to create enhanced digital images
- Humans will select between the **original** and **enhanced** images
- Based on the highest vote, we can create a data tuple (**original image, algorithm combination**)

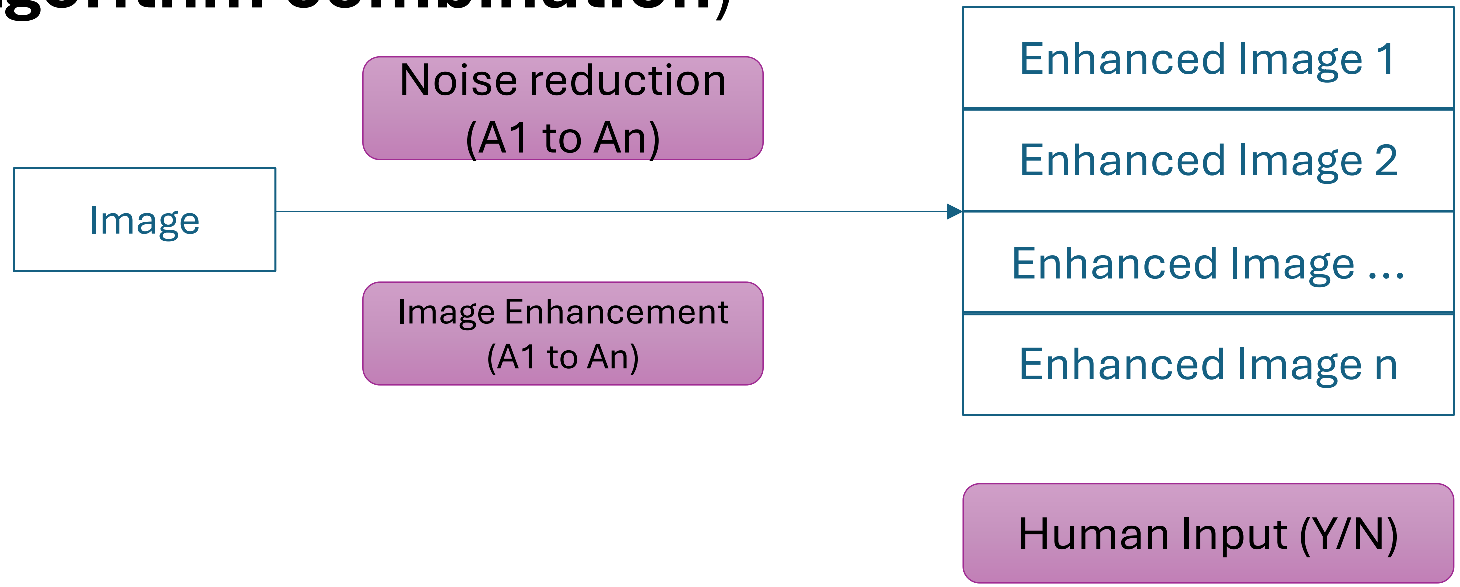


Image Enhancement Methods Selection

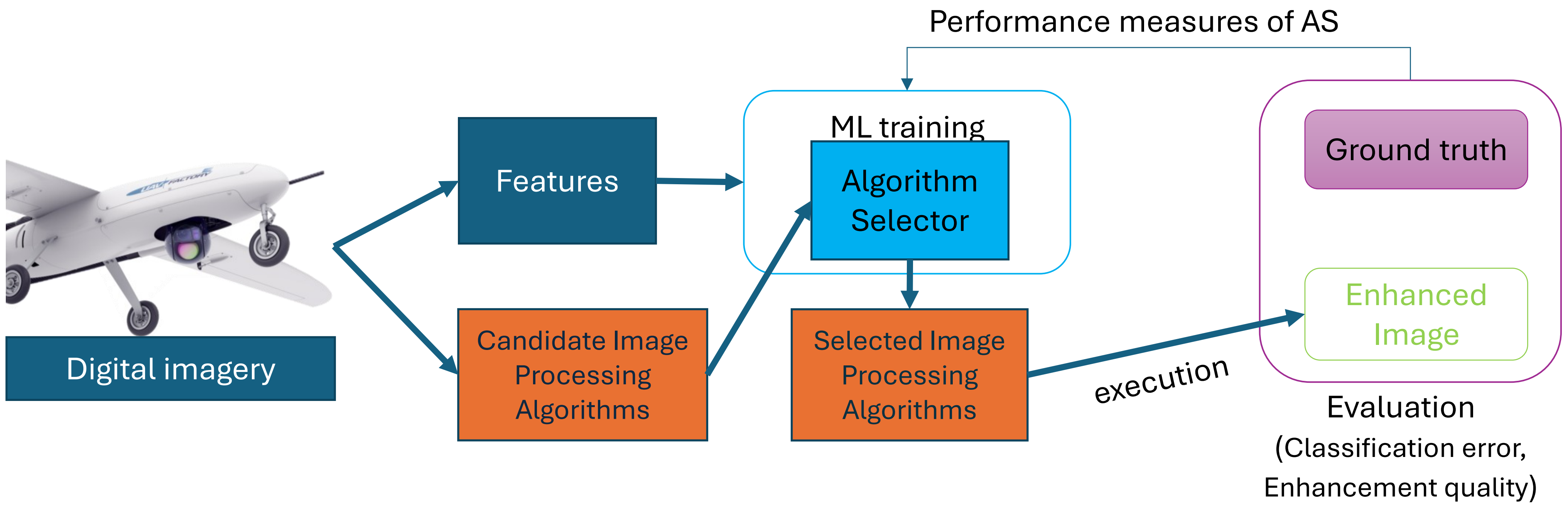


Fig: ML System Training Architecture

Proposed Research Plan II

- (Optional) **Preprocess digital images** to improve human visibility
  - Propose a new Algorithm Selector System on the new Dataset
  - Investigate it as a Classification problem
  - Find zero or more mutually non-exclusive image processing methods and apply as applicable

- Optional: Depends on the collection of user responses for image processing evaluation, which is pending
- If we fail to collect the necessary data, I will be unable to deliver this part.

1: **Preprocess hyperspectral images** to improve machine detection accuracy

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Background

Hyperspectral Anomaly Detection (HS-AD)

- HS-AD: Procedure to find anomalies in hyperspectral images
- Binary classification: anomaly or background class
- Unsupervised AD methods do not need any annotated data
  - They work differently in different scenarios due to their design assumptions.

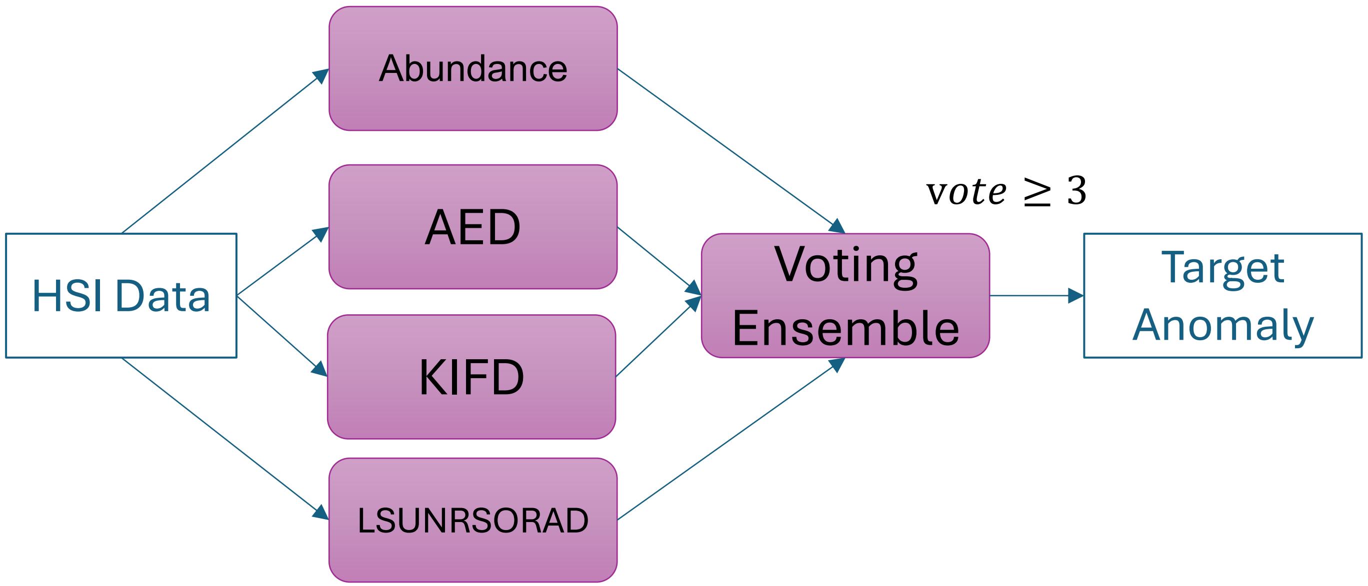
ML-based	▪ SVM, iForest
Statistics based	▪ RX[1], MD-RX, WIN-RX
Kernel-based	▪ KRX, GM-RX, KIFD[2]
Subspace based	▪ LSUNRSORAD[3], CSD, SSRX
Spatial–spectral based	▪ AED[4]
Cluster-based	▪ CBAD, FCBAD
Ensemble based	▪ ERRX-MF[5], ERCRD[6], SED[7], HUE-AD[8]

Previous Work

Hyperspectral Unmixing-based Voting Ensemble Anomaly Detector (HUE-AD)

- We tackled the shortcomings of the statistical AD methods by utilizing them in an ensemble.

- We used our domain knowledge to manually select input methods for HUE-AD[8].



- Abundance using Unmixing method: N-FINDR
- HUE-AD only takes in the binary vote (a vote for a pixel means the pixel is a detected anomaly)
- **Equal weight voting** for all methods

Weaknesses of HUE-AD

- Problems:
  - Manual selection of AD methods needs in-depth knowledge (different AD methods have different assumptions and perform well in different scenarios)
  - Equal weight assigned to every method
  - Low performance due to the manual section and equal weight

- Objectives: improve performance through automating the process
  - find a systemic way to select the best AD methods in each scenario
  - assign weights to the anomaly score from each method automatically

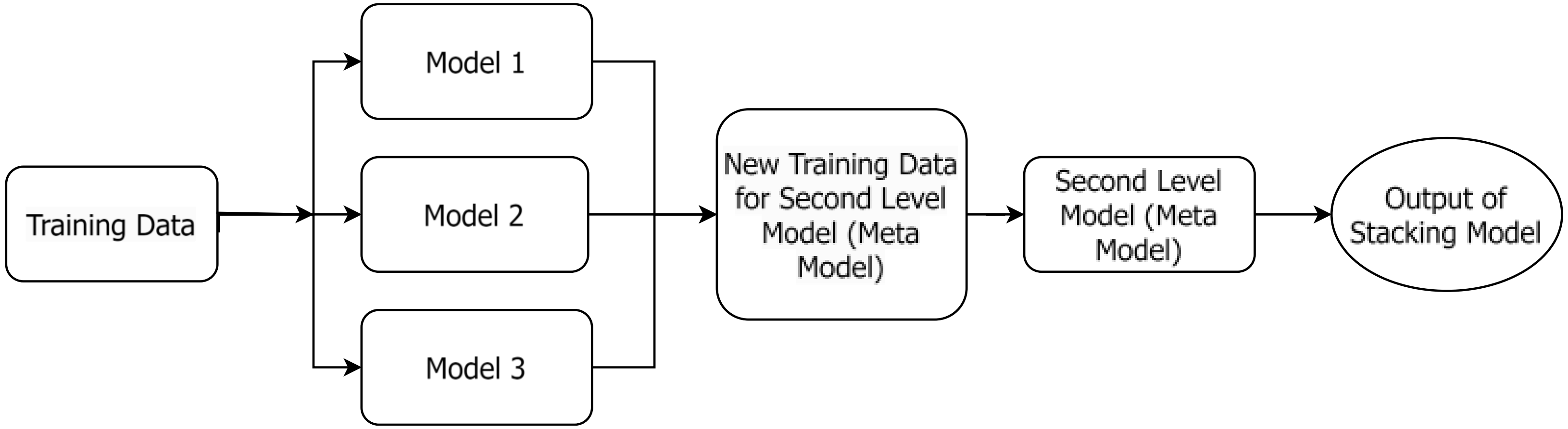
Proposed Research Plan III

- **Detect anomalies** in diverse scenarios with higher accuracy to aid humans
  - Investigate an equal vote ensemble (complete[1])
  - Propose a weighted vote ensemble (complete[2])
  - Investigate the use of normalization on the results of AD methods (complete[2])
  - Propose a search algorithm for the ensemble method (complete[2])
  - Generalize the ensemble method for various datasets (pending)

Proposed Method: Greedy Ensemble Anomaly Detection (GE-AD)

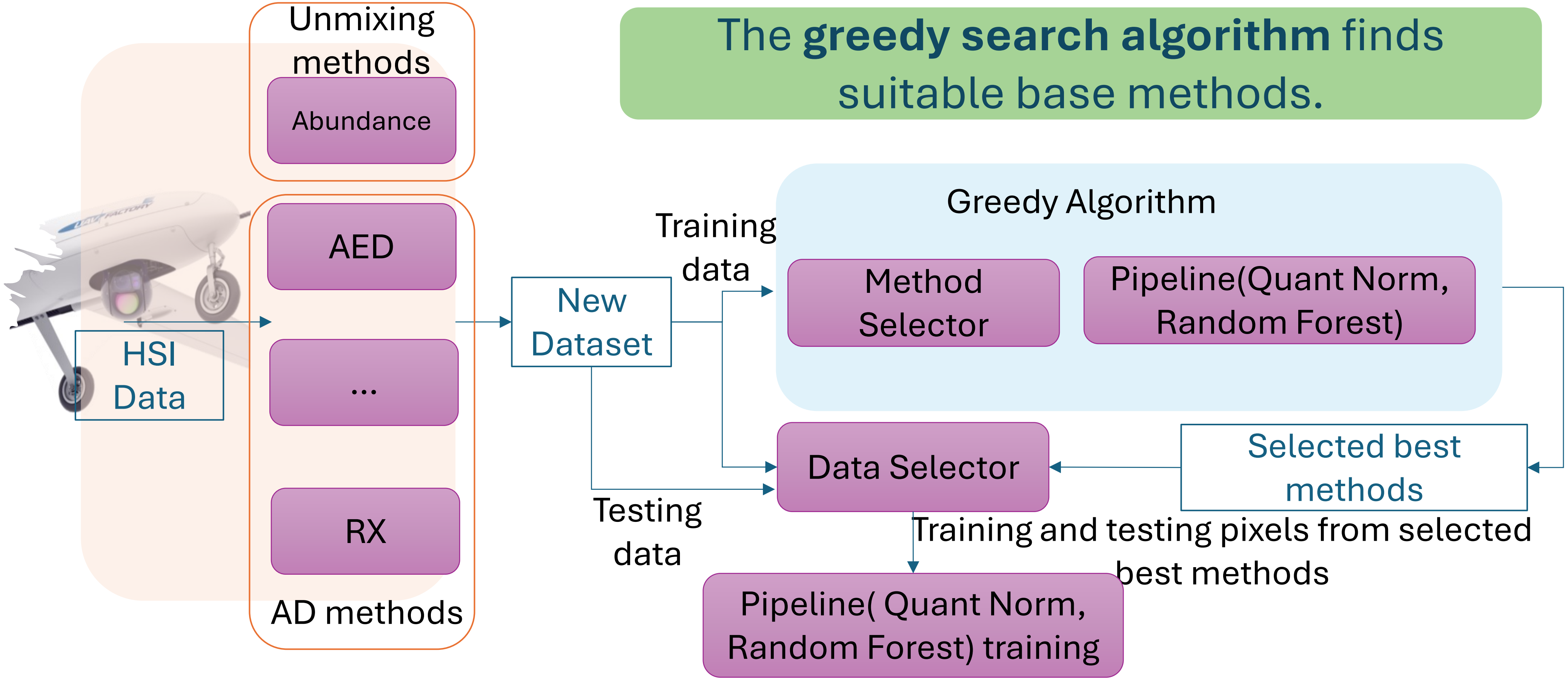
- We use the **greedy search algorithm** to find the best AD methods
  - Greedy search is a **problem-solving heuristic** of making locally optimal choices at each step to find a globally optimal solution.

- We use the **stacking ensemble** where the **meta-model** assigns weights to the anomaly score from each method automatically



Proposed Method: Greedy Ensemble Anomaly Detection (GE-AD)

The **greedy search algorithm** finds suitable base methods.



Normalization is needed as the anomaly score range varies between methods

Random Forest Pipeline learns the weights using the training data.

Evaluation Methodology

- Datasets
  - ABU- Airport Dataset
  - Arizona Dataset
  - San Diego Airport Dataset
  - Hydice Urban
  - Salinas
- Metrics
  - F1-macro
  - ROC-AUC (Area under the ROC Curve)
- Development
  - MATLAB
  - Python

- Area Under the ROC curve (ROC-AUC) that plots the true-positive rate against the false-positive rate at each threshold setting
- The F1 score is a harmonic mean of the precision and recall

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Compared to Other Ensemble Methods

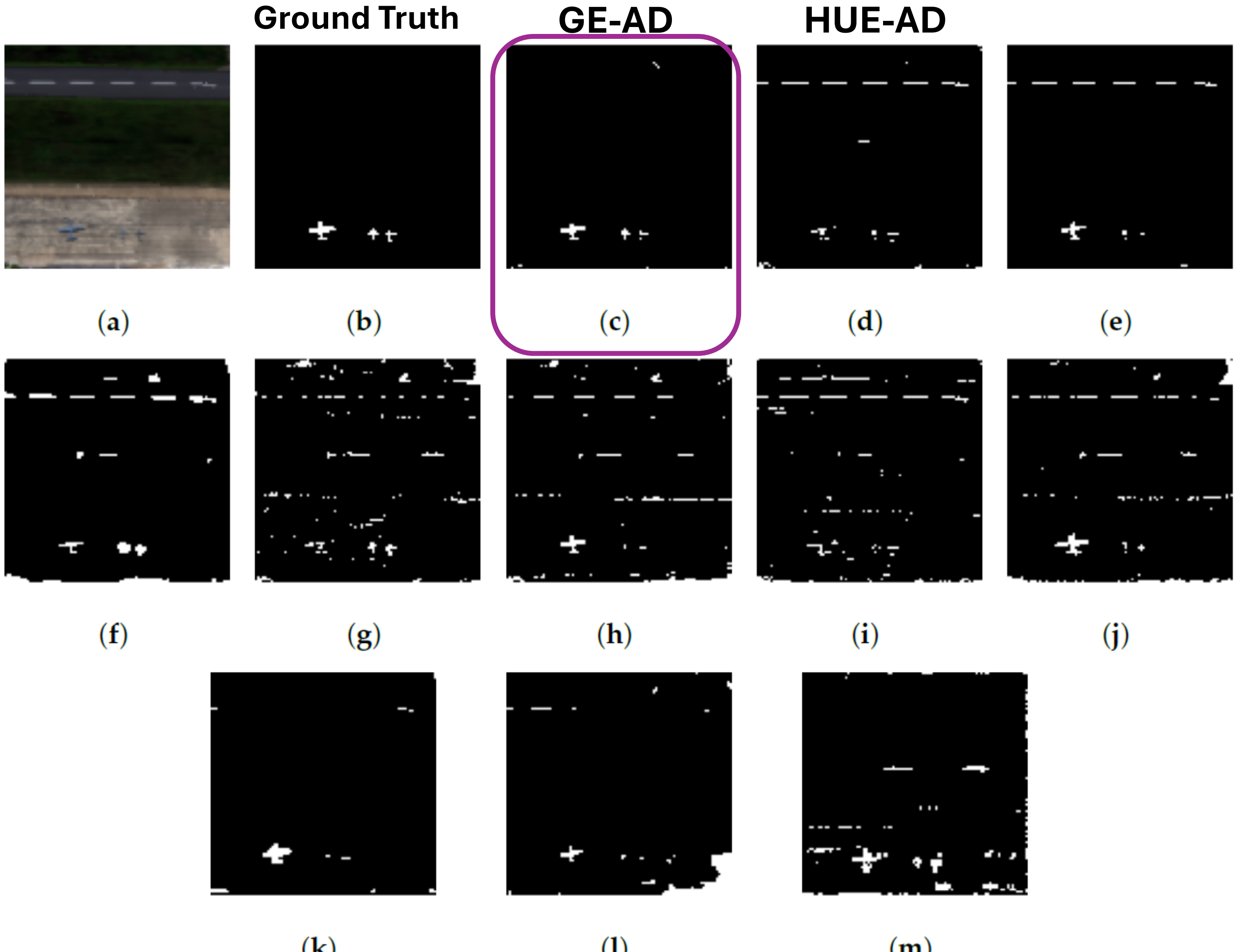
F1-macro	GE-AD	ERRX-MF	ERCRD	SED
ABU-Airport-IV	**0.856**	*0.666*	0.545	0.592

- F1-macro values (as we computed) comparison between our proposed ensemble method (GE-AD) and other ensemble methods

ROC-AUC	GE-AD	ERRX-MF	ERCRD	SED
ABU-Airport-IV	0.963	*0.997*	0.953	**0.998**

- ROC-AUC scores (as reported) comparison between our proposed ensemble method (GE-AD) and other ensemble methods
- Compared to other methods, the ROC-AUC score differs at the 2nd decimal place

Visual Comparison using the Abu-Airport Dataset

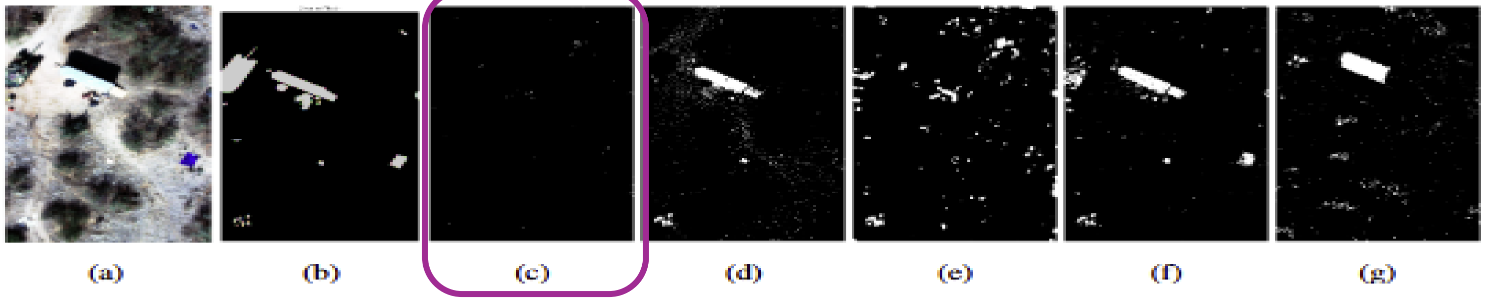


- GE-AD on ABU-Airport-IV data. (a) RGB, (b) Ground Truth, **(c) GE-AD (F1 = 0.856)**, (d) HUE-AD (F1 = 0.649), (e) Abundance (F1 = 0.735), (f) AED (F1 = 0.610), (g) KIFD (F1 = 0.587), (h) KRX (F1 = 0.604), (i) LSUNRSORAD (F1 = 0.569), (j) FCBAD (F1 = 0.631), (k) ERRX MF (F1 = 0.666), (l) ERCRD (F1 = 0.545), and (m) SED (F1 = 0.592)
- Other methods have more false positives.

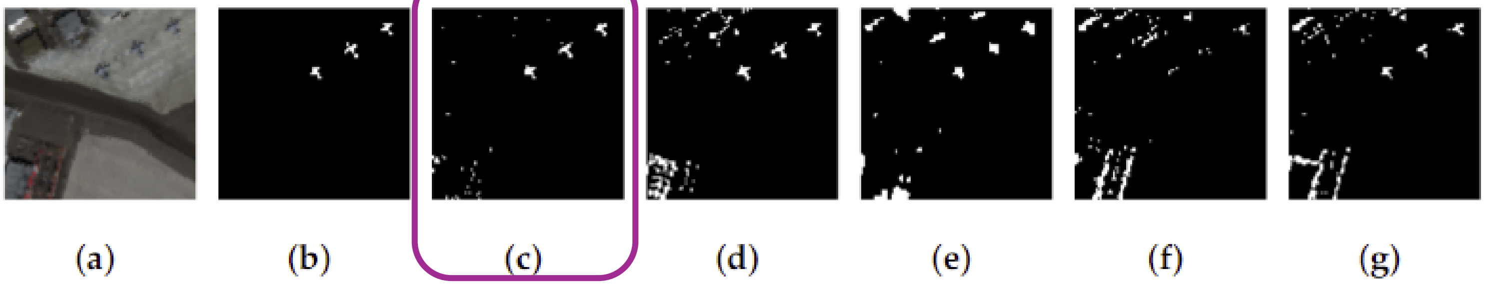
Generalization of Hyperspectral Anomaly Detection

- **Universality / Generalization**[1]: Achieving good results for all datasets
  - Indicates suitability for unknown scenes
- Challenges:
  - Correctly characterize algorithms on benchmark domains
  - Quantify algorithm performance for unknown datasets
- Approach: evaluate the generalizability of GE-AD[2]

Visual Comparison using the San Diego and Arizona dataset



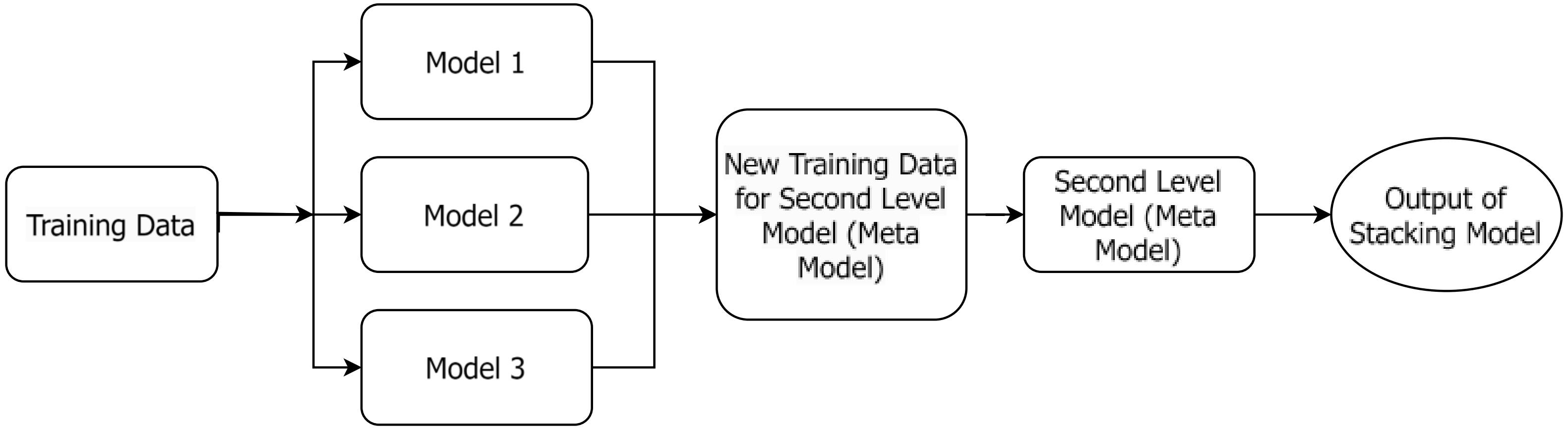
- GE-AD trained on the ABU-Airport Dataset, tested on Arizona-V. (a) RGB, (b) Ground Truth, (c) GE-AD (F1 = 0.490), (d) Abundance (F1 = 0.701), (e) AED (F1 = 0.584), (f) **FCBAD (F1 = 0.810)**, (g) KRX (F1 = 0.503).



- GE-AD trained on the ABU-Airport Dataset, tested on San Diego-02. (a) RGB, (b) Ground Truth, **(c) GE-AD (F1 = 0.826)**, (d) Abundance (F1 = 0.655), (e) AED (F1 = 0.636), (f) FCBAD (F1 = 0.536), and (g) KRX (F1 = 0.627).
- **GE-AD generalizes for some similar unseen data (both are airports).**

Unsupervised GE-AD

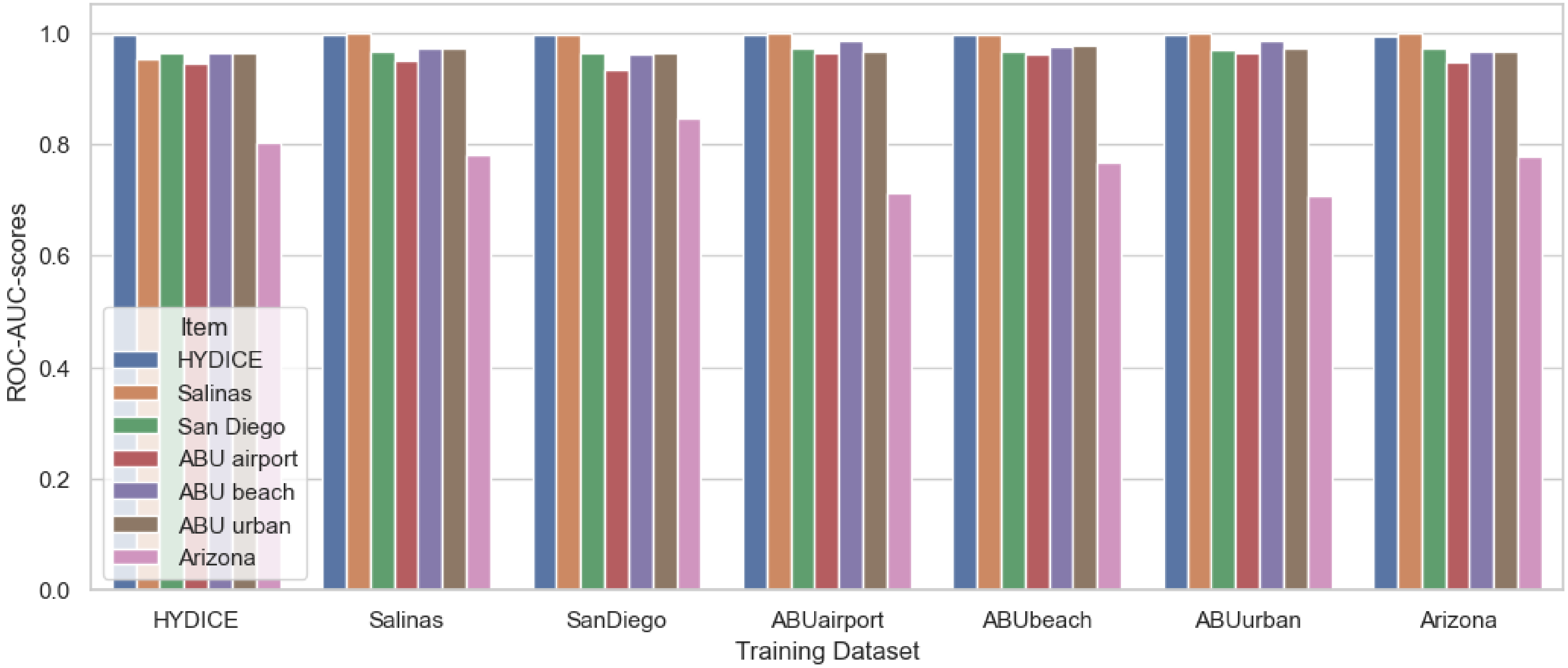
- Investigate all options used in improving supervised GE-AD
- Replacement of Random Forest with **unsupervised Mixture Model (GMM)** as the meta-model[1]



- Evaluation
  - Use only one dataset as training to find base methods

Preliminary Results

Evaluate UGE-AD using one-vs-others



- Average ROC-AUC scores of our UGE-AD over various datasets showing consistent performance against various training datasets.
- The X-axis shows the dataset used in the greedy search to find suitable base methods. The Y-axis shows the testing ROC AUC scores. Except where the dataset names in rows and columns match, those bars show the training score after the greedy search.

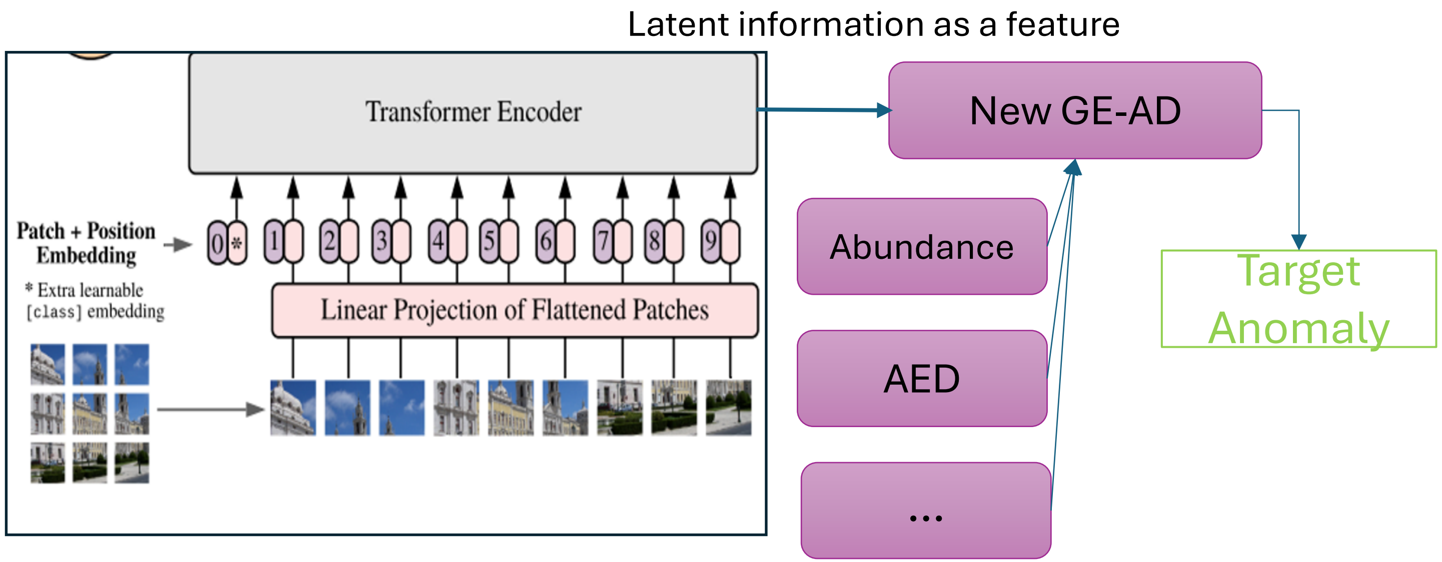
Improving Supervised GE-AD

- Spatial and Spectral information from HSI is not visible to GE-AD
- GE-AD can compute different weights based on features from the original data

- Initial investigation: **modify GE-AD to give thirty important spectral channels** along with four other base methods as input[3]

Future Plan for Domain Understanding

- Explore options to introduce spectral domain understanding to U-Nets
- Investigate **Deep Latent Features** from a Vision Transformer (ViT) and Auto-Encoder into a new GE-AD[1] (Greedy Ensemble Anomaly Detector)
- Use **Domain Adaptation** to align **Latent Features** between datasets



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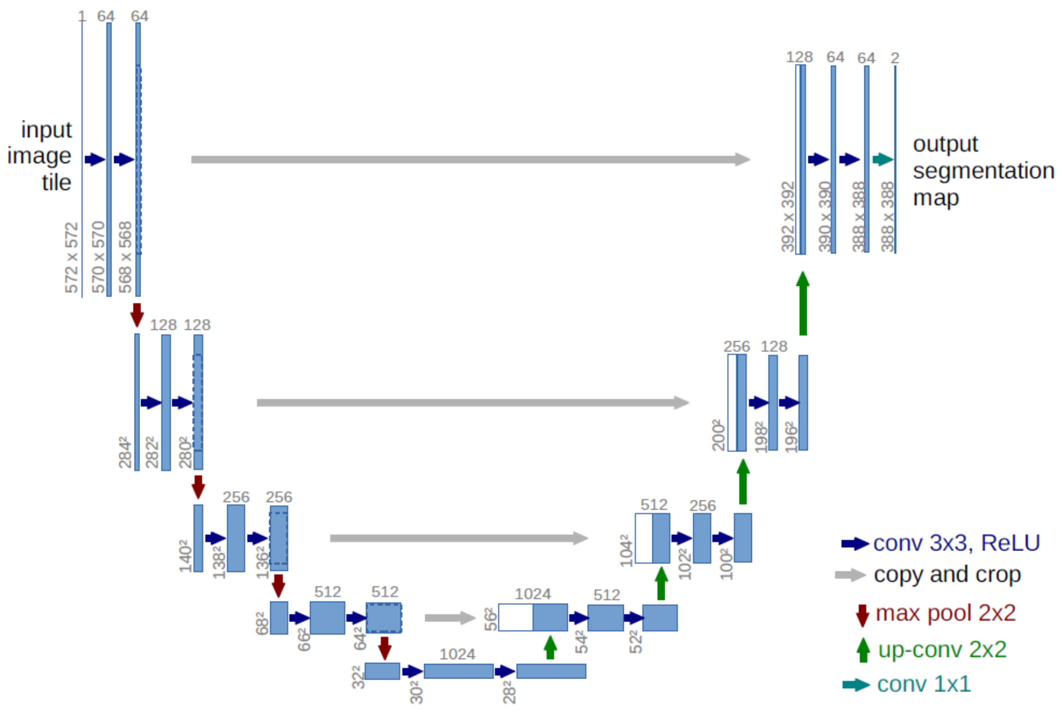
Background: Semantic Segmentation



- **Definition:** Classifies each pixel in an image to differentiate objects using a deep learning (DL) algorithm

- nnU-Net[1] (no new Unet) introduced an adaptive framework for vanilla U-Net
- TransUNet[2] replaced the bottleneck layer with ViTs, demonstrating promising results in medical imaging
- HSI-TransUNet[3] modified TransUNet with attention module

Preliminary Result: U-Net

- We evaluated the semantic segmentation performance of U-Net and Trans-U-Net
- Weakness: models are trained on RGB dataset and do not understand spectral information
- Dice co-efficient: 0.441 (Trans-U-Net)

RGB visualization

Ground truth

Trans-U-Net Prediction

Proposed Research Plan IV

- **Semantic Segmentation** scenes with higher accuracy to aid humans
  - Investigate the impact of the U-Net trained on RGB images (Complete)
  - Investigate the impact of modification to U-Net on HS images (Complete)
  - Investigate the impact of transfer learning for small datasets (pending)

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Summary: Generic AiTR algorithm system

Input sensor data → Preprocessing for Machines → Detection → Extraction → Identification

Preprocessing for Machines
- Noise removal
- Light scattering reduction

Detection
- Candidate Regions of Interest Detection
- Anomaly Detection

Extraction
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- Spectral features
- Spatial features

Identification
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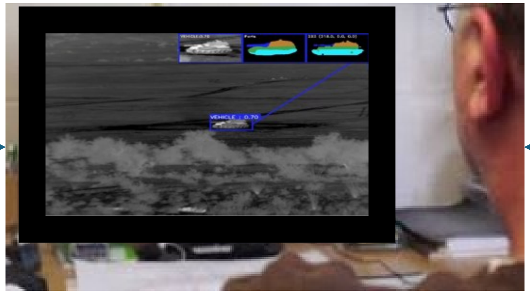
Input sensor data → Preprocessing for Humans →

Preprocessing for Humans
- Edge enhancement
- Super-resolution



Final Research Deliverables

- **Preprocess digital images** to help humans in AiTR
- **Preprocess hyperspectral images** to improve machine detection accuracy
  - **Detect anomalies** in HS images with higher accuracy
  - **Semantic Segment** HS images to identify targets
- **Detect anomalies** in diverse scenarios
  - No need for new training
  - Avoid the hassle of going back to square one repeatedly

Significance of the Study

- **Improved Accuracy:** developing new algorithms that can increase the accuracy of target detection methods

- **Robustness to Noise and Variability:** developing techniques that are robust to noise, atmospheric effects, and variations in lighting conditions

- **Adaptability to New Data Sources:** developing algorithms to analyze and detect anomalies in diverse data sets effectively

Timeline

Deadline	Work
May 01, 2025 (10 weeks)	Generalized hyperspectral AD
July 15, 2025 (4 weeks)	Investigate HS and digital image processing
August 15, 2025 (4 weeks)	Work on preparing Dissertation
September 18, 2025	Final Dissertation Defense
October 7, 2025	Submit the final copy of the dissertation