SUMMARY: INVESTIGATION OF TARGET DETECTION IN HYPERSPECTRAL IMAGES FOR AIDED TARGET RECOGNITION

by

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Abstract

Aided Target Recognition (AiTR) improves human target detection and tracking by enhancing sensor data for better accuracy and visual understanding. Remote sensing (RS) collects information from a distance, often via satellites or aircraft. We are exploring a network of unmanned aerial vehicles (UAVs) equipped with various sensors to enhance Intelligence, Surveillance, and Reconnaissance (ISR), agriculture, and environmental assessment applications. The combination of AiTR and remote sensing is a key advancement in military surveillance, and research is ongoing in this area. Our research involves the development of algorithms for target detection in collected hyperspectral sensor data. A key challenge we face is the need for lightweight CPU-based anomaly detection to reduce computation overhead and battery consumption, a crucial aspect in designing an optimized UAV surveillance system for long, steady flight missions with broad area coverage. We must also further investigate those scenes containing the anomalies on more capable drones or powerful ground stations.

Hyperspectral (HS) imaging, a powerful tool for capturing detailed spectral information, is susceptible to variations in data quality due to weather conditions. Factors such as time of day, cloud cover, dust, and water vapor can introduce noise and scattering, underscoring the necessity of image preprocessing techniques. These techniques, including noise reduction, brightness correction, and contrast enhancement, are crucial for improving data quality, bolstering feature extraction, and enhancing the performance of standard detection methods and machine learning models.

Statistical methods have been used extensively for anomaly detection. They typically make assumptions about the background in an HS image to detect anomalies. However, they can fail when the background does not meet their assumptions. In contrast, machine learning (ML) techniques can enhance anomaly detection in cluttered backgrounds. Thus, we propose a supervised stacking ensemble called GE-AD to combine the outputs from multiple statistical methods and ML algorithms (i.e., base methods to GE-AD). The selection of these base methods

is crucial, and we employ a greedy search algorithm to identify the most effective ones for the ensemble. However, GE-AD has difficulty handling HS datasets collected using diverse sensors or datasets collected using the same sensor but under different weather patterns, changed collection techniques, and other uncertainties. I propose generalizing our anomaly detection solution using domain adaptation to address this. Domain Adaptation (DA) is an ML technique that assumes no access to target domain data. It aims to learn a generalized model to differentiate between datasets from one or several training domains with different probability distributions, thereby achieving good out-of-distribution generalization.

Semantic segmentation proves to be a valuable asset when applications necessitate a more in-depth analysis of a scene for precise object localization and boundary delineation, such as in military surveillance scenarios. It allows us to comprehend the detailed composition of a scene by distinguishing different objects at a granular level. While high-performing image semantic segmentation models like U-Net, FCN, and DeepLab are readily available, their direct use on HS imager data, which has more channels than the RGB images they were designed and trained with, is not feasible. Simply updating the input layers of existing deep learning (DL) models may compromise their performance. Therefore, I propose a separate channel attention module to extract crucial spectral information from the hundreds of channels in HS images without disrupting the original DL model. By combining the spectral feature in the first layers of the original DL model and fine-tuning it, we can achieve improved results, thereby demonstrating the adaptability of this method for AiTR's use.

Keywords: hyperspectral remote sensing, near-infrared NIR, unmanned aerial vehicles UAV, aided target recognition AiTR, anomaly detection methods, machine learning, deep learning, crop classification, semantic segmentation, stacking ensemble learning

Chapter 1

Summary

Hyperspectral (HS) imaging helps analyze materials for **Aided Target Recognition (AiTR)** in military, agricultural, and environmental fields. AiTR [1] systems play a crucial role in enhancing how accurately we can understand sensor data for target detection, classification, and identification and assist in tracking. It involves preprocessing sensor data to improve detection accuracy, detecting and classifying potential targets [2], and enhancing the visual effects of data for human understandability. Whereas **Remote sensing (RS)** is gathering information about an area or object from a distance, typically using a satellite or aircraft. However, using these solutions on unmanned aerial vehicles (UAVs) is limited by UAVs' computing power and battery life. We are investigating the development of a network of multiple UAVs with different sensors affixed to each [3]. This network of UAVs aims to enhance imaging and reporting capabilities for intelligence, surveillance, and reconnaissance (ISR), potentially transforming military operations by providing better situational awareness and a clearer picture of what is happening. These UAVs or drones can also help in agriculture and environmental assessment applications.

HS imaging (HSI) is a promising tool with the potential to obtain detailed spectral information from a scene. The advancement of HSI technologies [4] combined with machine learning (ML) recognition techniques [5] holds the key to improved scene characterization in numerous applications. This scene characterization includes the detection of anomalies in a cluttered background, finding objects, or identifying materials. HS remote sensing combines spectroscopy and imaging to collect spatial and spectral information and process information across the electromagnetic spectrum. The advent of UAVs indicates that combining HS remote sensing with AiTR promises hope. Figure 1 shows various steps in the generic algorithm pipeline of an AiTR system. The top line shows different stages of processing on sensor data. The bottom pipeline shows the final AiTR stage: processing and presenting them to humans in the loop.

Our research involves the development of algorithms for target detection in collected HS

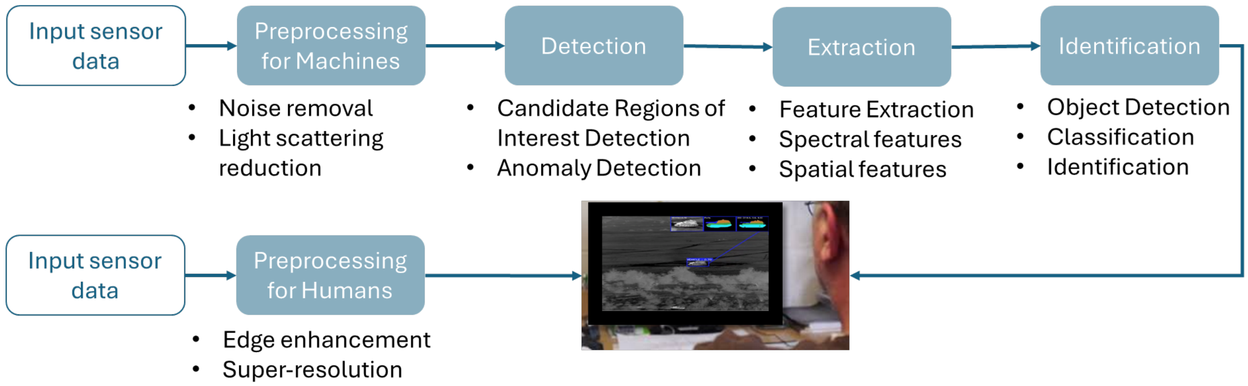

Figure 1: Generic algorithm processing pipeline for an AiTR system [1].

sensor data. A key challenge is that the AiTR's detection performance can degrade due to sensor variations, acquisition protocols, environmental conditions, and weather issues. HS imaging is excellent for spotting material-level issues. However, it's sensitive to environmental noise like clouds, dust, and changes in lighting. Thus, it underscores the necessity of image preprocessing techniques. These techniques, including noise reduction, brightness correction, and contrast enhancement, are crucial for improving data quality. It bolsters feature extraction and enhances the performance of standard detection methods and machine learning models. Another challenge is that standard anomaly detection (AD) methods, especially statistical ones, often struggle when design assumptions are unmet. On the other hand, deep learning models made for regular RGB images do not easily adapt to high-dimensional hyperspectral data.

We propose a lightweight, CPU-efficient anomaly detection framework that combines traditional statistical techniques with machine learning algorithms using a supervised stacking ensemble named GE-AD to address these limitations. A lightweight CPU-based anomaly detection is vital to reduce computation overhead and battery consumption, a crucial aspect in designing an optimized UAV surveillance system for long, steady flight missions with wide area coverage. A greedy search strategy is employed to select optimal base detectors, enhancing ensemble performance under constrained computational resources. However, due to spectral variability and acquisition inconsistencies, GE-AD's performance declines across domains.

To overcome this, we integrate unsupervised domain adaptation methods that align feature distributions between training and deployment domains, enabling robust, out-of-distribution generalization without requiring labeled target data.

Furthermore, we extend our approach with semantic segmentation for tasks requiring fine-grained scene understanding for AiTR identification. Recognizing that existing segmentation models (e.g., U-Net, DeepLab) are not optimized for HS inputs, we introduce a channel attention module to extract relevant spectral features without disrupting the original architecture. By fusing this module with early layers of deep segmentation models and task adaptation, we preserve their performance while adapting them to the rich spectral space of HS data.

Finally, our task-oriented digital image processing enhances human visibility to detect targets and better understand the scene. We can apply these image-processing techniques to 1- or 3-channel digital images (1-channel gray-scale and NIR images or 3-channel RGB and NIR-RG images). Compared to generic image processing, which can introduce artifacts and hinder scene understanding, our proposed framework will significantly improve scene understanding, anomaly detection, and semantic segmentation performance under real-world constraints, enabling effective, long-duration UAV operations across diverse sensing conditions.

This proposal aims to solve AiTR problems for HS data collected using low-flying UAVs, Unmanned Aircraft System (UAS) platforms, and aircraft by providing anomaly detection and segmentation solutions based on HS remote sensing. Here, UAV (Unmanned Aerial Vehicle) refers only to the drone or unmanned aircraft itself, whereas UAS (Unmanned Aircraft System) encompasses the whole system needed to operate a drone, including the aircraft, supporting ground control station and systems, communication links, and software. This work bridges the gap between high-performance HS analysis and domain-robust AiTR systems. The individual components are also valuable and advance the research frontier in various computer vision and remote sensing fields.

Goals and Future plan

The overarching goal of my proposal is to explore, investigate, and propose novel ways to improve HS anomaly detection and semantic segmentation for AiTR and efficiently quantify and measure their performance. The plan includes investigating ensemble anomaly detection and finding innovative ways to generalize the solution on various HS datasets. This plan also includes investigating task adaptation on an existing deep semantic segmentation model pre-trained on a large RGB dataset and spectral channel attention module to optimize it for HS inputs. It will also include unique ways to preprocess the HS images and measure their impact on detections. It will help with both remote sensing and aided target recognition. I will also plan to investigate a novel way to improve visualization for human understanding.

- **Process HS images** to improve machine detection accuracy
- **Identify anomalies** in HS images across various scenarios with greater accuracy to assist humans
- Scenes HS image **semantic segmentation**
- **Process images** to enhance human visibility

Achieving these goals presents multiple challenges. We have found that there is limited public HS data, and annotated data is even more scarce. To address this, we have comprehensively explored and combined unsupervised learning with supervised learning for anomaly detection. The HS image's numerous channels pose memory constraints on fitting deeper networks, leading us to employ no or limited deep-learning algorithms. Leveraging the HS imager's low spatial resolution at a high altitude and high spectral resolution, we have used spectral information and unmixing to improve accuracy. To overcome the biases of simple statistical solutions, We have developed an ensemble using meta-model to generalize them, thereby enhancing their accuracy. We have also devised a greedy solution to select base methods from various statistical HS-AD methods to use in an ensemble. As for future, our proposal includes the application of domain adaptation to ensure the widespread application of our solutions. Furthermore, This plan also includes investigate task adaptation to optimize an existing deep semantic segmentation pre-trained on large RGB dataset for HS inputs. Finally, we will investigate the impact of image processing on detection algorithms and human understanding, potentially leading to significant improvements.

Previous Work

Radiometric calibration is the first step in converting raw digital numbers to radiance values, and the sensor manufacturers usually supply these solutions to ensure the data represents physical measurements. We also apply geometric Correction (Orthorectification) to correct geometric distortions due to UAV movement (pitch, roll, yaw) and terrain [6]. Atmospheric Correction (AC) algorithms correct the atmospheric effects on remotely sensed HS imaging data acquired by air and space-borne systems. Analyzing the signal-to-noise ratio (SNR) for the HS images obtained from a new sensor is essential to ensure the sensor maintains excellent overall sensitivity and spectral resolution. We selected the Gaussian filter for noise reduction and better performance in our unmixing pipeline. Deblurring restores a sharp image from a blurred one, which can sometimes reduce noise. A Wiener low-pass filter is one of the first deblurring techniques to reduce additive random noise in images [7]. Aggarwal [8], and Zimek et al. [9] investigated ensemble methods and found base methods with wide ranges of output values introduce challenges for the ensemble since this often produces unbalanced ensemble results. We investigated and found quantile normalization [10] effective and thus used it in our work. Histogram equalization is a contrast adjustment technique that increases the global contrast of an image with a narrow range of intensity values [11–13]. It evenly distributes the densely populated intensity values into the full range of intensities in the histogram.

Hyperspectral Anomaly detection

Table 1 shows various types of individual HS-AD Algorithms. The Reed–Xiaoli (RX) Anomaly Detector algorithm is currently considered as the baseline for the performance comparison benchmark. The RX algorithm characterizes the HS image's background using the hypercube's mean and covariance [14, 15]. RX calculates the Mahalanobis distance [16] between the background and pixel under test.

Table 1: Examples from various types of HS-AD algorithms.

Type of HS-AD	Examples
Statistics based	RX, MD-RX, WIN-RX
Subspace based	LSUNRSORAD, CSD, SSRX
Cluster-based	CBAD, FCBAD
Spatial–spectral based	AED
ML-based	SVM, iForest
Kernel-based	KRX, GM-RX, KIFD

Real-life scenarios are much more complicated, which is why many classical anomaly detectors fail to identify anomalies. Ensemble anomaly detection techniques solve these anomaly detection methods' instability problems. To tackle the shortcomings of the statistical HS-AD methods, we utilized them in an ensemble. Aggarwal et al. [17] delved into the effects of using homogeneous weak outlier detectors in the bagging ensemble method in their research. However, combining heterogeneous weak detectors in an ensemble creates a better understanding of the background as it introduces multiple biases. Thus, we explored this direction using unsupervised heterogeneous weak detectors in our Hyperspectral Unmixing-Based Voting Ensemble Anomaly Detector (HUE-AD) [18]. An equal-weight voting method combines four detectors (Abundance, AED, KIFD, and LSUNRSORAD) to identify anomalies. We found that systematically assigning weights to inputs improved the accuracy during our evaluation. However, we found that selecting these algorithms from many options and assigning them weights is not systematic or efficient. We also found that the threshold selection for base methods can be a significant source of information loss, resulting in complete system failure in extreme cases. Thus, we developed our model stacking solution called the Greedy Ensemble Anomaly Detection (GE-AD) method with greedy search to find those base methods, a normalization method to use the complete information generated by the base AD algorithms without introducing bias, and a supervised meta-learner to learn their weight.

However, GE-AD suffers when there is a change in sensors and environment and needs new training from scratch. Thus, I plan to investigate the Subspace Alignment (SA) approach adopted by Pillai et al. [19] to **generalize the Hyperspectral Anomaly detection**. SA methods try to align the statistical measures of features of different domains. Pillai et al. [19] used semi-supervised DA. Semi-supervised DA helps if there are limited labels in target datasets. Their idea [19] of sub-sampling to find related examples in the source domain is intriguing. It helps a model become data agnostic, reducing the training time without sacrificing performance in a new dataset. Mancini et al. [20] proposed an ensemble learner with domain predictor to predict the probability of a sample belonging to each domain (weights). Ryu et al. [21] investigated the generalizability in random forests. As we have random forests as our meta-model, we can extend their solutions in our scenario. Wang et al. [22] generalized a zero-shot learning problem and presented a unified domain adaptation framework for both unsupervised and zero-shot learning conditions. Meegahapola et al. [23] uses an unsupervised adversarial-based domain adaptation (DA) method. I also plan to investigate the unsupervised DA method.

Image Semantic Segmentation

U-Net is a versatile semantic segmentation network among deep networks with various data types and architecture [24, 25]. Multiple researchers have included transformers [26, 27] and attention networks [28, 29] in the U-NET. Chen et el. [26] had proposed a U-Net-like Visual Transformer. Schlemper et al. [30] proposed an Attention-gated U-Net. Sadly, these deep SS models cannot achieve their full potential when training from scratch using HS image datasets because there are various large RGB datasets but very limited large HS image datasets for various tasks [31].

Compared to greyscale and RGB images, HS images contain hundreds of channels. Wang et al. [32] proposed a Channel Attention Module (CAM). Leveraging this spectral information in the CAM can help differentiate objects better in our new U-Net.

Preliminary Work

We first applied geo-rectification [6] for our Arizona dataset collected using the Pika-L sensor. Then, we computed the SNR for all bands using the Avhyas plugin [33] in QGIS. It is crucial to analyze the SNR to ensure that the sensor has an excellent overall sensitivity and spectral resolution. We then create a new hypercube consisting of the bands with signal-to-noise ratios above our predefined threshold. Instead of aggressively removing channels, noise reduction can recover some of the channels and preserve data. Once we removed all noisy bands, we selected the most informative bands using the method proposed by Du and Yang [34] to reduce the hypercube's dimensionality and improve the processing times without degrading performance.

We have enhanced images to improve human comprehension and tested methods like auto brightness adjustment and HSV CLAHE (Contrast Limited Adaptive Histogram Equalization). However, the effectiveness of enhancing images to help humans detect anomalies is very subjective. In this scenario, using task-oriented digital image processing to produce a helpful image for stakeholders is more important.

Greedy Ensemble Anomaly Detection (GE-AD)

Ensemble learning is a machine learning technique that combines multiple individual ***base models*** or weak learners to create a stronger, more accurate model with better predictions. We previously proposed HUE-AD [18], an equal-weight voting ensemble of four heterogeneous detectors. Drawing inspiration from Feature Weighted Linear Stacking (FWLS) [35, 36], we developed a two-stage weighted stacking ensemble with unsupervised weak HS-AD methods in the first stage and a supervised machine learning (ML) method in the second stage to compute the weights. For the first stage, we opted to use unsupervised HS-AD methods. For the second stage, as learning the appropriate weights to assign to multiple inputs requires much less training data than learning features from images, we can utilize a supervised ML method.

Additionally, our empirical analysis showed that the combination of base models that yields the best outcomes varies based on the given scenario. As a result, we proposed greedy search for identifying efficient methods for base model in a weighted voting ensemble. Figure 2 shows the overall flowchart of the GE-AD algorithm. For our ensemble fusion, we have considered one HS unmixing algorithm, FCLS, to generate an abundance map and nine AD algorithms, including AED, CSD, FCBAD, GMRX, KIFD, KRX, LSUNRSORAD, Median AD, and RX.

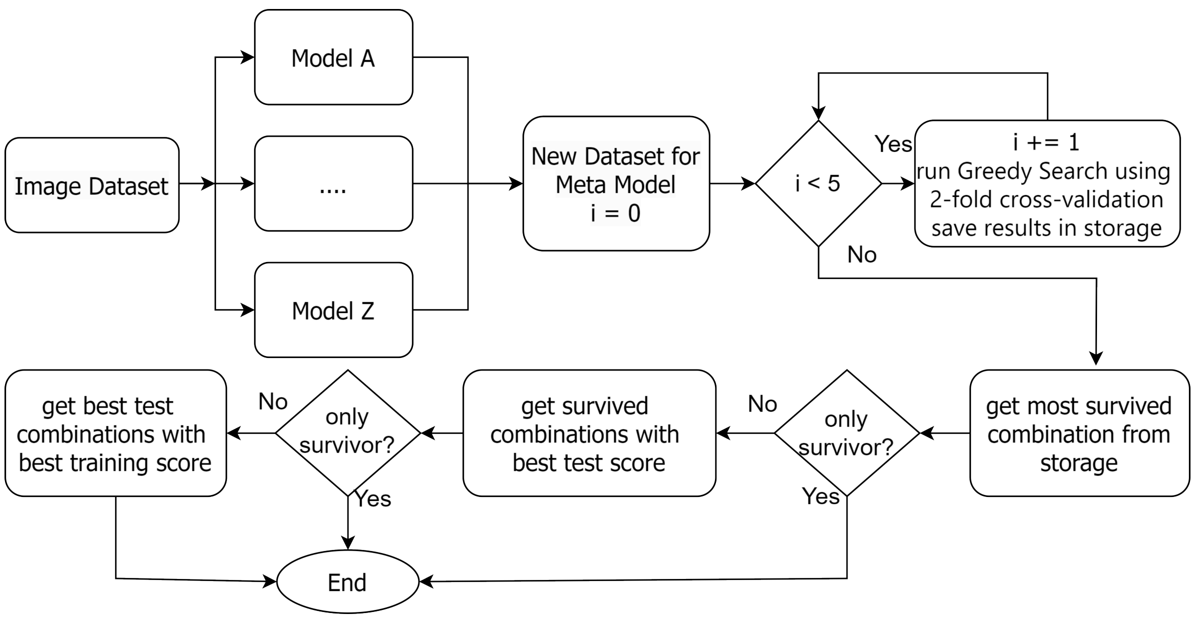

Figure 2: Overall flowchart of GE-AD to find the best AD methods for ensemble fusion.

Replacing Supervised Meta Method in GE-AD with Unsupervised Method

For our first evaluation, we replaced the Random Forest with an unsupervised Mixture Model (GMM) as the meta-model.[1] In our evaluation, we found that it has an AUC ROC score of

[1] We also tested the isolation tree, which did not work.

0.943 ± 0.088 and F1-macro score of 0.548 ± 0.048 among all datasets. We plan to investigate other unsupervised models in the future. We also plan to apply all options we used in improving our supervised GE-AD [37] to this new unsupervised GE-AD (UGE-AD) model and investigate their impacts.

Adding Spectral Information as Input to GE-AD

As GE-AD uses only the results from base models, the spatial and spectral information from an HS image is not visible. GE-AD can compute different weights for different datasets based on features from the input data. However, we cannot feed all the channels to the our model due to two concerns: (a) this approach may hinder our model from learning essential features from the base models; and (b) the curse of dimensionality leads to increased computational complexity, overfitting, and spurious correlations. As an initial investigation, we modified GE-AD (mGE-AD) to take thirty random spectral channels and four other base methods as input [38]. In our evaluation, we found that it has an AUC ROC score of 0.593 ± 0.070 and F1-macro score of 0.548 ± 0.048 among all datasets. Instead of randomly selecting spectral channels, we plan to use dimensionality reduction techniques.

Hyperspectral Image Semantic Segmentation

AiTR cannot use these deep semantic segmentation models, which are designed and trained with RGB images, directly for HS image SS. The main challenge here is the high dimensionality of HS images, which DL model cannot handle them effectively. One solution is updating and fine-tuning the input and final output layers. However, this can hamper their performance as middle layers still expect features from RGB. Another solution is end-to-end fine-tuning of existing DL models, which can compromise its general knowledge. Thus, I propose to use a channel attention network to utilize these hundreds of channels from HS images and extract crucial spectral information. A channel attention network is a neural network that learns to focus on vital channel information. By combining the spectral feature in the final layers of the DL model with the RGB image and fine-tuning it, we can expect to produce significantly improved results.

Our proposal to combine an HS channel attention network with U-Net and transformers, thereby enhancing the Trans-U-Net [26] trained on a large RGB dataset, offers a promising avenue for advancing HS image SS. Compared to other models, we integrate RGB and HS images through the fine-tuning technique to create a versatile model. Using the U-Net model further simplifies the implementation and testing of our new solutions. Importantly, we design a separate HS CAM network to avoid modifying the entire pre-trained Trans-U-Net model, thereby preserving its general knowledge and stability for new tasks, providing a reliable foundation for our approach.

By leveraging task adaptation and fine-tuning, we improve the accuracy of U-Net in segmenting crops [39]. Although visual transformers provide better results than convolution neural networks, they are hard to train and need hundreds of thousands of images. However, there are no hundreds of thousands of annotated HS images available. Thus, domain adaptation is the key factor in successfully using visual transformers. This approach is convenient when the source and target domains have different tasks, and the target domain is not only related but also accessible during training. In our case, we will use pre-trained U-Net and Transformers trained on large RGB ImageNet datasets [40]. We will further fine-tune these models on the RGB and HS image dataset. Transfer learning [41] or fine-tune helps to enhance a model's performance trained for one task and deployed for a different but related task. The original transformer cannot handle all hundreds of channels present in an HS image. In contrast, our model will be able to utilize the HS dataset.

Further Research Plan

Previously, we have Aggressively removed noisy bands below a fixed threshold (5 SNR) or below a certain percentage (97%) [37, 42]. However, it may cause data loss and reduce anomaly detection performance. I will investigate the impact of removing and recovering some of these bands. Data collection and stitching may introduce artifacts and noises. My objective is to improve the performance of detection methods by preprocessing. I am committed to finding a systematic way to select preprocessing methods. A hidden potential may be untapped due to the manual section of preprocessing methods. We aims to optimize input data for better outcomes in each scenario.

At the heart of this Image Enhancement Methods for Human Understandability research is the understanding that user feedback is invaluable to creating an efficient aided target recognition system. We can simultaneously apply various image processing and enhancement techniques to the same image. To ensure that our model is user-centric, we will pursue a classification model [43] as shown in Fig. 3. This classifier predicts mutually exclusive class labels (i.e., image enhancement methods) for a scene in a sequence based on latent space features created from a scene. The ground truth of the model will come from users who will vote on which image is better than the original image. This user feedback is crucial as the model learns to mimic high-quality pictures of what human eyes like for identifying targets rather than focusing solely on achieving a high quantitative performance score.

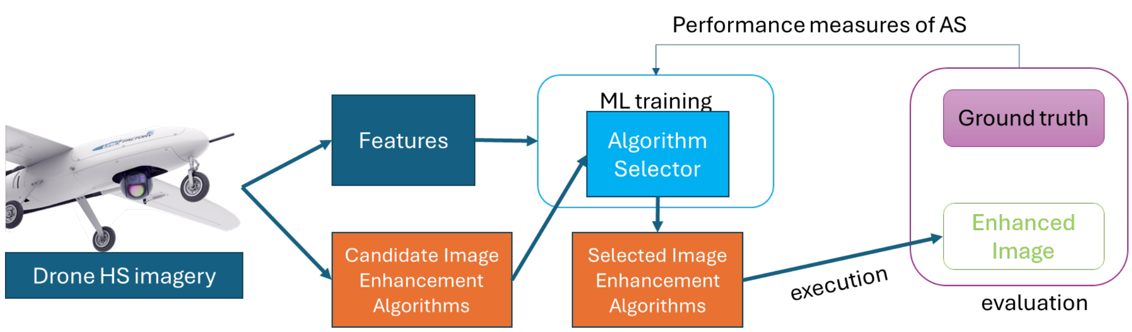

Figure 3: Image Enhancement Method Selection using ML Model

Generalization of Hyperspectral Anomaly detection

We plan to evaluate both types for our meta-learner and investigate other supervised and unsupervised models, as unsupervised models provide a stable result for each dataset irrespective of the training dataset and modification of supervised models are more straightforward.

Compared to transfer learning and domain adaptation that assume the availability of target domain data, Domain Generalization (DG) takes a step further and does not require access to target data [44]. We can use DA (domain adaptation) when the complete dataset is available during the model's devising and training. DA method SA (Subspace Alignment) aligns the statistical measures of features of different domains. We will investigate when to apply DA methods. We can use them for spectral information before providing them to the base methods of our GE-AD algorithm. We have investigated providing spectral information directly to the meta-model. We will explore dimensionality reduction techniques to reduce spectral information and apply DA and DG methods here to inspect its impact. We will also use these DA and DG methods to outputs from base methods without exposing spectral information to the meta-model.

Here, the challenge of DG (Domain Generalization) is that the target dataset is unavailable during training, which is usually the case in real life. DG aims to learn a generalized model from one or several training domains with different probability distributions that can achieve good out-of-distribution generalization. After completing the DA (domain adaptation) investigation, I will expand our investigation on DG if I have sufficient time and support from others.

Hyperspectral Image Semantic Segmentation

We plan to integrate the HS channel attention network into the Trans-U-Net to harness the spectral information from all those hundreds of channels. We will comprehensively analyze this model, focusing on complexity reduction without sacrificing performance. We will also incorporate dimensionality reduction techniques like unmixing to select the most informative channels [34], ensuring a constant number of channels with the best spectral information. This thorough approach will enable us to generalize our model across various datasets and examine the impact of fine-tuning on tiny datasets such as Indian Pines [45], which consists of just one image.

Proposed Work Timeline

Table 2 outlines the comprehensive timeline for this proposal. I will investigate the impact of image processing on machine detection, human visibility, and understandability.

Anomaly detection in HS imaging is the leading task we should address in AiTR first. Our stacking ensemble uses existing methods as base methods, reducing their variability for diverse scenes. We have published this work as a journal article in the MDPI Journal of Imaging. However, the hyperspectral sensor variability challenges our model's generalizability. Utilizing domain adaptation to enhance anomaly detection accuracy for unseen data shows great promise. By applying various domain adaptation methods within ensemble machine learning and deep learning frameworks, I, in close collaboration with my advisors and research team, can develop a robust tool for detecting anomalies in HS images, and present solutions we will introduce to handle new unseen datasets and novelty anomalies. In addition, I plan to investigate this solution over two months, produce a journal article with my collaborators, and submit it to the MDPI Sensors Journal.

Deadline	Work
Complete	Investigate Greedy Ensemble Anomaly Detection (GE-AD)
Complete	Publish GE-AD to MDPI Journal of Imaging
Complete	Investigate Semantic segmentation on UAV HS Agricultural Imagery
Complete	Publish HS image Semantic Segmentation to SPIE D+CS conference
May 01, 2025	Start Generalized HS AD
May 31, 2025	Start Preprocess digital images
June 30, 2025	Start Impact of image processing
August 15, 2025	Submit Generalized HS AD to MDPI Sensors Journal
August 15, 2025	Work on preparing dissertation
August 30, 2025	Apply to Graduate
September 18, 2025	Defend dissertation
October 7, 2025	Submit Final copy of dissertation

Table 2: Timeline to complete my proposed disssertation works.

Semantic segmentation, a key tool in our research, can help with AiTR identification. It is crucial when investigating scenes with registered anomalous targets. We aim to identify these targets if they are our object of interest. Semantic segmentation is widely used in scene understanding for autonomous navigation, agriculture, and the environment. Finally, I will tidy up all the chapters, update them with new findings, and submit the findings with my written dissertation.

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