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HYHSI: A HYBRID FRAMEWORK FOR HYPERSPECTRAL ANOMALY DETECTION AND CLASSIFICATION

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A B S T R A C T

Hyperspectral Imaging (HSI) is a new technology in remote sensing that records finer spectral and spatial data in hundreds of neighboring wavelengths. The pixel spectral signature is unique and allows one to identify materials accurately and makes HSI useful in environmental monitoring, agriculture, defense, and surveillance. The purpose of hyperspectral anomaly detection (HAD) is to detect pixels that differ to the background without prior information of any target signature.

HAD methods have also been developed to replace better traditional statistical methods such as the RX detector with modern machine learning and deep learning methods. Although the initial techniques were effective and analyzable, they were not able to analyze complicated backgrounds and nonlinear spectral variation. New deep learning algorithms, such as autoencoders, CNNs, transformers, and self-supervised algorithms have enhanced detection through learning rich spectral-spatial features. Nevertheless, there are also challenges of high cost of computation, limited labeled data, and real-time deployment. This paper will review the current developments and classify the HAD techniques into six broad categories to note the current trends and future and proposes a framework to synthesizes a number of other designs into a consistent framework.

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1. INTRODUCTION

The Hyperspectral Imaging (HSI) has emerged as the crucial technology in remote sensing, environmental monitoring, agriculture etc., due to its capability of extracting information from both spectral and spatial features across various bands. Each pixel in HSI image contains unique detailed spectral information making it more reliable and more precise in material classification rather than conventional image detection techniques. This high-resolution technique of image detection comes with challenges such as Data Redundancy, computational complexity where the motive is Anomaly Detection and working with Real-Time Data, and our goal is to find the divergence in spectral signature from then background. Anomaly Detection in hyperspectral imagery has been progressed over time with several different methods. In starting days, the Researcher focus on statistical method

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and the first and the prominent one was the Reed-Xiaoli (RX) detector which is based on the covariance modelling of background pixels to detect the anomaly region. As these are simple models with less computational requirements, they face challenges while working with complex data, background, and non-linear spectral behaviour. To address the challenges faced by the Statistical method, many Machine learning method and representation-based methods have been come forward like proposed in (Xu et al., 2022) and (Imani, 2023), these have shown the updates by introducing the feature learning and subspace projection technique in background modelling, additional advancement in techniques are shown in (Chang & Ghamisi, 2022) and (Wang et al., 2022) by combining the benefits of the spatial and spectral information extracted, and formulated the solution.

The recent advancement in the field of Deep Learning has changed the working of Hyperspectral anomaly detection. Autoencoders, Convolutional Neural Network, Recurrent Neural Network started to extract the new features and information from the raw data. Research done in (Müller et al., 2023), (Xiang et al., 2024), Milićević et al. (2025) and (Xiang et al., 2022) has shown the improvement and advancement in anomaly detection using the Deep Learning method. The models proposed in (Duan et al., 2023) and (Song et al., 2023) has used the theoretical knowledge of the RX and with neural representation which can lead to the hybrid model. In the recent time when Transformer and Attention-based architecture model came into work has opened new paths in the AD, the researches such as (Ahmad et al., 2025) , (Z. He et al., 2023) and (Ghosh et al., 2022) has shown that how the attention mechanism works efficiently and can see up to long-range spectral information. In addition to this, the combination of the Transformer with the Autoencoder in the study (Z. Li et al., 2023) and (J. Li et al., 2024) has started the work on the Hybrid model architecture. In the advancement of the Generalised model and led to the development of the framework and architecture proposed in (Braham et al., 2025) and (Yao et al., 2024) respectively, shows the advancement towards the large-scale pretraining and Transfer Learning to develop the generalize way for the AD.

Despite the advancement there are challenges remains, many DL model require large labelled datasets which is difficult to obtain real-time HSI data, the trade-off between the detection accuracy and computational cost remain unsolved till now. This manuscript highlights the evolution and breakthroughs in Hyperspectral Anomaly Detection by focusing on improvements in the span of 2022 to 2025, as well as identify the research gaps also and proposes a framework to fulfil some of these gaps.
In 2022, we mainly studied traditional machine learning techniques, along with reviews and key deep learning structures. By 2023, we noticed a clear shift toward hybrid and unsupervised learning methods that combine various strategies to enhance detection performance. With a focus on incorporating spectral-spatial features and attention mechanisms, the evolution continued in 2024. In 2025, new network designs and effective computational methods led to even more improvement. These works are divided into six different study themes according to their methodological approaches and application fields in order to facilitate understanding. This organised classification provides a clear overview of the numerous techniques and key developments shaping the current state of hyperspectral anomaly detection.

For clarity and readability, the abbreviations used throughout this paper are summarised in Table 1.

Table 1. List of Abbreviation

Abbreviation	***Full Form***
RX	Reed-Xialoi
AD	Anomaly detection
AE	Auto Encoder
DL	Deep learning
HAD	Hyperspectral anomaly detection
HSI	Hyperspectral imaging
RXD	Reed-Xiaoli Detector
LRX	Local Reed-Xiaoli Detector
PCA	Principal Component Analysis
RNN	Recurrent Neural Network
CNN	Convolutional Neural Network
ViT	Vision Transformer
VAE	Variational autoencoder
PC	Principal Component
TDD	Transfer Direct Detection
LRaSMD	Low-Rank Sparse Matrix
CTA	Convolutional inspired Transformer Autoencoder
SDENeT	Spectrum Difference Enhanced Network
VM	Variational Mapping
PAAE	Pixel Associated Autoencoder
GAED	Guided Autoencoder
SSAD	Spectral-Spatial Anomaly Detection
GAN	Generative Adversarial Network
BS3LNeT	Blind Spot Self-Supervised Network
YOTO	You Only Train Once
AETNeT	Anomaly Enhancement Transformation Network
MMC-BSN	Multi-scale Blind Spot Network
CR	Collaborative Representative
NCJCR	The Nonnegative-Constrained Joint Collaborative Representation
AWCR	Adaptive Window-Based
CRNN	Collaborative Representation Neural
TD	Tensor decomposition
MSSR	Multiple Spectral-Spatial Representation
TNN	Truncated Nuclear Norm
HTV	Hybrid Total Variation
TDNeT	Tensor Decomposition-Inspired Convolutional Autoencoder
CP	Canonical Polyadic

Figure 1 shows the overall structure of the literature review used in this study. The figure divides the current methods into six groups: Review analysis, Autoencoder-based, Blind spot & masking, CR-based, Tensor Decomposition-based, and Hybrid, Ensemble & Saliency methods. This structured representation helps identify research gaps and gives the proposed method a reason to exist.

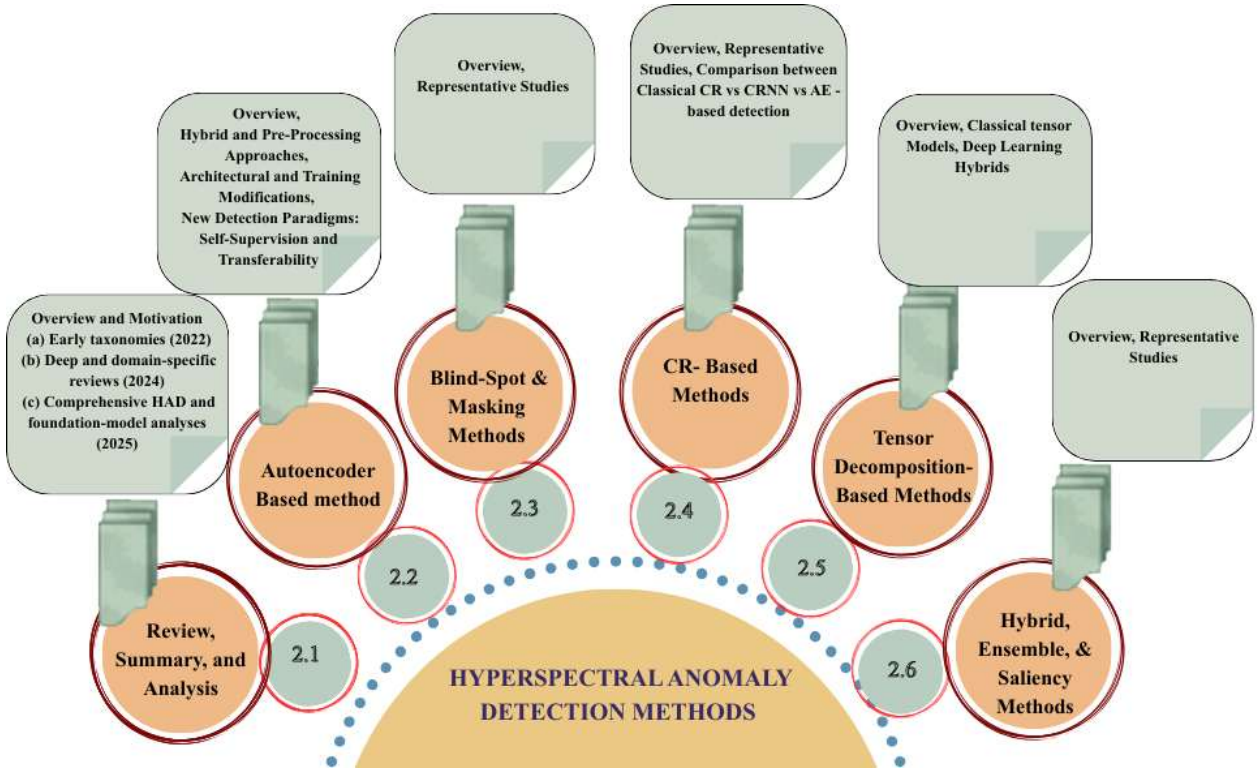


Figure1. Structure of Literature Review

2. LITERATURE REVIEW

Between 2022 and 2025, the hyperspectral anomaly detection (HAD) community developed significantly - from statistical detectors to deep-learning and foundation models - as the result of research that included survey and review articles that mapped the development of HAD and compared and highlighted many of the current trends that are shaping the field; with the community conducting broader evaluations of the research, the field of HAD has become more sophisticated - both technically and methodically.

- **Review, Summary, and Analysis**

In 2022, two studies (Ahmad et al., 2022) and (Yang et al., 2022) established a structured taxonomy of hyperspectral algorithms that categorized hyperspectral algorithms into three families: classical, shallow-deep, and sparse-representation. In addition, these studies pointed out the limitations of traditional detectors, specifically their susceptibility to noise and lack of ability to adapt to different environments and provided self-supervised reconstruction methods as alternatives to address those issues. In 2023-2024, the focus of review articles shifted toward more specialized architectures and domain-specific problems. For example, (Guerri et al., 2024) provided a review of hyperspectral imaging in agricultural settings, which emphasized spectral-spatial fusion; similarly, (Bhargava et al., 2024) provided a review of applications of hyperspectral imaging in medical, industrial, and environmental settings, and also discussed the commonly recognized limitation of limited data for training models and proposed fusion-based methods to help alleviate that limitation. At roughly the same time, there were a number of methodological articles published. In (Yao et al., 2024), author introduced SpectralMamba, a state-space based alternative to improve spectral efficiency at the transformer level. Another research (Ahmad et al., 2025) concentrated on transformers and transfer learning models and demonstrated their effectiveness in adapting to multiple data sets. Reviews of HAD by (Pant et al., 2025), (Hossain, Robinson, et al., 2024) and (Braham et al., 2025) indicated that the research community is beginning to adopt more simple modelling paradigms and the use of multimodal spectral integration evidence that the community is continuing to move away from traditional boundaries of HAD research.

(a) Early taxonomies (2022)

These are the studies that create a first taxonomy of a new field. For example, (Ahmad et al., 2022) provide one of the very first structured reviews on the topic of HAD, relating current deep learning techniques (autoencoders,

CNNs etc.) to the traditional statistical techniques (RXD, LRX, PCA etc.). Although they noticed that there are now more and more unsupervised deep models being developed, most of them require huge amounts of labelled data. This highlights an important problem in the area of HAD, supervised learning requires huge amounts of labelled training data, but in many cases, there is no such data available. This is why the work proposed in (Xu et al., 2022) , which compare classical handcrafted methods and deep learning methods on several datasets, is important. It shows that although deep learning models outperform handcrafted ones, the lack of standards (e.g., common evaluation metrics, common datasets etc.) is still a major problem. Research articles (Ghosh et al., 2022) and (Yang et al., 2022) add another layer of understanding to this, because they point out that one of the key problems is domain transfer, i.e. transferring learned knowledge from one domain to another, and they emphasize that flexible spectral-spatial representations are needed.

(b) Deep and domain-specific reviews (2024)

Deep and domain-specific reviews , which appeared later than the taxonomic studies, connect innovations in algorithms to real-world applications. Researchers in his paper (Guerri et al., 2024) classify CNN, RNN, and transformer networks as three key technologies for the detection of anomalies in vegetation and crops, and they show how deep models support the use of hyperspectral images for agricultural purposes, in (Bhargava et al., 2024) expand the analysis to include medical and industrial imaging, and show how the preprocessing, dimensionality reduction, and the choice of model influence the performance of HAD, in (Yao et al., 2024) they proposed SpectralMamba, and shown that it is simpler and more accurate than transformer-based methods, and the author(s) and in (Ahmad et al., 2025) researchers had examined architectures like ViT and SpectralFormer, and show that these networks can efficiently learn long-range spectral dependencies.

(c) Comprehensive HAD and foundation-model analyses (2025)

Comprehensive HAD and foundation-model analyses , which appear recently, follow a more benchmark-oriented approach. Recent reviews move toward a more benchmark-driven perspective. For instance, researchers (Pant et al., 2025) conducted a large-scale HAD focused survey, and classified 62 algorithms into five paradigms (statistical, sparse, autoencoder-based, masking and hybrid) and evaluated them using well-known HAD datasets such as AVIRIS and HAD100. They identify reproducibility and interpretability as two major open challenges. (Braham et al., 2025) proposed SpectralEarth, a large-scale foundation model that was trained using millions of spectral patches in order to evaluate the cross-task generalization capabilities as well as the scalability of SpectralEarth. (Hossain, Robinson, et al., 2024) investigated HAD systems based on multimodal and fusion techniques and the integration of Hyperspectral, LiDAR and RGB data for improving the generalization capability and the robustness of such HAD systems.

There is a clear progression visible among these studies from 2022 to 2025. The HAD research area transitioned from hand-crafted, feature-based methodologies to deep and foundation models during this time frame. The first set of studies provided foundational taxonomies and comparative reference points for review; the middle period of analysis (2024) investigated architecture type (domain-specific and transformer) and; the most recent survey studies (2025) have progressed to multi-modal and scalable frameworks.

The four primary themes are:

1. Transition to Self-Supervised Learning: To mitigate the problem of over reconstruction in auto-encoders, researchers have developed new techniques like blind spot learning, self-supervised masking, etc.
2. Standardization and Benchmarking: Creation of common, standardized datasets (Braham et al., 2025), HAD 100 (Pant et al., 2025) has allowed fair comparison between algorithms to occur.
3. Large Pre-Trained Spectral Encoding: Several studies have shown classification, un-mixing and anomaly detection can now be performed using a single, pre-trained, spectral encoder.
4. Ongoing Challenges: Despite advancements in HAD research areas, problems such as limited labelled data, sensor variability and lack of interpretability continue to exist.

Overall, the series of studies create a cohesive image of the progress in HAD research and provides a base for the subsequent stage of research focusing on auto-encoder based, blind spot, collaborative representation, tensor and hybrid methodologies.

- **Autoencoder Based method**

Advancement in Deep Learning techniques AEs have come out as one of the important parts of deep learning-based method in HAD. The basic structure of an Autoencoder consist of encoder and decoder part and based on unsupervised, reconstruction-based method. As the anomalies are very rare and their reconstruction is poor so it can be discriminated from the background.

However, the primary challenges seen across the studies is that standard AE architecture, the assumption made often result in learning all features of the data result in proper reconstruction of anomaly. This reconstruction of anomalies results in low reconstruction error for both background and anomalies reducing the performance. By identifying these limitations, recent research made and going beyond the standard AE architecture, different model came with effective result and detecting anomalies. Thus, the further divided section will be explored about the innovation made in each different innovation style.

Rather than going further with only using the reconstruction error researcher have worked with combining the AE with classical RX detector and LRaSMD. The AE-RX hybrid model has combined the feature of both DL and statistical method, researchers in (Song et al., 2023) proposed VAE, that follows Gaussian Distribution. The resulting latent feature become input for the RX detector. In has proposed the KPCA and MKPCA as a part of data preprocessing, this transformation of data make the anomalies to be find easily and during further detection it can increase the AE's accuracy. One of the major changes in architecture and to use the information of both local and global features of Transformers has been combined. In (Z. He et al., 2023), researchers used the CTA which combine the feature of convolution for local features and the attention mechanism of transformers for global features. (S. Liu et al., 2024) proposed SDENeT uses AE with combination of CSWIN-Transformers. Some researchers had introduced the methods which control the latent space generated by AEs. The Guided AE proposed in (Xiang et al., 2022) which reduces the features of anomalous areas and during backpropagation, makes it hard to reconstruct the anomalies and reconstruct the normal background well. The CTA model tries to detect using clustering based which can difference between the pseudo-background and anomalies. (S. Liu et al., 2024) proposed the VM Module that changes the feature space and make a significant difference between the spectral signature of background and anomalies. From the fundamental working of the AE to reconstruct the background, in 2024 (Xiang et al., 2024) introduced the PAAE, it creates the two dictionary one for background and anomalies and they are divided according to the super pixel distance, and then the AE is trained on these dictionaries according to the similarity between the pixels. Due to the challenges in fundamental reconstruction method opened way for self-supervision and transferability. The SSAD (Y. Liu et al., 2023) works instead of relying on reconstruction, it trains a classifier which creates the PC images created from input, and then the feature extracted from the fully connected layer of classifier fed into another model for AD. To address the limitation of the previous mentioned methods have been overcome by TDD model proposed by (J. Li et al., 2024), in this is showed how reconstruction-based method are "two-step paradigm" which is not that much optimal. The TDD model proposed the "one-step paradigm" which create the final anomaly map by using the unsupervised manner which uses the anomaly sample simulation strategy to generate training pairs. By learning the general relationship, the TDD model achieves the transferability which can trained on one dataset and can be applied on the new unseen dataset without fine-tuning it.

One of the most recent and the advanced approach and can be stated as the better solution as they find that the reconstruction method is having the major problem so they made a shift in solving the problem, the SSAD it doesn't rely on the reconstruction-based method, it trains the data on the basis of the principal components which learn to separate different types of features. The performance comparison of the recent AED-based HAD methods is given in Table 2.

Table 2. Performance comparison of the recent Autoencoder-based Hyperspectral anomaly detection methods

Dataset	Method	Accuracy
San Diego I, San Diego II, Pavia	GAE	San Diego I: 0.9959, Pavia: 0.9941
ABU (Airport, Urban, Beach)	AE with KPCA/MKPCA Pre-Processing	ABU Airport 4: ~0.9943-0.9955, ABU Beach 3: ~0.9999
HYDICE, AVIRIS-1 (San Diego), Cri	TDD	HYDICE: 0.9960, AVIRIS-1: 0.9728
HYDICE Urban, Qingdao	CTA	HYDICE Urban: 0.9979, Qingdao: 0.9999
Pavia, San Diego, Gulfport	AE-IT	Pavia: 0.9970, San Diego: 0.9013
San Diego I, San Diego II, Pavia	PAAE	San Diego I: 0.9971, Pavia: 0.9967
San Diego, ABU (Airport, Urban)	SDEN	San Diego: 0.9996, Airport: 0.9981
San Diego I, San Diego II, Los Angeles I	VAE + RX	San Diego I: 0.991, San Diego II: 0.985
Strawberry, Blueberry	SSAD	Strawberry: 0.913, Blueberry: 0.932

- **Blind-Spot & Masking Methods**

The blind-spot and masking approach was established as a self-supervised learning method in hyperspectral anomaly detection, especially in tackling the identity-mapping problem Issue shared by the reconstruction-based techniques. According to (Gao et al., 2023) that when using older autoencoders and GAN, the background will be reconstructed with high fidelity pixels together with anomalies leading to low contrast. This was also observed by (Z. Li et al., 2023) in concern for the older Autoencoder-based HAD networks needing scene-specific retraining. According to our studies we see that self-supervised networks tend to learn a perfect pixel by pixel identity in input and output hyperspectral images which in turn causes over reconstruction of the input.

To get over this issue researchers came up with the blind spot strategy (Gao et al., 2023), in which we purposefully make a neural network blind to some particular pixels during training which in turn it has to predict from its spatial and spectral neighbours. By doing away with the atypical signatures this mechanism forces the model to put forth the background's statistical regularities. Anomalies that break the local spatial–spectral continuity are, thus, not well reconstructed and their residue errors could be large and serve as discriminative materials of anomalies. The seminal work proposed in BS3LNet, is the first ever blind-spot self-super- vised network

specifically designed to handle Hyperspectral data. Based on this, (Z. Li et al., 2023) introduced the YOTO pipeline, which generalized the concept of masking through random masks and accomplished cross-scene generalization without retraining. Their ablation experiments demonstrated a notable practical progress. This paradigm was further refined via multiscale masked convolutions, specifically modelled to capture the problem of anomaly detection with anomalies of multiple spatial scales and textures as present in past blind spot networks.

The overall workflow of the proposed Deep RX-based anomaly detection framework is illustrated in Figure 2. It illustrates that encoder takes the input hyperspectral data cube and turns it into small feature representations. The RX detector processes these features to find problems, and then it decodes them so they can be put back together. The final output shows the anomalies that were found in the hyperspectral image.

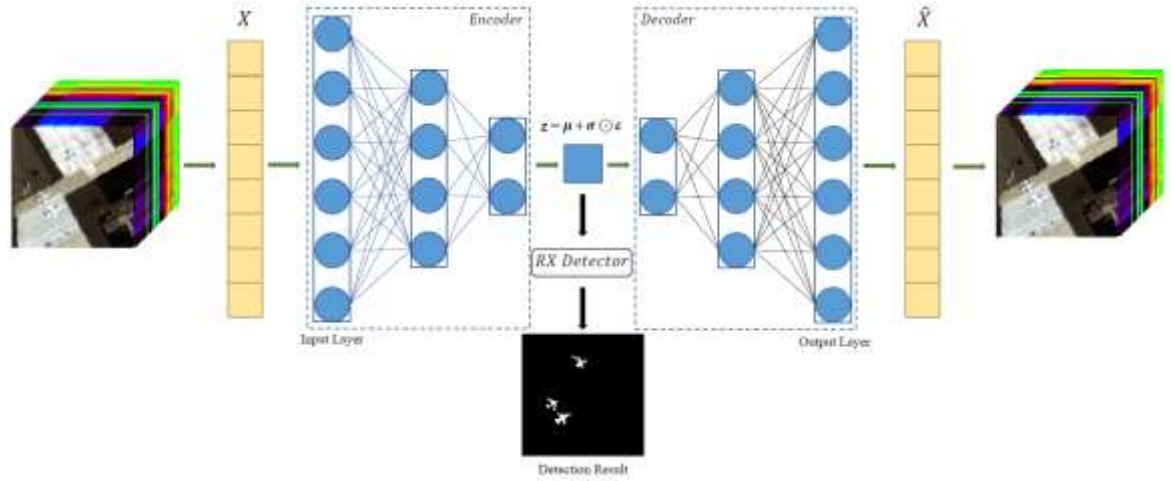


Figure 2. The overall pipeline of the Deep-RX method (Song et al., 2023).

The foundation of contemporary self-supervised HAD research is now blind-spot and masking-based frameworks (performance comparison given in Table 3). They are all based on the same idea : using contextual reasoning to reconstruct background pixels, they naturally eliminate anomalies because of their spectral and spatial inconsistencies HAD's evolution toward contextual , scalable, and domain-independent detection is best illustrated by the research trajectory from BS3LNet, which introduced the blind-spot mechanism, to YOTO, which achieved dataset-level generalization, and finally MMC-BSN, which established multi scale adaptability. But there are still challenges. The optimal mask-size selection and computational cost were identified as major unresolved issues. The challenges of stimulating complex mixed pixels and suggested integration with spectral attention or transformer backbones as a future direction.

Table 3. Performance Comparison of masking and blind-spot based hyperspectral anomaly detection methods

Dataset	Method	Accuracy
AVIRIS-I (San Diego), HYDICE-I, Hyperion	BS3LNet	AVIRIS-I: 0.9985, HYDICE-I: 0.9971
HAD100 Dataset	AETNet	mAUC: 0.9925
Four real HAD datasets	MMBSN	Superior to 9 state-of-the-art methods (exact AUC not tabulated)

- **Collaborative Representation (CR) Based Methods**

The CR method roots from the principle of expressing a pixel in a HSI as a linear combination of background pixels, which is different from Sparse representation-based methods. The essential assumption is that each hyperspectral pixel can be well represented as a linear combination of the nearby pixels, whereas the Sparse representation methods represent each pixel using only the most significant pixels. CR builds upon the fact that normal pixels in hyperspectral imaging can be accurately represented as a linear combination of other background spectra while the anomalous pixels will be poorly represented in such cases. The theory is that the background pixels have a correlation and can reconstruct one another, whereas anomalous pixels will result in a high reconstruction mismatch (Chang & Ghamisi, 2022). Between 2022 and 2023, the research in this domain transitioned from optimised CR techniques towards hybrid deep learning paradigms that led to the development of CR steps with neural networks such as NCJCR, AWCR and CRNN where CR is integrated into advanced neural networks to automatically extract the most discriminating spectral spatial features for separating the background from anomalies, thereby significantly enhancing performance and speed.

The NCJCR framework is a notable enhancement over the traditional CR based anomaly detection methods. The conventional CR models allow the reconstruction

coefficients to take both positive and negative values. The NCJCR mandates the reconstruction coefficient to be precisely non-negative. This constraint results in a more credible spectral reconstruction. Traditional CR methods also consider pixels individually, not taking into account that the pixels in HSI image are spatially and spectrally correlated. NCJCR addresses these issues by applying nonnegative and sum-to-one constraints over the coefficients, optimising jointly over the pixels, ensuring spatial smoothness, thereby allowing a clear discrimination between anomalous and background pixels in complex scenes. Evaluations in (Chang & Ghamisi, 2022) show that NCJCR gave better discrimination between anomaly and background in scenes with non-trivial background discrimination.

Adaptive Window-Based Collaborative Representation (AWCR) extended by (Imani, 2023) is a major improvement in CR -based hyperspectral anomaly detection that presents a subtle, multi-tiered learning mechanism to achieve robustness and precise spatial identification in contrast to conventional CR methods that use a constant spatial windowing mechanism for background dictionary construction. AWCR automatically adjusts the spatial window size on the basis of homogeneity of the environment. If in the neighbourhood there exits high homogeneity larger window size is selected. Alternatively, if the region is heterogeneous a smaller window is chosen to prevent to avoid the inclusion of irrelevant pixels .Another innovation of AWCR This versatile strategy is the key reason for AWCR to perform more robustly across diverse datasets. As per the analysis for complex environments AWCR achieves higher accuracy and low false alarms showing the importance of flexible neighbourhood selection and helps detect anomalies in highly diverse backgrounds. The CRNN model by (Duan et al., 2023) combines traditional collaborative representation with modern neural networks for anomaly detection. The goal is to maintain CR approach of detecting anomalies while addressing its shortcoming in capturing nonlinear interactions enhancing its capacity to handle intricate spatial spectral patterns. CRNN enhances its paradigm helping the model learn complex patterns and variations found in the real world.

To frame the progress from classical collaborative-representation (CR) techniques and to situate them against the broadly used Autoencoder-based anomaly detection, a comprehensive comparison is shown in Tables 4 and 5.

Table 4. A detailed comparison between Classical CR vs CRNN vs AE Based Detection

Criteria	Classical CR	CRNN (CR+Neural Network)	AE-based HAD
Model interpretability	Very high	High	Low
Reason	Clearly defined representation weights and residual measures	Retains CR logic, but deep features reduce transparency	The internal representations and error metrics are not transparent.
Speed	Fast	Moderate	Slow
Strengths	Highly explainable and stable in simple backgrounds	Combines feature learning, noise reduction and interpretability	Suitable for non-linear and varied patterns.
Weakness	Struggles with heterogeneous backgrounds	Requires training time and hyperparameters	Susceptible to the anomaly problem reconstruction

Table 5. Comparison of collaborative-based hyperspectral Anomaly detection methods.

Dataset	**Method**	**Accuracy**
San Diego, CRi, Viareggio	NJCR & Kernel NJCR	San Diego (KNJCR): 0.9944, CRi (NJCR): 0.9978
San Diego, Texas Coast, Indian Pines	AWCR	San Diego: 0.9703, Texas Coast: 0.9993
San Diego, HYDICE, XiongAn, Urban	CRNN)	San Diego: 0.9965, HYDICE: 0.9999, XiongAn: 1.0000

- **Tensor Decomposition (TD)-Based Methods**

TD techniques, which take advantage of the intrinsic three-dimensional structure of HSI, have greatly advanced HAD. Tensor-based models, instead of viewing a HSI as a traditional two-dimensional image, view it as a third-rank tensor, i.e. a multi-dimensional cube made up of two spatial dimensions (height and width) and one spectral dimension (bands) as proposed by (Wang et al., 2022) and (Sun et al., 2022).

In TD-based HAD, the fundamental premise is that a HSI can be expressed as the sum of two different components: a dispersed anomaly tensor and a low-rank background tensor. The sparse component mimics anomalies -rare and spectrally unique pixels that differ from their surroundings, while the low rank characterises the background. However, traditional TD approaches solely rely on iterative optimisation procedures to lessen dependence on low rank and sparsity constraints, which can make these algorithms computationally costly and noise sensitive in spite of their effectiveness. To overcome these problems, newer TD methods integrate regularisation terms(extra rules) and combined assumptions (hybrid priors) for increasing the accuracy

and addressing these issues. For example, (Wang et al., 2022) introduced a MSSR method. Classical tensor decomposition models are based on the notion that a hyperspectral image can be divided into two separate components -a low ranked background and a sparse anomaly component The mathematical expression for this decomposition is:

$$\boldsymbol{Y} = \boldsymbol{X} + \boldsymbol{S} \qquad (1)$$

Where X is the low-rank component and S represents the sparse components. To effectively separate these two parts, classical models often use extra mathematical rules (called Regularisation constraints) to better guide the decomposition process.

As an illustration consider the MSSR that employed removes redundant data and captures global background information using a TNN constraint and HTV to preserve edges and ensure spatial smoothness. Classic TD plays a key role in modern HAD because they strike a balance between clarity, robustness and accuracy in their results, they are effective in the separation of background and anomalies, but often face challenges like heavy computation, slow convergence and sensitivity to noise.
To address these issues researchers have recently investigated hybrid approaches that combine deep learning architectures and tensor decomposition principles. TDNet is the most notable example of this integration. The core idea is to use a deep convolutional autoencoder that can automatically learn low-rank structure of hyperspectral data in an end-to-end manner. It does so by simulating the canonical polyadic (CP) tensor decomposition process within a neural network enabling the model to capture the background patterns directly by learning as opposed to using mathematical calculations. Evaluations reveal that TDNet achieved the highest detection accuracy (AUC above 0.98) on all datasets. In short, it effectively combines the learning capabilities of neural networks with the mathematical foundation of tensor decomposition. Compared to conventional TD or AE methods it is both highly accurate and efficient as it can automatically learn to differentiate between anomalies and background.

Tensor decomposition is seen as a paradigm shift in hyperspectral anomaly detection. They enable simultaneous exploitation of spatial spectral dependency by handling HSI as a 3D tensor. While sophisticated hybrid models incorporate deep learning to achieve generalisation and reliability, traditional models like the MSSR offer robust mathematical frameworks as seen in Figure 3. On combining these techniques significantly increases the accuracy of anomaly detection, linking data driven learning and interpretable mathematical frameworks, thereby guiding the future evolution in hyperspectral anomaly detection research.

The method uses tensor decomposition to collectively model spectral and spatial correlations, thereby providing a better result as seen in Table 6**.** It has a higher computational complexity and requires thorough tuning of regularization parameters.

Table 6. Spatial-Spectral Representation and Autoencoder Based HAD Performance

Dataset	Method	Accuracy
San Diego, ABU (Beach-1, Urban-1), HYDICE	MSSR	San Diego: ~0.9898, MUUFL Gulfport: 0.9985
AVIRIS-I, EI Segundo, Texas Coast	TDNet (Convolutional Autoencoder)	EI Segundo: 0.9943

Figure 3 shows the MSSR framework, where input $Y$is decomposed into sparse anomaly (S) and low-rank background (X). These are optimized via ADMM to obtain $S'$and X', producing the final detection map. This approach is adopted due to its effectiveness in separating anomalies from complex backgrounds.

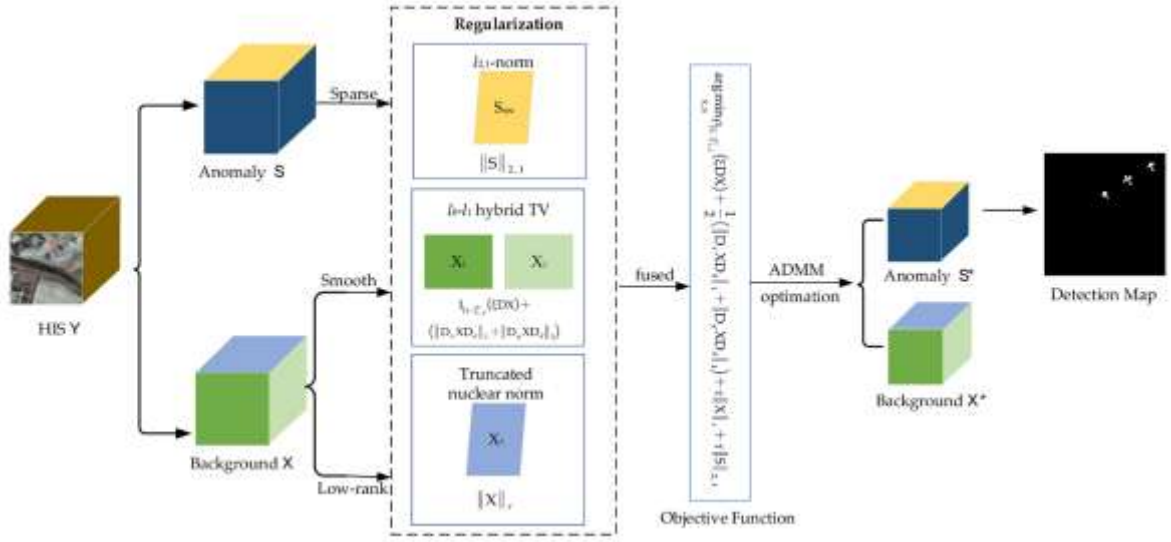


Figure 3. Illustration of MSSR in (Wang et al., 2022).

- **Hybrid, Ensemble, & Saliency Methods**

Recent developments in hyperspectral anomaly detection have seen significant improvement through hybrid, Ensemble and saliency methods. Hybrid methods such as (F. He et al., 2023) combine a classic RX detector with spectral-spatial features to improve detection. Ensemble methods like (Hossain, Younis, et al., 2024)use greedy selection and stacking techniques to combine multiple base detectors for better anomaly detection. These methods improve strength by collecting multiple detectors, which individually might have limitations but collectively offer more stable and better detection performance. Saliency-based approaches including (Ma et al., 2025) support the human visual perception mechanism to detect small anomalies more accurately. These methods are good at detecting regions that look different in complex scenes, and they work well in parallel to other standard anomaly detection methods. New graph convolution and frequency domain filtering approach in model hyperspectral images as graphs to capture nonlinear spatial relationships for better anomaly detection under noise and complex backgrounds. Additionally, the intrinsic image decomposition and background subtraction method utilises physical modelling of material and lightning components in hyperspectral data, to improve anomaly separation (Jiao et al., 2025).

Table 7. Performance Comparison of Hybrid, Ensemble based and Saliency Methods

Dataset	Method	Accuracy
HYDICE Urban, AVIRIS Airport	Dual-guided filtering in Wavelet + DCT domain	Comparable to RPCA/LSMAD (0.97-0.99)
San Diego I & II, ABU-Urban-1, Salinas-simulate	Recursive RX with EMAP (RRXEMAP)	San Diego I: 0.9940, ABU-Urban-1: 0.9961
HAD100 Dataset	Small Target Aware Detector (STAD)	AUCD,F: ~0.9899
Beach, Pavia City, San Diego-I, Gulfport	Spectral-Spatial Information Fusion (SSIF)	Highest AUC among compared methods on listed datasets
ABU, San Diego, Salinas	Greedy Ensemble (GE-AD)	Test F1-macro: ABU ~0.94, San Diego ~0.89
San Diego (AVIRIS-II), ABU Urban, HYDICE	BWGCND (Graph Neural Network)	San Diego: 0.9986, HYDICE: 0.9988
San Diego I, Cat Island, Bay Champagne	Intrinsic Image Decomposition & Background Subtraction	San Diego I: 0.9996, Bay Champagne: 0.9997

All the hyperspectral anomaly detection approaches based on Hybrid, Ensemble, & Saliency Methods offer essential gain in accuracy, adaptability and strength, especially in real-world complex and noisy environments where classical methods struggle to detect anomalies. These methods maintain a practical balance between computational efficiency and detection performance on complex hyperspectral datasets, see performance comparison in Table 7. Overall, these approaches show development from simple, fast, and training-free methods to more complex, perception-inspired, fused, and combined detectors. Each approach improves detection in different ways, but also brings new difficulties like computation cost, parameter tuning, and data requirements. Together, these paper shows that combining different perspectives like statistical, structural, perceptual and algorithmic is a key to advancing anomaly detection in demanding real-world applications. The graph given in Figure.4 compares the accuracy of anomaly detection methods by major papers.

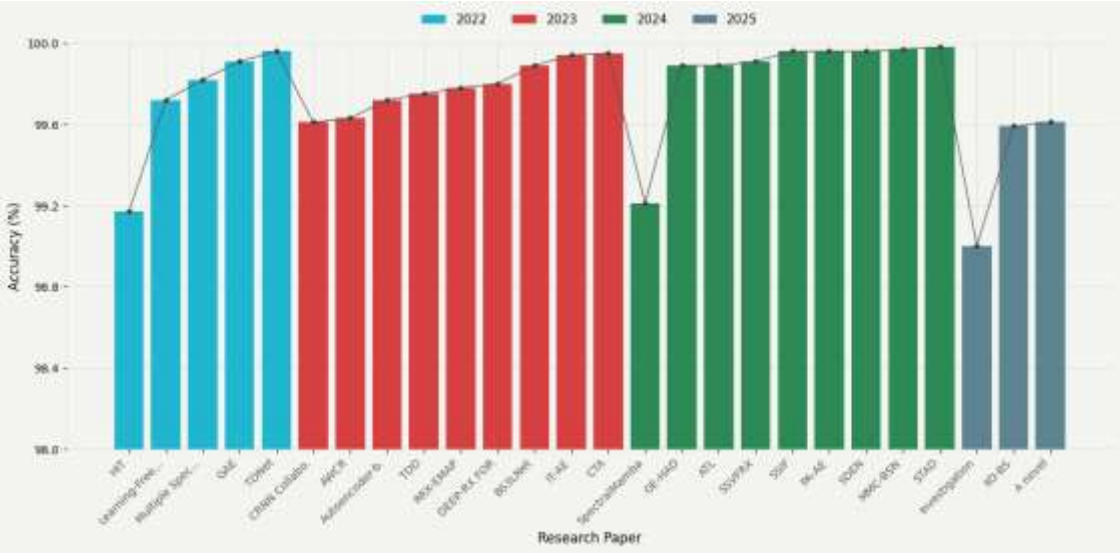


Figure 4. HAD Accuracy with Temporal Trends

The performance is shown by the bar, whereas the progression tells us about the improvement of methods over the timeline from 2022 to 2025. The accuracy levels of HAD methods have been plotted by year in this graph, it is clear that the recent models are getting closer to nearly accurate anomaly detection, highlighting the effectiveness of spectral-spatial feature analysis. Figure 5 explains the Hyperspectral imaging methodological transition.

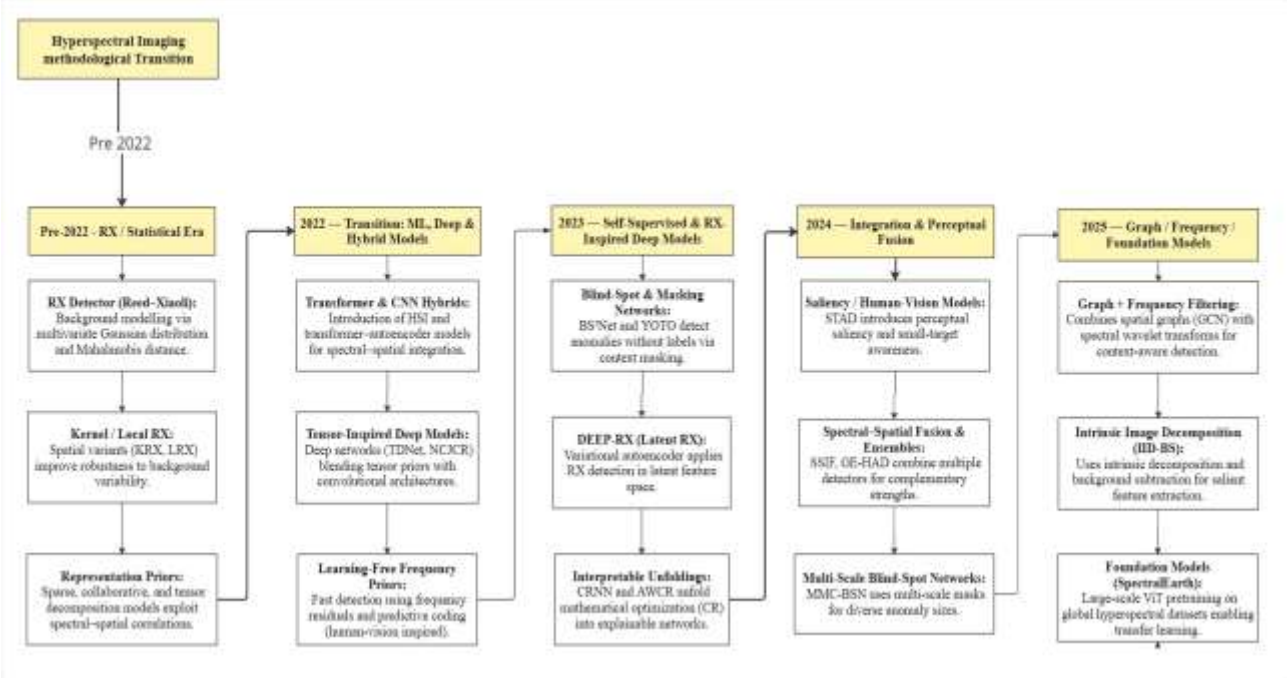


Figure 5. Hyperspectral imaging methodological transition

3. GAP SYNTHESIS

On close examination of the existing HAD methods, it is evident that each method does not fully tackle the issues of high spectral dimensions, small, labelled samples, variation in the background and long-range spectral interactions. Statistical detectors such as the RX algorithm are based on the assumption of Gaussianity and do not work well in complex scenes. Spectral separation techniques are very noise-sensitive and require precise endmember estimates. Autoencoders learned with deep learning procedures have better feature representations, but most of them rely solely on reconstruction error, resulting in false alarms in changing backgrounds.
Transformer-based attention models have recently been found to be useful in modelling world-wide dependencies. They are however expensive to compute and typically require large, labelled datasets. Conventional machine learning techniques such as SVMs are suitable when using small datasets but they are very sensitive to the quality of features.

4. IMPLEMENTATION

Based on these observations, the current work has suggested a hybrid framework that combines unsupervised representation learning, anomaly focus with attention, and the use of differential classification. It is not intended to be a totally novel algorithm but rather a type of an analytical structure which combines the advantages of the previous studies.

- **Overview of proposed Hybrid Framework**

The given framework breaks down the process of hyperspectral anomaly detection into three continuous processes:

a. Autoencoder based Feature Representation Learning.
b. Transformer attention module based on context-Aware Anomaly Scoring
c. Support Vector Machine used to classify the decision level.

The hyperspectral image cube may be defined as:

$$X \in \mathbb{R}^{H \times W \times B} \quad ..(2)$$

Where H and W are spatial dimensions and B is the number of spectral bands. After preprocessing and patch extraction, each pixel-centre patch is transformed into a feature vector:

$$x_i \in \mathbb{R}^d \quad ..(3)$$

which is the input of the network of autoencoders.

a. Autoencoder-Based Feature Learning

Autoencoders are optimized to encode small latent representations which defend strong background

attributes but deny noise. The encoder function $f_\theta(\cdot)$ maps the input feature vector to a latent space:

$$z_i = f_\theta(x_i) = \sigma(W_e x_i + b_e) \quad ..(4)$$

where:

- $\mathbf{W}_e$ and $\mathbf{b}_e$ are learnable parameters,
- $\sigma(\cdot)$ denotes a nonlinear activation function,
- $\mathbf{z}_i \in \mathbb{R}^k$, with $k \ll d$.

The decoder reconstructs the input as:

$$\hat{\mathbf{x}}_i = g_\phi(\mathbf{z}_i) = \sigma(\mathbf{W}_d \mathbf{z}_i + \mathbf{b}_d) \quad ..(5)$$

The reconstruction loss minimized during training is defined as the mean squared error (MSE):

$$\mathcal{L}_{AE} = \frac{1}{N} \sum_{i=1}^{N} \| \mathbf{x}_i - \hat{\mathbf{x}}_i \|_2^2 \quad ..(6)$$

Unlike traditional reconstruction-based anomaly detectors, the reconstruction error is not directly used as the anomaly score. Instead, the learned latent representations are forwarded to the next stages to improve contextual analysis.

b. Transformer-Based Attention for Contextual Anomaly Emphasis

Autoencoders do not have explicit mechanisms to model long-range dependencies, although they are useful at capturing important spectral structures. In order to overcome this weakness, an attention module using transformer is applied to the latent representations.

Given a sequence of latent feature vectors Z = [z_1,z_2, ... z_n], the self-attention mechanism determines the query, key and value spaces as learnable linear transformations

$$\mathbf{Q} = \mathbf{Z}\mathbf{W}_Q, \mathbf{K} = \mathbf{Z}\mathbf{W}_K, \mathbf{V} = \mathbf{Z}\mathbf{W}_V \quad ..(7)$$

The scaled dot-product is defined as:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d_k}}\right)\mathbf{V} \quad ..(8)$$

where d_k denotes dimensionality of the key.

The model can focus on a number of sub-spaces of representation: Multi-head attention

$$\text{MHA}(\mathbf{Z}) = \bigoplus_{h=1}^{H} \text{Attention}_h(\mathbf{Q}, \mathbf{K}, \mathbf{V}) \quad ..(9)$$

Transformer output highlights the latent characteristics that deviate contextually out of the background and actually reinforces the anomalous characteristics.

c. SVM-Based Decision-Level Classification

Following a method of using attention for feature extraction, latent features will be used by an SVM in order to classify the enhanced latent features. In this case, SVM is trained on examples (z_i,y_i), so it is possible to represent the optimization task for SVM as follows:

$$\min_{\mathbf{w},b,\xi} \frac{1}{2} \| \mathbf{w} \|^2 + C \sum_{i=1}^{N} \xi_i \quad ..(10)$$

subject to:

$$y_i(\mathbf{w}^\top \phi(\mathbf{z}_i) + b) \geq 1 - \xi_i, \xi_i \geq 0$$

where:

- $\phi(\cdot)$ denotes the kernel function
- C controls the regularization tradeoff,
- ξ_i are slack variables.

The RBF kernel is commonly adopted:

$$K(\mathbf{z}_i, \mathbf{z}_j) = \exp\left(-\gamma \| \mathbf{z}_i - \mathbf{z}_j \|^2\right) \quad ..(11)$$

Class weights have been added to balance out the different amounts of background data and anomaly data.

5. RESULTS AND DISCUSSION

In this section, the analysis of data and qualitative results of proposed hybrid hyperspectral anomaly detection framework is described. Here the emphasis will be on the operation of the framework, the clarity of the individual steps involved and the visual appearance of the resultant output.

A. Framework and Processing Pipeline Implementation: The hybrid analytical tool is composed of 3 key modules see Figure 6:

i. An autoencoder that automatically determines features in an unsupervised method.
ii. A support vector machine (SVM) that decides if a pixel is an outlier.
iii. A self-attention transformer module that utilizes an autoencoder's output to identify anomalies based upon the autoencoder's ability to determine mismatches within the contextual information.

The first step is to normalize the raw hyperspectral cube, followed by a PCA reduction. A limited spatial-spectral patch is then extracted from the reduced dataset and fed into the autoencoder, allowing the autoencoder to develop a ripped-off latent representation. Next, the transformer module re-weights the output of the autoencoder to emphasize anomalous contextual patterns. The final step involves using the SVM with the weighted-output of the previous two modules, resulting in the assignment of an anomaly label.

By separating the three modules, users can select either speed or expressiveness depending upon their requirements. Even when the number of labeled examples is minimal, the user is able to run the entire pipeline through the system.

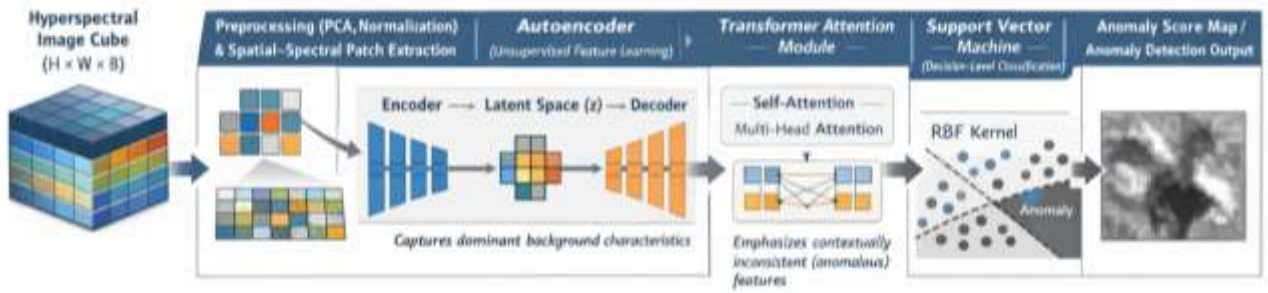
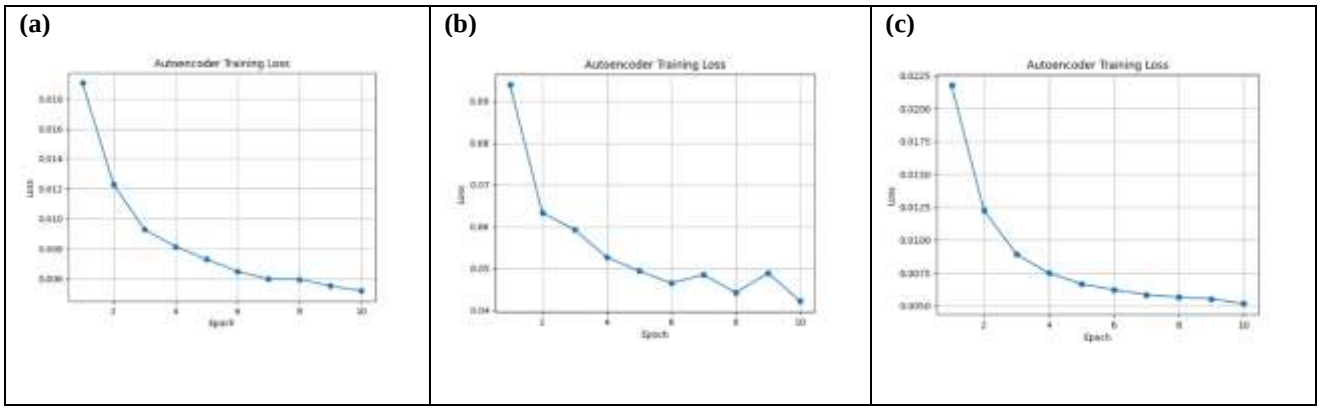


Figure 6. proposed hybrid pipeline of the hyperspectral anomaly detection

B. Evaluation of Autoencoder Training Stability: We evaluated the degree to which the autoencoder is capable of learning and determined this without reference to any labels for training purposes. These evaluations were completed using three standard hyperspectral datasets, focusing on the mean reconstruction error for each dataset at the end of each epoch. The main results are as follows:

i. Reconstruction loss on both datasets was steadily decreasing and at any point it was not resuming the growth phase hence the network was capable of learning the important background spectral patterns.
ii. Loss jumping or loss diverging did not occur, which was a positive sign of the training process being stable and the network being large enough.
iii. The datasets had some variances as far as the decline of the losses were concerned. This has been attributed to the different amounts of scene complexity, number of bands, and noise in the background.

The reconstruction error is not considered to be the anomaly score. Once the autoencoder weights settle, the latent vectors are sent to the transformer to analyze spatial context. By skipping the raw error, we prevent numerous false alarms that purely reconstruction-based methods face in complicated, yet normal backgrounds. Figures 7 (a -c) shows the training loss curves of Pavia University, Indiana Pines other than Salinas respectively.



Figures 7 (a -c) Training loss curves

C. Visualizing Pixel Scores for Anomaly Detection: To evaluate whether our proposed hybrid method works well we decided to show how the superimposed sets of pixel scores appear when placed back onto their respective source images. On each of the hyperspectral images tested, the bright pixels represent the pixel's farthest away from the trained background while the dark pixels represent the pixel's most representative of normal background activity, see figure 8(a-c).

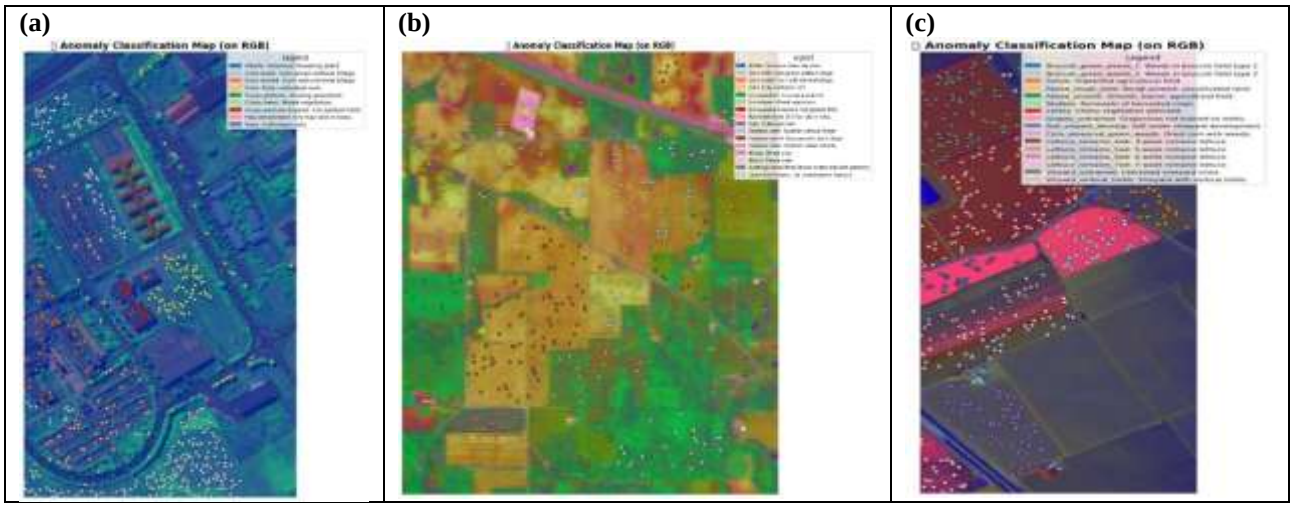


Figure 8(a - c). images of scores of three sets of images

Following are the observation:

i. The bright area in each image is always singular and contiguous and represents the target and there are no instances where the bright area is divided into multiple sub-areas.
ii. Most background pixels or stray noise have a dark appearance; i.e., the method exhibits very few false positives.
iii. When the background consists of a mix of various materials and different amounts of lighting, the method ignores the background and clearly indicates the location of the target pixels.
iv. The previously developed methods that evaluated each pixel individually or used only reconstruction had the result of providing the target with a soft gray marginal. Our method provides the target with a distinct white edge and therefore, it is more easily perceived.

The above observations collectively indicate that by combining a contextual attention module with a learned low-level space, the likelihood of identifying hyperspectral anomalies which are both visually and spectrally hidden is significantly increased

D. Analysing the Latent Space and its Implications: To analyse how the internal properties of the model evolve over time, we plotted the latent vectors which emerge from the attention layer. To evaluate the presence of any emergent patterns in these vectors, we reduced each of the aforementioned vectors to a two-dimensional representation using both PCA and t-SNE, see figure 9 (a-c).

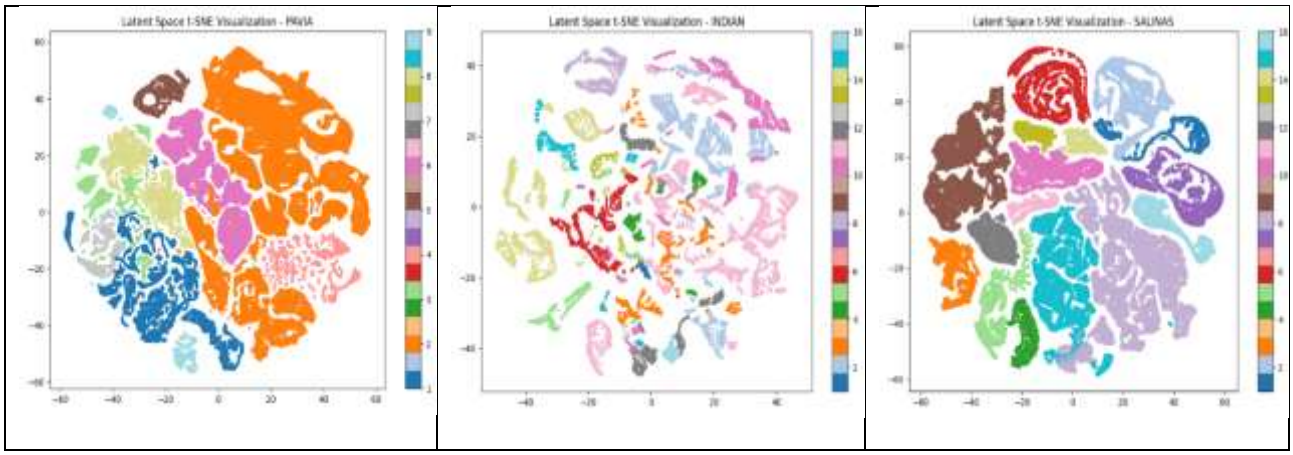


Figure 9 (a-c). A two-dimensional representation of the latent vectors after applying the attention step, as generated by either PCA or t-SNE

Four distinct results were observed during the investigation:

i. We identified each background spectrum within a distinct and very densely clustered area; thus, the autoencoder was successful at capturing the dominant surface of the data.
ii. We also found that each anomaly existed outside of the clusters of background and/or was alone or on the edge of one of the clusters.
iii. Beyond the transformer layer, the re-weighting of the vectors caused the clouds and the anomalies to move farther apart and therefore

indicated that the contextual model was functioning appropriately.

iv. After the transformer layer re-weighted the vectors and re-weighed the vectors, SVM was applied to the reduced and better separated number of points and was able to generate more reliable predictions based upon the limited amount of training spectra.

Ultimately, the transformer does not simply compress the data again; instead, the transformer identifies and emphasizes the signals that contradict their proximity, and thus, makes the anomalies more visible and easier to understand

E. Other Methods: This section provides a brief overview of the conceptual comparison between the proposed method and other approaches. As shown in Table 8, the hybrid design clearly represents the best of both worlds by optimizing the strengths of the traditional component (i.e., accuracy), and the learned component (i.e., interpretability and computational expense)

Table 8. The characteristics of the methodological comparisons

Method Category	**Representative Techniques**	**Detection Capability**	**False Alarm Handling**	**Suitability for Limited Samples**	**Computational Requirement**
Statistical Detectors	RX, LRX, KRX	Low to Moderate	Weak	Highly Efficient	Low
Representation / Subspace Methods	SR, CR, LRR, RPCA	Moderate to High	Moderate	Moderate	Medium to High
Autoencoder-Based Methods	AE, DAE, VAE, PAAE	Moderate to High	Moderate	Moderate	Medium
CNN-Based Approaches	2D/3D CNN, GAN-assisted models	High	Moderate	Low	High
Transformer-Based Models	Spectral Transformer, SST, SDENet	Very High	Strong	Low	Very High
Self-Supervised Learning	BS3LNet, SSAD, AETNet	High	Strong	Highly Efficient	Medium to High
Graph and Saliency Methods	BWGCND, STAD, IID	Superior	Strong	Highly Efficient	Low to Moderate
Ensemble Techniques	GE-AD, mGE-AD	Very High	Strong	Moderate	High
Foundation Models	SpectralEarth	Exceptional	Very Strong	Excellent (after pretraining)	Moderate
Proposed Hybrid Framework	**Autoencoder + Attention + SVM**	**High**	**Strong**	**Highly Efficient**	**Moderate**

The primary advantage of the experimental evidence and visual representations demonstrate the utility of modeling hyperspectral anomaly detection as a multi-step approach, as opposed to a single-step anomaly detector. The advantages of the proposed framework include the following:

- Uncorrelated feature extraction, where no large-scale, annotated datasets are required, and
- Longer-term, spectral relationships via transformer attention can be more effectively modeled, and
- A sufficient level of generality exists via decision modeling with SVM, and
- Contextual improvement facilitates fewer false positives.

The framework design proposed in this manuscript is not grounded on a new detection algorithm, rather this design synthesizes a number of other designs into a consistent framework.

6. FUTURE WORK

Build Methods That Work Directly on the Problem: Future research should directly focus on anomaly detection instead of solving simpler intermediate problems like recreating an image. Models should learn universal spectral deviation relationships appropriate for different images rather than specific background distributions. The model should learn what makes something different from normal, rather than just memorising the normal pattern.

Make Models Work Across Different Images and Satellites: In future, we should develop methods that work on any satellite image without retraining. Instead of adjusting settings for every test image method use auto-detect good settings. Method should be developed on a practical approach that is to train once on many diverse images, test anywhere without adjustment.

Combine Space and Spectrum Better: The new method should process spatial-spectral features together from the beginning. A visual transformer combined with a convolutional layer has the potential to capture both global patterns and local details. An attention mechanism could help the network focus on truly different spatial-spectral patterns.

Explore Graph-Based Methods: Graph-based method represents a satellite image as an interconnected network where each pixel is connected to its nearby pixels. The approach can capture spatial features that a simple convolutional network misses. Combining the graph with other techniques, like a transformer or filtering, could further improve anomaly detection.

Analyse Frequency: Research shows anomalies sometimes have a unique pattern in the frequency domain. Further methods should carefully analyse these spectral patterns using wavelet transforms and other frequency analysis tools.

Create Better Benchmark Datasets: To develop more methods that work well on different datasets that contain data from different satellites, we need large, standardised test datasets with diverse anomalies, multiple satellites, and different environments. Everyone testing on the same datasets would make a fair comparison of methods possible, but to make anomaly detection better, we need better benchmark datasets.

7. CONCLUSION

This analysis covers a critical time of innovation and changes from 2022 to 2025 as the field of hyperspectral anomaly detection continues to expand. The strategies and developments described here show the opportunities and challenges driving innovation in this field. The hybrid structure has been compensated with a large quantity of data-sets with regard to training consistency, anomaly localization precision, and elucidation of the gained illustrations. The integration of autoencoders and transformer with SVM classification plus focus on context is a promising trend in future technology of hyperspectral anomaly detection. This implies that the reference structure in this paper can be recreated in the future on better data-sets, alternative attention methods or novel feature encoders.

Ultimately, it is hoped that this synthesis not only documents the current state of the field, but also serves as a strategic roadmap for guiding future inquiry. By clarifying how methods have evolved and where unresolved challenges lie, this study aims to support the development of more reliable, efficient, and adaptable hyperspectral anomaly detection systems, contributing to both academic research and real-world remote sensing applications.

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