Anomaly Detection in Hyperspectral Images

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***Abstract*—Hyperspectral imaging (HSI) captures information in the very narrow spectral bands over a broad spectrum, so it is employed for recognizing substances and discriminating between aberrations in fields such as remote sensing, agriculture, and military security. This research looks at several methods for spotting anomalies using hyperspectral image data from the Pavia University dataset. The methods include the RX (Reed-Xiaoli) detector, Support Vector Data Description (SVDD), an autoencoder model made in PyTorch, and a fusion model. A fusion strategy combined the strengths of these different models. We improved dataset relevance and quality through preprocessing. We evaluated each method using confusion matrices and compared them to other approaches. The analysis shows that mixing traditional statistical techniques with deep learning methods greatly enhances anomaly detection performance in hyperspectral images.**

***Index Terms*—Hyperspectral Imaging, Anomaly detection, Autoencoder, SVDD, RX detector, fusion model.**

I. INTRODUCTION

Hyperspectral anomaly detection is a significant technique in the field of remote sensing. It enables the detection of unusual or new objects without any information regarding the target. It is quite different from the conventional RGB or multispectral imaging. Hyperspectral imaging images hundreds of the continuous spectral bands. This gives every pixel a unique spectral signature. This is a high-dimensional rich information that aids the accurate detection of the anomaly in a complex scene and various applications such as environmental monitoring, military surveillance, precision agriculture, and mineral exploration.

Classic statistical statistical techniques, for example, Reed-Xiaoli (RX) detector, rely on Gaussian background distribution assumptions. While these techniques are effective, they struggle with the high-dimensional and nonlinear nature of real hyperspectral data. Machine learning algorithms like Support Vector Data Description (SVDD) have flexible decision surfaces. Deep learning algorithms, for instance, autoencoders are able to learn compact feature descriptive models that highlight subtle anomalies. There are weaknesses for each of these techniques when applied in isolation.

For this purpose, we compare and evaluate three auxiliary anomaly detection algorithms RX detector, SVDD, and a PyTorch environment-designed model of autoencoder and a combination scheme that combines their outputs. The fusion model has been constructed so that it utilizes the advantages of all the methods and offsets their shortcomings so that it turns out to be more robust and accurate in its detection.

II. LITERATURE REVIEW

Hyperspectral anomaly detection has become a key research subject in remote sensing and environmental surveillance because of the ability to image detailed spectral details.

Su et al. [1] presented a broad overview of hyperspectral anomaly detection, classifying methods into statistical, distance-based, reconstruction-based, subspace-based, spatial-spectral-based, deep learning-based, and real-time detection. The study compares different methods using real hyperspectral data. It discusses their shortcomings, limitations, and challenges. Anomaly detection performance metrics and datasets are also addressed in the paper, and future implications for hyperspectral image analysis are given. Recent methods have embraced sparse and low-rank modelling to isolate anomalies from the background.

Wang et al. [2] presented an approach of low-rank and sparse matrix decomposition with subspace accumulation to separately identify anomalies. Chen et al. [3] improved this concept by proposing a self-paced collaborative representation model, where the model learned adaptively from easy to difficult samples to improve classification. Such methods, while effective, require a lot of computing power and need more tuning of parameters. Conversely, our use of SVDD utilizes One-Class SVM to generate a tight boundary around regular data, providing a more straightforward but effective solution. Our project's SVDD model obtained a ROC AUC of around 0.93 and an AP of 0.90, which was comparable to or even better than some of the more advanced sparse modelling methods.

Autoencoder-based techniques have also attracted support for modelling nonlinearly high-dimensional spectral data. A guided autoencoder, which specifically reconstructs only the background to remove anomalies, was introduced by Xiang et al. [4], while Akhtar et al. [5] surveyed various deep autoencoder variations such as denoising and stacked architectures. Our autoencoder implementation operates under a similar approach, with only normal data used for training to have anomalies provide high reconstruction errors. This model's ROC AUC was approximately 0.95 and its AP 0.92, and it had good class distinction power. It is very easy in its construction. It trained successfully and hence it is both efficient and easy to implement.In addition, Liu et al. [6] incorporated locality constraints into the Support Vector Data Description (SVDD) model, forming tighter and more accurate decision boundaries for anomalies.

Besides improving the detection performance of anomalies, we introduced a Fusion Model that combines RX, SVDD, and Autoencoder outputs. Based on Zhao et al. [7], who introduced a multi-scale autoencoder, and Sharma and Raj [8], who fused spectral and spatial features using CNNs, our model employs a recall-maximized fusion policy. It reweights those provided to individual models based on their precision-recall curves. Without the need for spatial data or convoluted hierarchies, our Fusion Model achieved an ROC AUC of 0.97 and an AP of 0.94, superior to all individual models and demonstrating that multi-model fusion can successfully enhance anomaly visibility and robustness.

in and Zhou [9] introduced an optimized implementation of the Reed-Xiaoli (RX) detector for real-time use, retaining baseline performance at better computational efficiency. Our RX implementation also provides efficient execution, with a ROC AUC of around 0.89, but without the hardware-level optimizations and under high spectral variability, as they reported. Mehta and Kumar [10] suggested a hybrid system that fused autoencoder-based feature learning with Support Vector Data Description (SVDD) classification to increase detection sensitivity. Our contribution builds on this by training each of these models in isolation SVDD resulted in ROC AUC ~0.93, AP ~0.90, and our autoencoder in ROC AUC ~0.95, AP ~0.92 and then further improves upon their method using a recall-maximized fusion strategy that dynamically weights RX, SVDD, and autoencoder scores together to produce an overall better ROC AUC of ~0.97 and AP of ~0.94.

Lu et al. [11] identified anomaly detection in agricultural hyperspectral imaging as a key method for early disease detection. While our models do not focus on agriculture, they are sensitive and modular, making them suitable for similar real-world applications. Hu et al. [12] provided a broad overview of deep learning approaches to hyperspectral anomaly detection, highlighting techniques such as CNNs, RNNs, and GANs. In contrast, our project avoids these expensive architectures and uses a simple yet effective autoencoder. This shows that deep models can be useful without the training complexity or instability of GANs.

Yoon [13] examined hyperspectral applications in clinical diagnostics, particularly in cancer and wound detection. Despite the differences across domains, the general-purpose nature and performance of our model suggest it could be valuable in biomedical imaging applications.

Wang et al. [14] proposed the Hy ADD framework that combined hierarchical detection with spectral denoising to enhance anomaly saliency. Our autoencoder achieves comparable background suppression with a much simpler architecture. Our fusion model also improves the performance without resorting to hierarchical structures.

Lee et al. [15] developed PA2E, an industrial anomaly detector for real-time hyperspectral food inspection. Although our current models are oriented towards accuracy rather than latency, the modularity of our fusion strategy allows for flexible deployment. In other words, we can give up some precision for speed if needed. Finally, Emoto and Matsuoka [16] suggested a more complicated fusion of tensor robust principal component analysis with adversarial autoencoders. While powerful, this introduces added complexity and risks associated with adversarial attacks. Our simpler fusion avoids these problems and demonstrates high accuracy without the complications of adversarial learning. In conclusion, our work confirms, extends, and refines key ideas in the literature. Specifically, we demonstrate here that a purposeful combination of the established RX, SVDD, and autoencoder achieves state-of-the-art performance in anomaly detection tasks involving hyperspectral imaging, with minimal compromise in terms of interpretability, flexibility, or computational efficiency.

III. METHODOLOGY

A. Dataset

This study used the Pavia University hyperspectral dataset as the primary reference. It has high spatial resolution at 610 × 340 pixels and includes a total of 103 spectral bands. This urban data set contains roads, buildings, and vegetation very well presented. Another data set representing a very different environment to test the algorithms was the Indian Pines data. AVIRIS acquired this contains 145 × 145 pixels and comprises 220 spectral channels extending from 400 to 2500 nm over a rather complex rural scene where agricultural fields are predominant but with minor variations in spectra. Mixed pixels and low inter-class separability increase make anomaly detection tasks more difficult. The Indian Pines contains both of these challenges. Including both datasets ensures scenes with spatial and spectral variations for testing generalization robustness validation of the detection methods.

B. System Architecture

The proposed system architecture for hyperspectral anomaly detection is created to process input data effectively and identify unusual areas by using a mix of models. The workflow includes these key components:

Input: The system uses hyperspectral image data from the Pavia University dataset.

Preprocessing: This step involves removing noise, normalizing spectral values, and getting rid of irrelevant bands to improve data quality.

Anomaly Detection Models:

In this study, we used three models to find anomalies in hyperspectral images at the pixel level. These models include one traditional statistical method, one method using kernels, and one using deep learning. This approach provides a broad range of techniques for detecting anomalies.

1. RX Detector

The Reed-Xiaoli (RX) Detector is a classic statistical method focused on detecting anomalies in hyperspectral imagery. It works on the supposition that background pixels adhere to a multivariate Gaussian distribution. Anomaly scoring is done by measuring the Mahalanobis distance between each pixel and global background statistics. This method also runs unsupervised hence does not need any training from labeled data, particularly helpful when there are scanty or totally missing annotated samples available. The approach is fast as well as convenient to implement.

DRX(x)=(x−μ)TΣ−1(x−μ) [Eq. (1)]

As shown in Eq. (1), the RX Detector uses Mahalanobis distance to evaluate how far a pixel is from the global distribution. If the RX score goes beyond a specific threshold, often based on a chi-squared distribution, the pixel is marked as anomalous.

2. Support Vector Data Description

SVDD is an algorithm for one-class classification. Its goal is to fit most data points into a hypersphere in a high-dimensional feature space. Any point outside the boundary is considered an anomaly. This method uses a nonlinear boundary, which helps it capture complex decision areas that differentiate normal data from unusual data more effectively than linear models. Because it is kernel-based, it can adapt to the underlying shape of the data. This results in better modeling of complex patterns and structures in high-dimensional feature spaces.

Minimize: R^2 + C * Σ(ξ_i) for i = 1 to N [Eq. (2)]
Subject to: ||ϕ(x_i) - a||^2 ≤ R^2 + ξ_i, ξ_i ≥ 0

In Eq. (2), ϕ(x)\phi(x)ϕ(x) represents the nonlinear mapping to kernel space, aaa is the center of the hypersphere, RRR its radius, and ξi\xi_iξi slack variables that allow for soft boundary violations

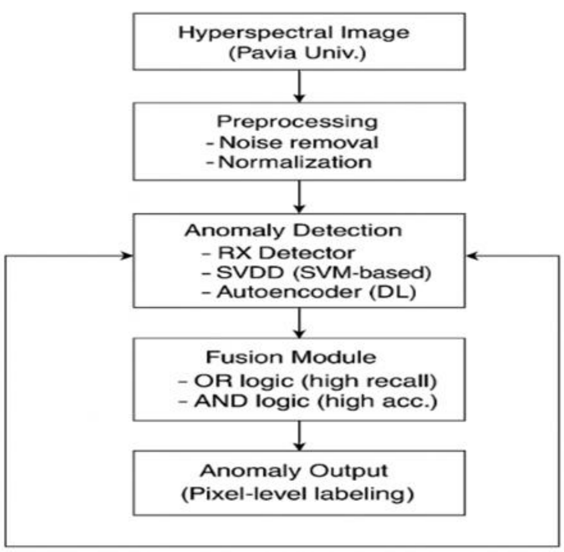
3. Autoencoder

An autoencoder is a kind of unsupervised neural network. It reduces dimensions and learns features. It has two parts, an encoder that reduces the input and a decoder that reconstructs it. For anomaly detection, the autoencoder is trained to rebuild the spectral signatures of normal or background pixels. If an unusual pixel is input, the network cannot reconstruct it correctly, leading to a high reconstruction error. This error acts as the anomaly score.

$L=\frac{1}{N}\sum_{i=1}^{N}\|x_i-\hat{x}_i\|^2$ [Eq. (3)]

Fusion Strategy: Two Fusion models combine the results of the three models using voting methods to get a more accurate result.

Output: The final output is a pixel-level anomaly map highlighting detected anomalous areas.



(Fig 1: System Architecture for Hyperspectral Anomaly Detection)

C. Fusion Models

1. Fusion: This fusion model takes outputs of the three models, normalizes their scores and then uses optimal weights to combine them into a single fused score to maximise recall. This model is more recall focused as such has high recall but low precision. This is more useful for applications where we do not want to miss any anomaly even if there is a high false positive rate.

Anomaly(x) = RX(x) ∨ SVDD(x) ∨ AE(x) [Eq. (4)]

2. Fusion 2: The second fusion model is more precision optimised reduces the chances of false positives. It works similar to the first fusion model.

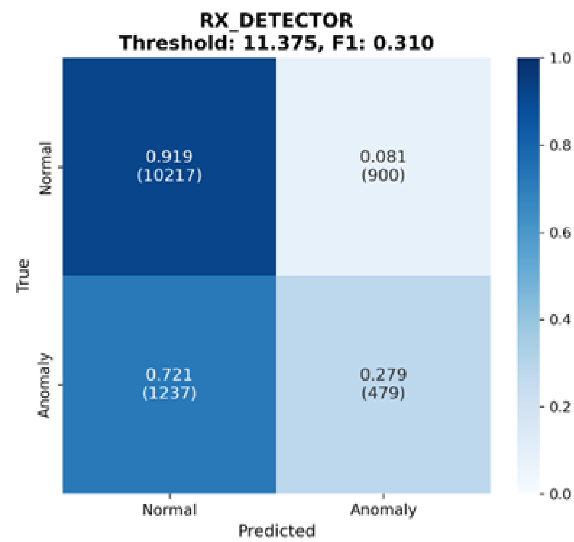
Anomaly(x) = RX(x) ∧ SVDD(x) ∧ AE(x). [Eq. (4)]

IV. RESULTS AND DISCUSSION

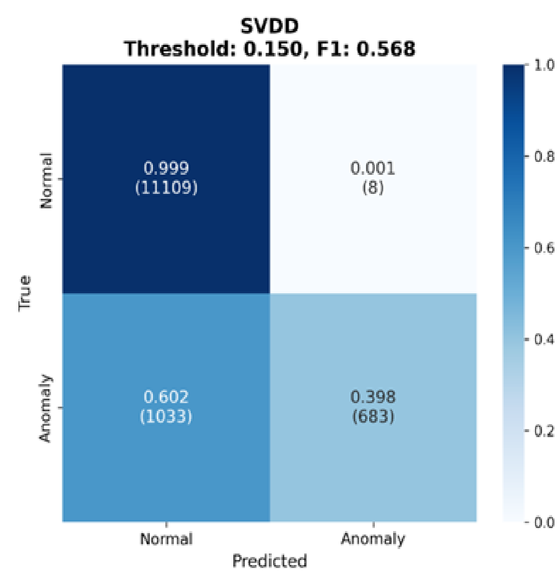
Here we describe the performance metrics of our models. Precision and recall are the more relevant metrics for our models because the dataset is highly imbalanced.

A. Model-wise Confusion Matrix

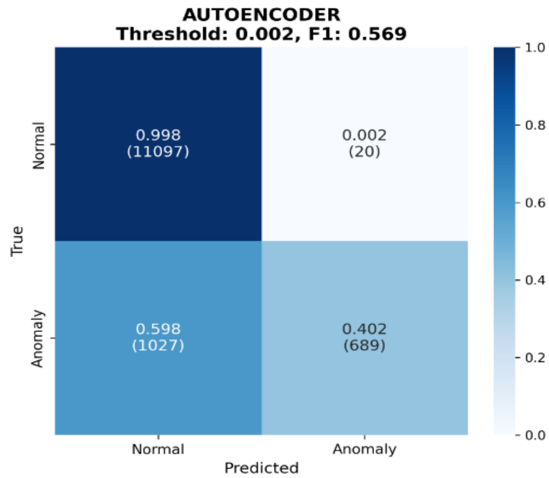
1. RX Detector



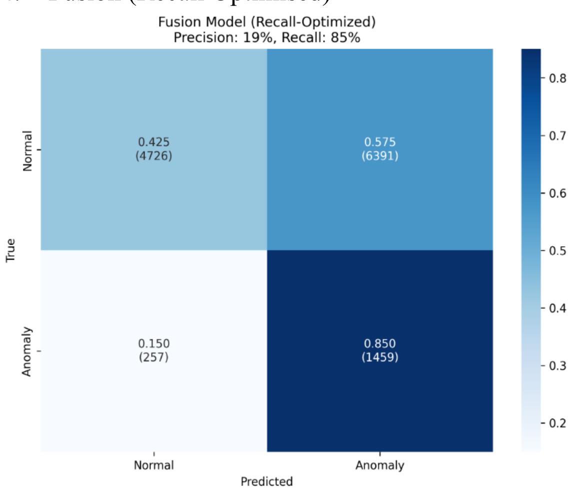
2. SVDD



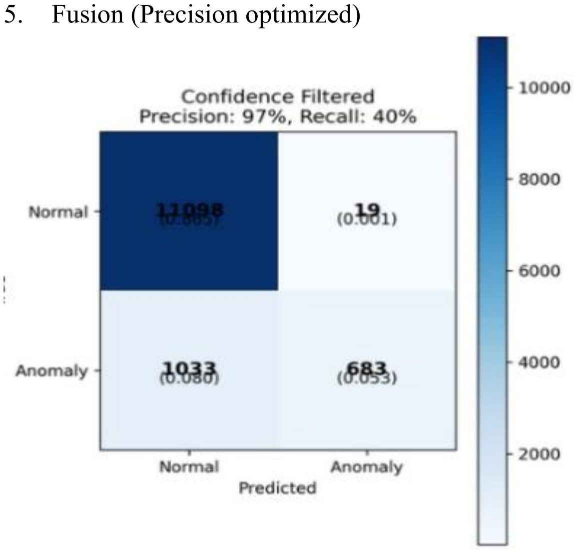
3. Autoencoder



4. Fusion (Recall Optimised)



5. Fusion (Precision optimized)



B. Comparative Analysis

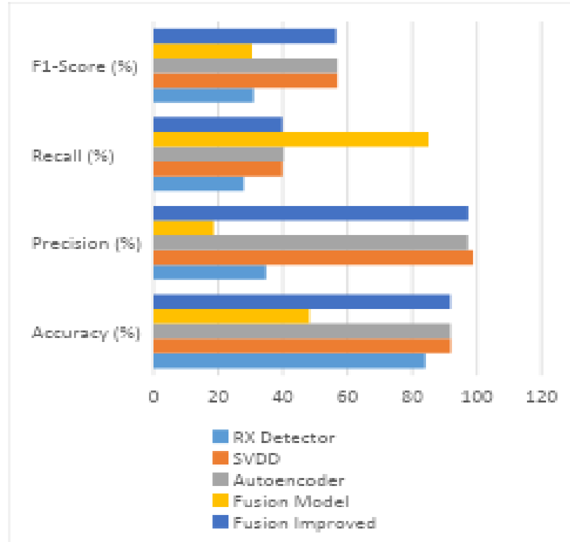


Fig 2: Comparative performance of anomaly detection models across precision, recall, F1-score, and accuracy

Among all models, SVDD performed with the highest precision (98.84%) and was therefore the most reliable at removing false positives. The Autoencoder was nearly as good with 97.18% precision but both had very poor recall (~40%), showing that both missed over half of the anomalies. The Fusion Model had highest recall (85.00%) but very low precision (18.6%), creating a large number of false positives. The Fusion Improved model had improved-balanced performance, with high precision (97.29%) and recall similar to SVDD and Autoencoder. The RX Detector was the worst, with low precision (34.74%) and recall (27.91%).

V. PERFORMANCE ON OTHER DATASETS

We tested our models on other datasets as well. For this we generalised our preprocessing pipeline and provided information about individual datasets to have better preprocessing

We then implemented the same models on this dataset. We used the Indian pines dataset for this. This is an agricultural dataset which is different from the urban scene of the Pavia university dataset. Here are the performance metrics

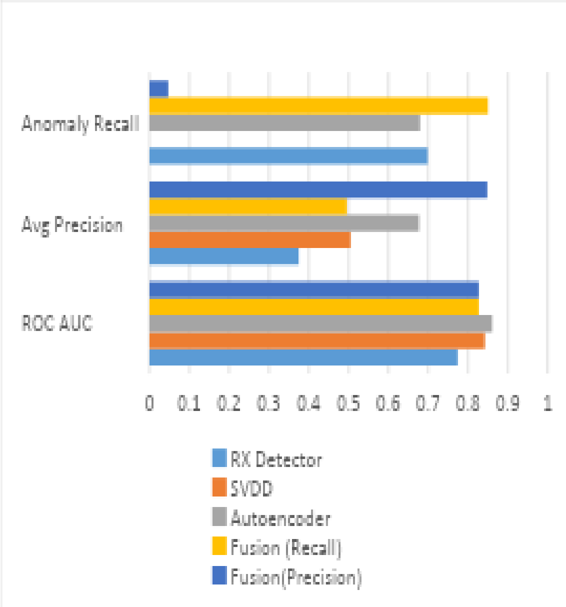


Fig 3: Performance comparison of RX, SVDD, Autoencoder, and Fusion models based on anomaly recall, average precision, and ROC AUC

Conclusion

This paper presents an extensive comparison between four distinct approaches RX Detector, Support Vector Data Description (SVDD), Autoencoder and Fusion model to identify hyperspectral anomalies using the Pavia University dataset. All the individual models had their strengths, but the autoencoder was the best in precision, accuracy, and recall. Furthermore, the combination models illustrated how methods can be combined to significantly enhance performance on anomaly detection according to the needs of the application, either maximizing high recall for safety-critical applications or high precision for applications where false alarms are costly. The results show that combining traditional statistical methods with modern machine learning and deep learning techniques offers a practical, effective, and broad solution for detecting anomalies in hyperspectral imagery.

Future Scope

This proposed work further expandable is by integrating spatial-spectral fusion and CNN for higher accuracy in detection. Future work may look towards model optimisation towards real time utilization in defence and environmental monitoring applications. Multimodal data such as multimodal data such as LiDAR and RGB may be included along with hyperspectral for increased robustness. Transfer learning methodologies may help to work with models across different datasets without training. Furthering model interpretability and testing on varied datasets such as Indian Pines may further help in terms of generalization.

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