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Hyperspectral Anomaly Detection

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ABSTRACT –

Hyperspectral anomaly detection focuses on identifying rare or unexpected targets within hyperspectral imagery, which captures detailed spectral information across hundreds of bands per pixel, enabling fine discrimination between materials. This process is crucial for various applications such as environmental monitoring, surveillance, and agriculture, as it allows the detection of objects or phenomena that differ spectrally from the surrounding background without requiring prior knowledge of target signatures. Traditional approaches, such as the Reed–Xiaoli (RX) detector and its derivatives, utilize statistical modeling and spectral distance calculations, while modern methods incorporate machine learning, subspace analysis, and both spatial and spectral features to improve detection capability and robustness in complex, real-world scenarios where data often exhibits high dimensionality, strong noise, and non-Gaussian distributions.

Key Words**:** Hyperspectral anomaly detection, Hyperspectral imagery, Spectral information, Anomaly targets, Background modelling, Reed–Xiaoli (RX) detector

1.INTRODUCTION

This project introduces an integrated approach to hyperspectral image anomaly detection by combining the strengths of both the Reed-Xiaoli (RX) algorithm and K-means clustering. By first segmenting the hyperspectral data into distinct clusters using K-means, the diversity and complexity of background materials are effectively captured. The RX detector is then applied within each cluster rather than across the entire image, allowing for more accurate identification of anomalies relative to localized background statistics. This integration enhances sensitivity to subtle or locally distributed anomalies, reduces false alarms, and improves detection performance in heterogeneous scenes by leveraging both global statistical analysis and local adaptive clustering.

This paper focuses on the comparative analysis of classical statistical methods, such as the RX detector, and modern deep-learning techniques for anomaly detection in hyperspectral images. It examines the strengths and limitations of each approach, evaluates their effectiveness across different types of hyperspectral data, and discusses their suitability for various real-world anomaly detection applications.

2.METHODOLOGY

2.1 Reed-Xiaoli (RX) detector

The Reed-Xiaoli (RX) detector is a classical statistical method for hyperspectral anomaly detection that assumes the background follows a multi-variate Gaussian distribution and

uses the Mahalanobis distance to measure how much a test pixel deviates from the background. It is simple, interpretable, and widely used as a baseline due to its relatively low computational demands and unsupervised nature. However, it suffers from key limitations: the performance depends on the accuracy of the Gaussian and background homogeneity assumptions, which often do not hold in real hyperspectral scenes. RX also struggles to capture non-linear relationships among spectral bands and can yield high false alarm rates, particularly in noisy or complex environments.

2.2 K-means clustering

K-means clustering is a widely used unsupervised machine learning algorithm that groups similar data points—in this case, hyperspectral pixels—into distinct clusters based on their spectral characteristics. In hyperspectral anomaly detection, the algorithm partitions the image pixels into a predefined number of clusters, each representing a type of background material or common surface in the scene. The cluster centers (centroids) represent typical spectral signatures of the background, while pixels with spectral signatures significantly different from any cluster center are considered anomalies. The process begins by randomly initializing cluster centroids, assigning pixels to the nearest centroid based on spectral distance (usually Euclidean), then updating centroids by computing the mean of assigned pixels. This assignment and update cycle repeats until convergence, meaning pixels no longer change clusters.

2.3 False colour variation

False colour variation is a visualization technique used in hyperspectral and multispectral imaging where colours are assigned artificially to different spectral bands to enhance the interpretation of data that is often invisible to the human eye. Because hyperspectral sensors capture information across many narrow spectral bands, including wavelengths beyond visible light such as near-infrared, false colour composites map selected bands to red, green, and blue channels in a way that highlights specific features or phenomena. For example, healthy vegetation strongly reflects near-infrared light and can be shown as bright red in a false-colour image, making it easier to differentiate from other land cover types like soil or water.

This technique improves visibility of subtle differences and patterns that natural colour images (which use red, green, and blue visible bands in their natural mapping) might miss due to low contrast or being outside the visible spectrum. False colour images help in identifying and analysing vegetation health, mineral deposits, water bodies, urban areas, and other surface characteristics with greater clarity. Different combinations of bands can be selected to emphasize various properties, allowing analysts to tailor visualization to specific applications such as crop monitoring, geological mapping, pollution detection, or environmental change assessment. By assigning non-visible wavelengths to visual colours, false colour variation expands the amount of interpretable information from hyperspectral data and is essential for effective remote sensing analysis.

3. Experimental Setup

3.1 Data Collection

The experiment begins with the acquisition of hyperspectral image datasets from publicly available sources such as AVIRIS or EO-1 Hyperion, or through direct capture using hyperspectral sensors. It is important that the datasets cover a variety of scenes and include known anomalies to effectively evaluate detection methods. Before analysis, the data undergoes preprocessing steps which may include atmospheric correction, noise reduction, and normalization to ensure accuracy and consistency.

3.2 Algorithm Implementation

The core stage involves implementing anomaly detection algorithms on the preprocessed data. Classical methods like the RX detector are used, which compute anomaly scores based on statistical measures such as the Mahalanobis distance. Clustering techniques, including k-means, segment the image into regions of similar spectral characteristics and isolate outliers as anomalies. Visualization techniques such as false color composites are generated by selecting informative spectral bands to facilitate visual examination and validation of detected anomalies**.**

3.3 Experimental Procedure

Once the algorithms are implemented, the experiment involves running them on the chosen datasets and systematically recording results. Anomaly detection performance is evaluated quantitatively using metrics like precision, recall, and false alarm rate by comparing against ground truth anomaly maps where available. Additionally, visual inspection of false color images helps validate spatial and spectral patterns of anomalies. The procedure also includes comparing the computational efficiency of different

methods to assess their practical usability.

3.4 Environment Setup

This phase focuses on the technical infrastructure for experimentation. Programming environments such as MATLAB or Python, equipped with libraries like scikit-learn, TensorFlow, and OpenCV, are used to develop and run the detection algorithms. Given the large size of hyperspectral datasets, a computing platform with sufficient CPU and GPU resources is necessary to enable efficient processing and experimentation.

3.5 Final Analysis

The final phase involves comprehensive analysis of the collected data and detection outcomes. Quantitative metrics provide objective measurement of success and failure points of each method, while false colour visualizations assist in qualitative understanding. The insights gained help refine algorithm parameters and experimental design, improving robustness and accuracy for future iterations. Balancing detection quality with computational cost guides recommendations for operational applications.

This structured experimental setup ensures thorough validation of hyperspectral anomaly detection techniques while providing clear insights into their relative strengths, limitations, and suitability for real-world use.

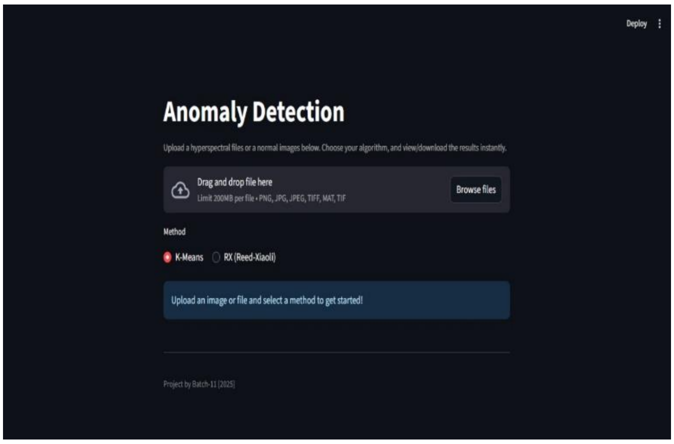

Fig 1: Dashboard

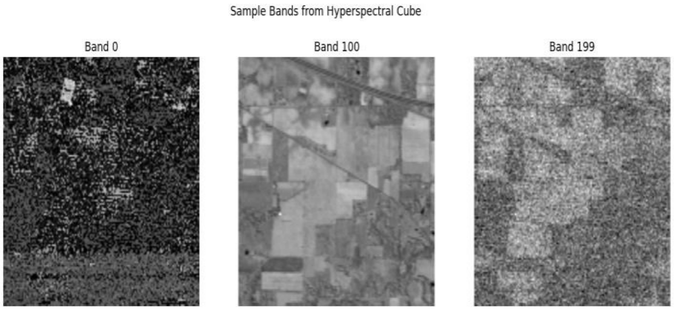

Fig 2: Spectral Bands of Data

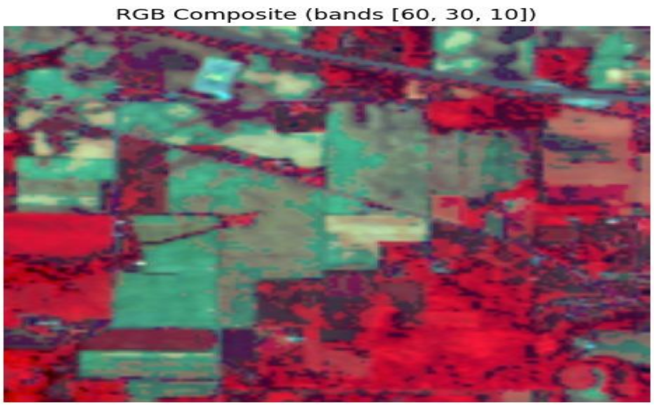

Fig 3: Adding False Colour To K-Means Clustering

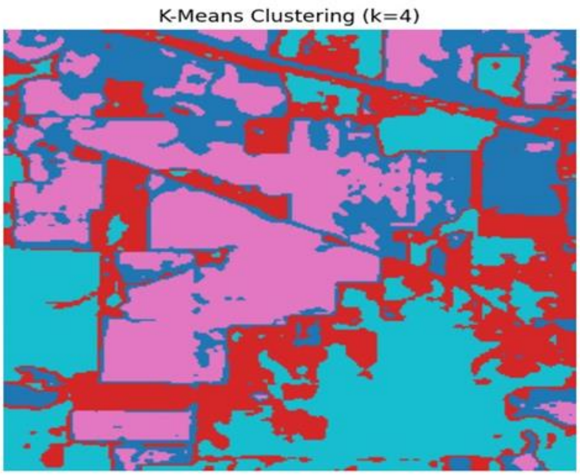

Fig 4: K-Means Clustering

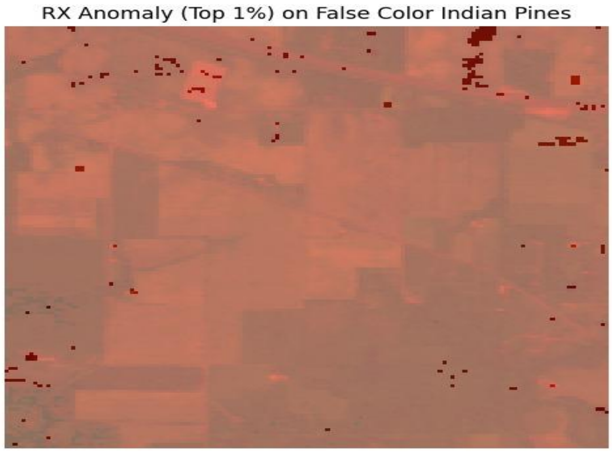

Fig 5: Adding False Color to RX Algorithm

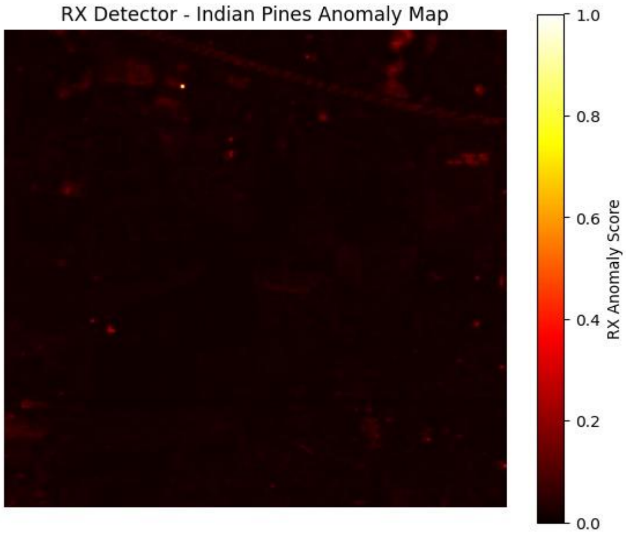

Fig 6: RX Overlay

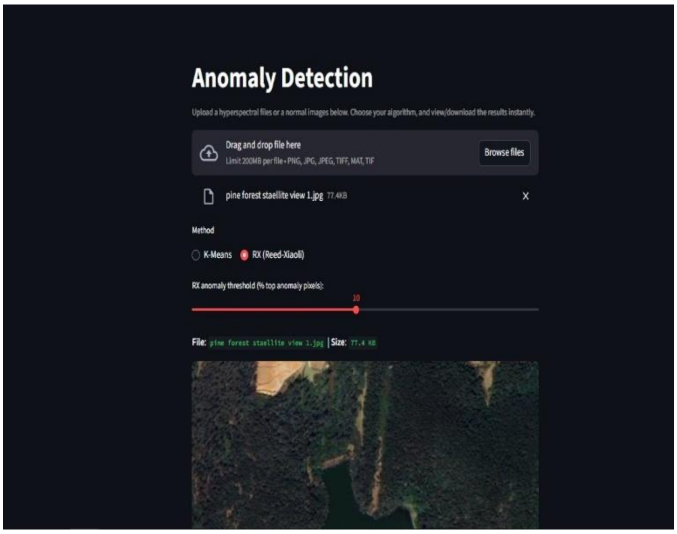

Fig 7: Image Uploading Section

4. RESULTS AND DISCUSSION

4.1 Performance Comparison

Existing hyperspectral anomaly detection systems rely heavily on hyperspectral image sensor and Kernel RX, which offer simplicity and fast processing but often fail to detect anomalies in complex, real-world data due to their strong background assumptions and sensitivity to noise. The proposed system improves upon this by combining spectral and spatial subspace analysis with modern algorithms, enhancing accuracy and robustness across diverse scenes while minimizing false alarms and computational inefficiency. This approach ensures more reliable anomaly detection in practical applications by leveraging advanced machine learning techniques and adaptive processing.

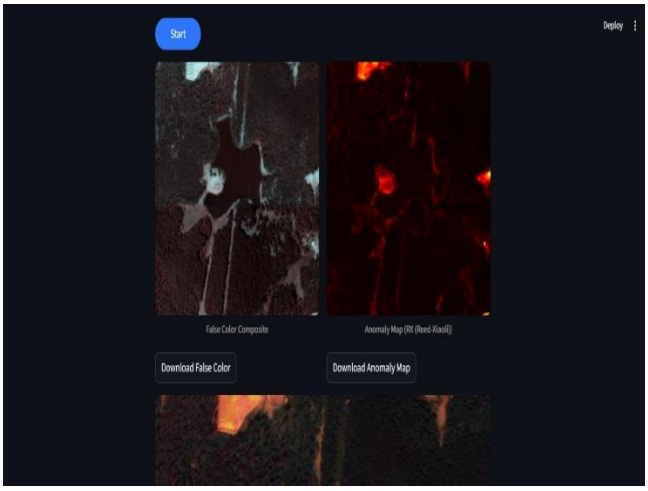

Fig 8: Colour Corrected Images

Fig 10: Final Output

4.2 Strengths and Limitations

The proposed system for hyperspectral image anomaly detection offers significant strengths, including the ability to leverage both spectral and spatial information for more accurate and robust detection across diverse and complex environments. By integrating advanced algorithms such as subspace analysis and deep learning, the system effectively minimizes false alarms and improves adaptability to various background conditions, enabling reliable identification of subtle or rare anomalies that traditional methods may miss. However, these benefits are coupled with certain limitations: the system often requires more computational resources and time due to the increased complexity of its models and data processing steps. It may also depend on the availability of large, well-labeled datasets for training, especially when using deep learning approaches, and can be sensitive to parameter selection or domain adaptation challenges when deployed on new, unseen scenes. Despite these challenges, the proposed system represents a notable advancement in balancing detection accuracy and practical application needs in the field of hyperspectral image analysis.

5. CONCLUSION

In conclusion, the proposed system for hyperspectral image anomaly detection marks a significant step forward in the field by combining advanced spectral and spatial analysis with modern machine learning techniques. This approach enables more accurate, robust, and adaptive identification of anomalies, addressing key limitations found in traditional detection methods. While the system may require greater computational resources and careful parameter selection, its ability to reduce false alarms and adapt to diverse environments makes it well-suited for practical, real-world applications. Ultimately, this project contributes to more reliable remote sensing, enhances situational awareness, and paves the way for future advancements in hyperspectral image analysis for both scientific research and industry needs.

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