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The Study of Anomaly Detection in Patterns from Remotely Sensed Images

Mayur V. Tiwari[1], *Sanjay V. Dudul*[2]
[1]*Research Scholar, Department of Applied Electronics, SGBAU, Amravati, India.*
[2]*Professor & Head, Department of Applied Electronics, SGBAU, Amravati, India.*
Emails: *mayurvtiwari@gmail.com*[1], *svdudul@gmail.com*[2]

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Abstract
Anomaly detection in remotely sensed images is a critical task with diverse applications, ranging from environmental monitoring to smart agriculture. Various methodologies have been developed to enhance the detection of anomalies, which are deviations from expected patterns in image data. These methods leverage advanced computational techniques and machine learning models to improve accuracy and efficiency. Anomaly detection in remotely sensed images can be employed using different methods such as heterogeneous and edge computing, convolutional neural Networks, multi-dimensional feature space, unified anomaly detection, unsupervised learning for burnt area detection, etc. This paper discussed different methods and cutting-edge technologies for anomaly detection. While all these methods show significant advancements, challenges, limitations remain in terms of computational resource requirements and the need for real-time processing capabilities. Future research may focus on optimizing these models for broader applications and improving their adaptability to new data sources.

1. Introduction

Anomaly detection in objects from remotely sensed images is a critical task in remote sensing, involving the identification of patterns that deviate from expected norms. This process is essential for applications ranging from environmental monitoring to military surveillance. Various methodologies have been developed to enhance the accuracy and efficiency of anomaly detection in remote sensing images. These methodologies leverage advanced machine learning models, feature extraction techniques, and computational strategies to address the challenges posed by noise, complex object shapes, and high-resolution data. Advanced Machine Learning Models like FlexVisionNet-YOLO utilizes a vision transformer architecture to capture global and local features, improving detection accuracy for radiation anomalies in optical remote sensing images. It incorporates multiscale feature fusion and adaptive optimization techniques to enhance performance metrics such as precision and recall. The JointNet is a multitask learning framework that integrates denoising and anomaly detection in hyperspectral images. It uses an autoencoder with the minimum noise fraction rotation to separate noise from anomaly targets, maintaining critical features for accurate detection. Feature Extraction Techniques like Feature-Associated CNNs employs object tokens and global information features to enhance feature representation and correlation in CNNs, improving object detection in remote sensing imagery. Also the Pixel Descriptors utilized in anomaly segmentation models to handle high-resolution imagery, employing deep one-class classification and multi-level feature extraction to improve segmentation accuracy. Computational Strategies such as Heterogeneous and Edge Computing strategy Implements parallel algorithms on multi-node platforms to accelerate anomaly detection in multispectral images, optimizing for energy efficiency and computational speed. While these methodologies significantly advance anomaly detection capabilities, challenges remain, such as handling diverse anomaly types and ensuring robustness across different datasets. Continuous research and development are necessary to address these challenges and further improve detection accuracy and efficiency. Anomaly detection in remotely sensed images is crucial for identifying irregularities caused by sensor malfunctions or data transmission errors, which can significantly impact image quality and analysis. This process involves categorizing various types of anomalies, such as CCD noise, stripe noise, and missing images, to enhance the reliability of remote sensing data. Advanced techniques, including deep learning architectures like FlexVisionNet-YOLO, leverage multiscale feature fusion and adaptive optimization to improve detection accuracy and classification performance, thereby facilitating more effective monitoring and analysis of environmental changes. The generalized block diagram for anomaly detection in remotely sensed images is shown in figure 1. Anomaly detection in remotely sensed images involves identifying pixels or regions that deviate significantly from the expected patterns of the background, often indicating the presence of unusual objects or phenomena. This process is particularly challenging in hyperspectral imaging due to the presence of noise, which can obscure anomalies. Effective methods, such as multitask learning frameworks, can enhance detection accuracy by simultaneously addressing denoising and anomaly identification, ensuring that critical features are preserved while minimizing the loss of anomaly targets during the analysis. The paper [41] addresses forcibly displaced populations (FDP) in settlement areas. Over 108.4 million forcibly displaced people exist globally. Earth observation technology aids humanitarian emergency assistance. Deep learning models enhance information retrieval for FDP settlements. The study focuses on unsupervised localization and counting of dwellings. Variational autoencoders (VAEs) are utilized for anomaly detection. The research aims to improve operational humanitarian response efficiency. Anomaly detection in remotely sensed images involves identifying patterns that deviate from expected behaviour, particularly in high-resolution multispectral images captured by unmanned aerial vehicles. This process is crucial for monitoring environmental integrity, as it can reveal human-made constructions that may impact fluvial ecosystems. Techniques such as the Reed–Xiaoli (RX) method, combined with spatial information extraction through extinction profiles, enhance the detection of these anomalies. The integration of heterogeneous and edge computing further accelerates the analysis, enabling efficient processing of large datasets in real-time scenarios. An instance of anomaly detection from remotely sensed images is shown in figure 2.The paper [40] addresses earthquake-damaged building detection challenges. Quick detection is crucial for effective disaster management. Existing datasets for this task are limited or non-existent. The study introduces a new dataset from the 2023 Turkey-Syria earthquakes. The dataset includes over 4000 building images and annotations. It combines SAR and optical imagery for analysis. The detection task is framed as binary image classification. Baseline methods and results are provided for comparison.

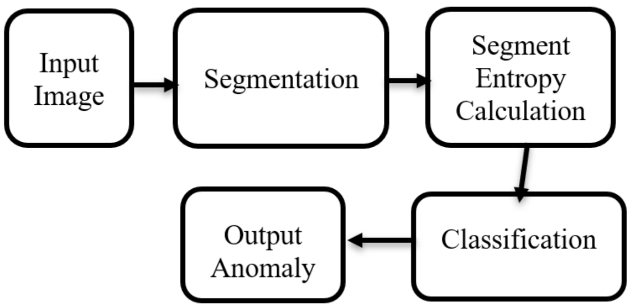

Figure 1 Anomaly Detection General Block Diagram

2. Literature Survey

The paper [41] discusses deep learning's performance in classification and segmentation. It highlights limitations of supervised models in humanitarian response. The need for speed in information retrieval is emphasized. Generalization issues under distribution shift are identified. Previous studies on dwelling extraction from temporary settlements are referenced. The paper

[40] presents a novel dataset for earthquake-damaged building detection. It addresses challenges in training data scarcity for robust algorithms. The dataset includes over 4000 building footprints and satellite images. It formulates damaged building detection as a binary classification problem. The study area is affected by the 2023 Turkey-Syria earthquakes. The dataset aims to expedite algorithm development for future events. The review [39] focuses on marine environmental threat detection methods. It evaluates direct and anomaly detection methods. Five major families of methods are identified. Index computation methods utilize spectral signatures for material identification. Statistics and machine learning methods include various classical techniques. Supervised deep learning methods detect specific events. Self-supervised deep learning methods identify anomaly events. Image reconstruction deep learning methods measure reconstruction error for anomaly detection. The literature review [38] focuses on Earth's surface anomaly detection. It includes related works on remote sensing (RS) and GNN. The integration of GNN in RS is discussed. The study [35] builds on previous research using MERSI-II data. It explores lead detection using brightness temperature images. Previous studies utilized SAR for distinguishing leads from thick ice. The impact of wind on backscatter coefficients is acknowledged. Comparisons are made with MODIS data for validation. The paper [34] proposes a new spectral anomaly detection method. It operates under sparse representation and low-rank framework. The method distinguishes anomalies on the sea surface. A spectral dictionary for normal scenes is formulated. The ADMM method optimizes the spectral dictionary. The method detects anomalies using an error matrix. It shows generality for various sea surface anomalies. Experimental results demonstrate superior performance on HY-1C datasets.The researcher [32] discussed Precision agriculture which uses IoT devices for environmental data collection. Multidevice systems monitor vegetation and improve crop growth. Data heterogeneity poses challenges in sensor integration. Various solutions exist for data interface and integration. Quantum-inspired algorithms improve energy consumption in sensor networks. Ontologies support data integration and contextualization in agriculture. CANDELA project bridges big data and earth observation data. Anomaly detection systems classify agricultural areas based on anomalies. The paper [30] reviews traditional and deep learning HAD methods. It summarizes various machine learning techniques for HAD. Deep learning models show significant progress in HAD tasks. The review highlights unsupervised and GAN-based approaches for HAD. It contrasts existing HAD surveys with this comprehensive review. Figure 2 shows Remotely Sensed Images and Corresponding Anomaly Detected. [1-10]

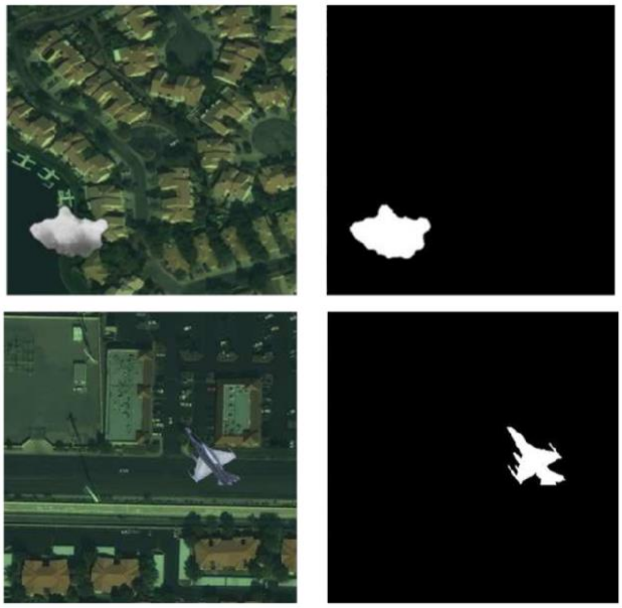

Figure 2 Remotely Sensed Images and Corresponding Anomaly Detected

The research [29] discusses various anomaly detection approaches. Anomalies are defined as significant deviations in data. Civilian applications of anomaly detection are highlighted. Related works include mineral exploration and ecosystem disturbances. The paper [28] focuses on geothermal anomaly detection methods. Multitemporal Landsat 8 images are utilized for analysis. Emphasizes the significance of NNE-trending faults in geothermal research. Discusses the impact of impervious surfaces, water, and vegetation. Highlights the need for multitemporal TIR remote sensing data. One researcher [25] focused on Anomaly Detection methods. AD methods are categorized by learning techniques and algorithms. Supervised, semi supervised, and unsupervised learning are common in AD. Novelty detection learns normality to identify unobserved events. Outlier detection identifies inconsistent data points in training sets. Subtle data deviations may not indicate crop anomalies. Established AD techniques include autoencoders and one-class SVM. HMMs have been applied to solve AD problems in literature. The paper [24] addresses airport detection in large areas. Previous frameworks struggled with small airport detection. Airports significantly impact transportation and economy. Limited studies exist on large-area airport detection. The researcher [22] worked on Background dictionary construction which affects target detection performance. Unsupervised clustering methods are commonly used for background dictionary construction. K-means clustering is simple but sensitive to anomalies. Density peak clustering extracts pure background and anomalous pixels. Generative adversarial networks are examined for hyperspectral anomaly detection. Proposed SSBD method integrates SAD and sparse representations theories. Numerous ship detection algorithms have emerged recently. Traditional methods use low-level hand-crafted features. Deep learning methods include anchor-based and anchor-free algorithms. Deep learning requires large labelled samples for training. Convolutional neural networks are applied for feature extraction. Traditional algorithms struggle in complex scenes like cloud interference. Real-time processing faces challenges due to hardware limitations [21]. Literature review [20] categorizes works into top-down and bottom-up approaches. Top-down works build large datasets with many object classes. Bottom-up works focus on specific problems with few object classes. The paper targets detection of airports and electrical substations. It summarizes current datasets and deep learning approaches. The paper [17] discusses 2-D approaches for remote sensing data. It references 3-D convolution operations in literature. Previous studies focused on pixel-based and spatial correlation methods. The model is compared to unidimensional AR models. Literature supports the need for robust parameter estimation methods.The paper [15] reviews Cook's distance in multivariate statistics. It discusses influential points and leveraging in statistics. The literature includes methods for detecting anomalous changes. It highlights challenges in remote sensing image analysis. The paper mentions existing approaches and their computational burdens. The paper [10] focuses on iceberg detection using SAR images. Previous work addressed large iceberg detection and tracking. Small iceberg identification remains challenging in sea ice. The proposed detector uses dual-polarization SAR images. It improves contrast between icebergs and sea ice clutter. The methodology enhances detection probability significantly. The researcher [9] discusses anomaly detection in hyperspectral imagery. It highlights the need for unsupervised detection methods. Progressive band processing allows real-time anomaly detection. RX detector is a widely used anomaly detection algorithm. Causal RXD is a notable variant of RX detector. The Local detection algorithms calculate new correlation matrices for each pixel. Significant pixels need replacement to reduce computation time. Streaming background statistics (SBS) simplifies local background statistics calculation. SBS matrix updates require adding and removing pixels efficiently. Inverse matrix real-time updates are performed using Sherman-Morrison formula [8]. The paper [5] focuses on anomaly detection in hyperspectral images. A likelihood ratio test-based decision rule is proposed. Automated data-driven estimation of background PDF is emphasized. Both semiparametric and nonparametric models are investigated. Challenges in learning model parameters without operator intervention are noted. Experimental evaluation uses two real hyperspectral images. [11-20]

3. Challenges Observed in The Research

Confusion between dwellings and non-dwelling instances across datasets. False positive localization of non-anomalous targets observed. Inherent complexity of dwelling structures affects model performance [41]. Limited availability of VHR SAR images in disaster areas. Absence of labels for damaged buildings. Lack of accurate terrain models for alignment [40]. Detectability and responsiveness for effective environmental monitoring. Adaptability to various types of threats without limitations. Resource efficiency for deployment on different hardware configurations. Limited accessible satellite datasets and labels [39]. Absence of prior knowledge hinders anomaly detection accuracy. Anomalous targets and backgrounds are reconstructed simultaneously. Local feature loss during background reconstruction is a concern. High data dimensions increase computational costs significantly. Difficulty in creating a background dictionary without anomalous interference [38]. Sudden-onset anomalies threaten human life and property security. Lack of public datasets for anomaly detection. Response time delay in data collection and pre-processing. Limited node information in GNN methods [37]. Real HSIs often do not follow Gaussian distribution. Anomalies and noise interfere with statistics estimation. Establishing a unified statistical model is difficult. Nonlinear characteristics limit performance of representation-based methods [36]. Misclassification of bright-dark lead in visual interpretation. Difficulty in obtaining accurate small-scale wind data. Low accuracy in thin ice identification due to rapid changes. Incompatibility due to satellite acquisition time differences. Cloud cover affecting judgment on open water and thin ice [35]. The need for accurate spectral dictionary representation. Balancing low-rank and sparsity constraints in optimization. Variability in anomaly types on sea surface [34]. Optimal filtering through a single FO is non-robust. Intratextural variation must be considered for accurate processing. Conventional methods involve high iterative complexities. Noniterative and optimization-free procedures are needed to reduce complexity. Environmental artifacts affect image quality and require suppression [33]. Limited use of spatial information in anomaly detection. Anomaly pollution problem affecting detection accuracy [31]. Spectrum complexity due to illumination and environmental changes. Strong correlation and redundancy between adjacent spectral bands. Limited spatial resolution leading to mixed pixel issues [30]. Anomaly detection faces high-dimensional data challenges. Aleatoric uncertainty complicates data distribution analysis. Class overlap and label noise affect data quality. Curse of dimensionality impacts anomaly detection effectiveness [29]. Extracting geothermal anomalies is affected by external interference factors. Daytime data cannot accurately show geothermal distribution. Terrain negatively impacts geothermal anomaly extraction results [28]. Seasonal influences affect inversion results in geothermal exploration. Single-temporal data leads to flawed geothermal exploration outcomes. Pseudo-anomalous areas are easily extracted during detection. Complicated terrain increases entropy values, causing outliers. Difficulty in identifying debris in rocky coastlines. Ocean debris is widely scattered and hard to capture. Ground truth data may be inaccurate or underestimated. Class imbalance problem in debris classification. Background deviations introduce errors in image analysis [27]. Defective pixels may arise between calibration steps. Subtle signal values complicate defect detection. [21-30]

Table 1 Challenges in Anomaly Detection

Challenges	Description
Data Volume	The extensive volumes of remote sensing data necessitate the implementation of effective processing and analytical methodologies to promptly detect anomalies.
Noise and Interference	Remotely acquired imagery may be influenced by atmospheric variables, sensor-induced artifacts, and additional sources of noise, which can mask or warp anomalies.
Dependency on Context	Anomalies may exhibit significant dependence on context, necessitating a comprehensive comprehension of the foundational environment and its anticipated behavioral patterns.
Interpretability	Effective methodologies for anomaly detection must yield results that are interpretable, thereby facilitating subsequent inquiries and informed decision-making.

Residual nonuniformity noise affects image quality. Banding effect identified but not addressed in this work [26]. Difficulty in obtaining labelled training instances for anomalies. Subtle deviations may result from external factors, not anomalies. Variance changes can affect anomaly detection performance [25]. Airports are difficult to detect in vast areas. Complex geographical backgrounds hinder accurate airport detection. Existing airport databases have incomplete data and spatial inaccuracies. Single model mining struggles with complex remote sensing images [24]. Anomalies in InSAR data are poorly estimated. Low absolute numbers of labelled deformation instances. High-dimensional, noisy, and imbalanced data challenges. Overlapping sequences complicate anomaly detection. Requires unsupervised learning due to limited labelled data [23]. Limited supply of infrared data for ship detection. Imprecise sea-land segmentation under conditions. Low contrast between target and background. Cloud interference affecting detection accuracy. New artificial buildings complicating segmentation. Insufficient unbalanced data for improved detection performance [21]. Following table 1 shows challenges in anomaly detection in remote sensing.

4. Limitations Observed in The Previous Research

Supervised models require extensive annotated data for training. Models struggle with generalization across different geographies and times. Classical VAE poorly localizes dwelling objects in anomaly score maps. VAE fails to learn good latent code from diverse datasets [41]. Limited availability of VHR SAR images in disaster areas. Absence of labels for damaged buildings. Lack of accurate terrain models for alignment. Dataset constrained by limited quantity and imbalance [40]. Limited datasets for Phsat-2 and IMAGIN-e missions. Small size of anomalies affects detection accuracy. Custom dataset may introduce selection bias. Detection thresholds can impact performance. Latency in image processing affects responsiveness. Algorithms need to be lightweight for embedded hardware [39]. Missing local features in background reconstruction. Overcoming limitations of ViT in learning local structures. Excessively high masking rate restricts feature learning. Low masking rate leads to overfitting and noise neglect [38]. Lack of a public dataset for anomaly detection. Limited solutions for rapid anomaly detection. Need for more comprehensive anomaly types in future research [37]. Real HSIs often do not follow Gaussian distribution. Anomalies and noise interfere with statistics estimation. Unified statistical model is difficult for many real HSIs. Nonlinear characteristics limit performance of linear modelling methods [36]. Wind data at small scale is difficult to obtain accurately. Misclassification of bright-dark leads affects detection accuracy. Low accuracy in thin ice identification due to rapid changes [35]. Optimal filtering through a single FO is non-robust. Iterative methods exhibit high computational complexity. Lack of texture-dependent processing in conventional methods. Existing methods do not adaptively evaluate FOs [33]. Limited use of spatial information in existing detectors. Anomaly pollution problem affects detection accuracy [31]. Spectrum complexity due to various environmental factors. Strong correlation between adjacent bands causes redundancy. Limited spatial resolution leads to mixed pixels. Low detection rates and high false alarms from mixed pixels [30]. Performance is limited without pre-event images. Radiation differences affect detection accuracy. Recent pre-event images are necessary for effective analysis [29]. Extracting geothermal anomalies is influenced by external factors. Daytime data cannot accurately show geothermal distribution. Terrain negatively impacts temperature inversion results. Single-temporal data is flawed for geothermal exploration. Inaccurate gradient due to insufficient inversion data. Visual interpretation needed after NDBI extraction for buildings [28].

5. Future Research

The future scope of anomaly detection in remotely sensed images is promising, driven by advancements in deep learning, heterogeneous computing, and novel algorithmic approaches. These technologies are enhancing the precision, efficiency, and applicability of anomaly detection across various remote sensing contexts. The integration of these methods is expected to address current challenges and expand the capabilities of remote sensing applications. The use of deep learning models like FlexVisionNet-YOLO, which incorporates a vision transformer architecture, significantly improves the detection of radiation anomalies in optical remote sensing images. This model enhances precision, recall, and classification accuracy by employing multiscale feature fusion and adaptive optimization techniques. The application of heterogeneous computing and edge computing accelerates anomaly detection in multispectral images. This approach utilizes multi-core CPUs and GPUs to efficiently process high-resolution data, enabling real-time anomaly detection in remote environments. The following table 2 shows the applications in anomaly detection in remotely sensed images and their corresponding case studies. Tree topology-based anomaly detection (TTAD) for hyperspectral images offers a novel approach by leveraging the sparse distribution of anomalies. This method improves the separability of anomalies from background data, enhancing detection precision without relying on traditional model assumptions. Unsupervised learning methods, such as Vector Quantized Variational Autoencoder (VQ-VAE), are being explored for burnt area extraction in satellite images. These methods show potential for scalable and effective anomaly detection in emergency risk monitoring scenarios. Future frame prediction networks, based on convolutional variational autoencoder networks, are being developed for detecting anomalies in aerial videos. These networks offer superior performance in identifying suspicious events, highlighting their potential in surveillance applications. While these advancements are promising, challenges such as data heterogeneity, computational demands, and the need for real-time processing remain. Addressing these issues will be crucial for the broader adoption and effectiveness of anomaly detection in remote sensing. [31-41]

Table 2 Applications and Case Studies

Applications	Case Studies
Environmental Monitoring	Detect changes in land cover, deforestation, or pollution levels
Urban Planning	Identify unauthorized construction, infrastructure issues, or traffic anomalies
Disaster Response	Quickly identify and locate areas affected by natural disasters
Security and Surveillance	Detect unusual activities or potential threats in critical infrastructure

Conclusion

The literature survey on anomaly detection in remotely sensed images highlights the diverse methodologies and applications in this field. Anomaly detection is crucial for identifying unusual patterns in data, which is particularly challenging in remote sensing due to the complexity and volume of data. Techniques such as machine learning, hyperspectral analysis, and change detection are commonly employed to address these challenges. These methods are applied across various domains, including environmental monitoring, urban planning, and disaster management, showcasing their versatility and importance in real-world applications. Machine learning (ML) techniques, including supervised, unsupervised, and semi-supervised learning, are extensively used for anomaly detection in wireless sensor networks (WSNs) and remote sensing data. These techniques help in identifying unusual patterns and diagnosing anomalies in noisy and unreliable data. Deep learning advancements have significantly improved the performance of change detection tasks in satellite imagery, offering robust solutions for urban growth monitoring and climate change studies. Hyperspectral sensors capture data in numerous spectral bands, enabling detailed anomaly detection without prior knowledge of the scene. These unsupervised learning techniques are effective in discovering rare features in hyperspectral images. The mathematical framework for anomaly detection in hyperspectral images includes structured and unstructured background models, which are crucial for accurate detection statistics. Change detection methodologies, such as supervised and unsupervised approaches, are vital for monitoring environmental changes and urban development. These methods are tailored to handle multi-source and multi-objective scenarios in remote sensing. The integration of diverse data sources and the development of a comprehensive change detection pipeline are essential for effective analysis and application in various domains. While the survey highlights the effectiveness of these techniques, it also points out the challenges, such as computational complexity and the need for more robust algorithms to handle diverse data sources. Future research directions include improving data fusion techniques and developing more efficient algorithms for real-time anomaly detection in remote sensing applications.

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