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# AI and Computer Vision in High-Resolution Remote Sensing for Oil Tank Monitoring: A Survey

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## Abstract

The integration of Artificial Intelligence (AI) and computer vision into remote sensing has significantly advanced the monitoring of oil tanks, particularly through the utilization of high-resolution optical satellite imagery. This survey explores the transformative impact of AI methodologies, such as deep learning and explainable AI, on image analysis and object detection, enhancing accuracy and interpretability in remote sensing applications. The incorporation of computer vision techniques complements these advancements by providing sophisticated tools for analyzing complex visual data, thereby improving the identification and monitoring of oil tanks in optical remote sensing images (ORSIs). The survey also highlights the critical role of high-resolution satellite imagery in environmental monitoring and resource management, facilitated by AI and computer vision technologies. Despite these advancements, challenges persist, including data quality, model interpretability, and computational constraints. Addressing these challenges is essential for the continued advancement of AI-driven remote sensing applications. Future research directions emphasize the need for advancements in AI algorithms, integration of diverse data sources, and enhancement of model interpretability and robustness. In conclusion, the integration of AI and computer vision into remote sensing represents a pivotal advancement, offering enhanced capabilities for effective oil tank monitoring and contributing to sustainable environmental practices.

## 1 Introduction

### 1.1 Significance of AI and Computer Vision

The integration of artificial intelligence (AI) and computer vision into remote sensing applications has significantly enhanced data analysis capabilities and accuracy, particularly in high-resolution remote sensing, where AI methodologies enable detailed information extraction from optical satellite imagery for precise oil tank monitoring [1]. Despite the rapid adoption of these technologies, concerns regarding their consistency and associated risks persist, as the assumption of predictable behavior akin to traditional software can lead to quality and maintainability issues [2].

AI's role in remote sensing extends beyond data analysis to its integration with unmanned aerial vehicles (UAVs), which are pivotal for environmental monitoring and resource management [3]. This integration not only advances the field but also addresses emerging trends and challenges across various industries. Recent surveys highlight the importance of AI in systematically analyzing and categorizing Earth Observation (EO) datasets, underscoring its critical role in managing the vast data generated by remote sensing technologies [4].

Moreover, AI's application in remote sensing encompasses marine environments, aiding in the detection, prediction, and assessment of oil spills, thereby contributing to environmental protection efforts [5]. The multifaceted applications of AI and computer vision technologies illustrate their extensive impact on enhancing the capabilities and scope of remote sensing.

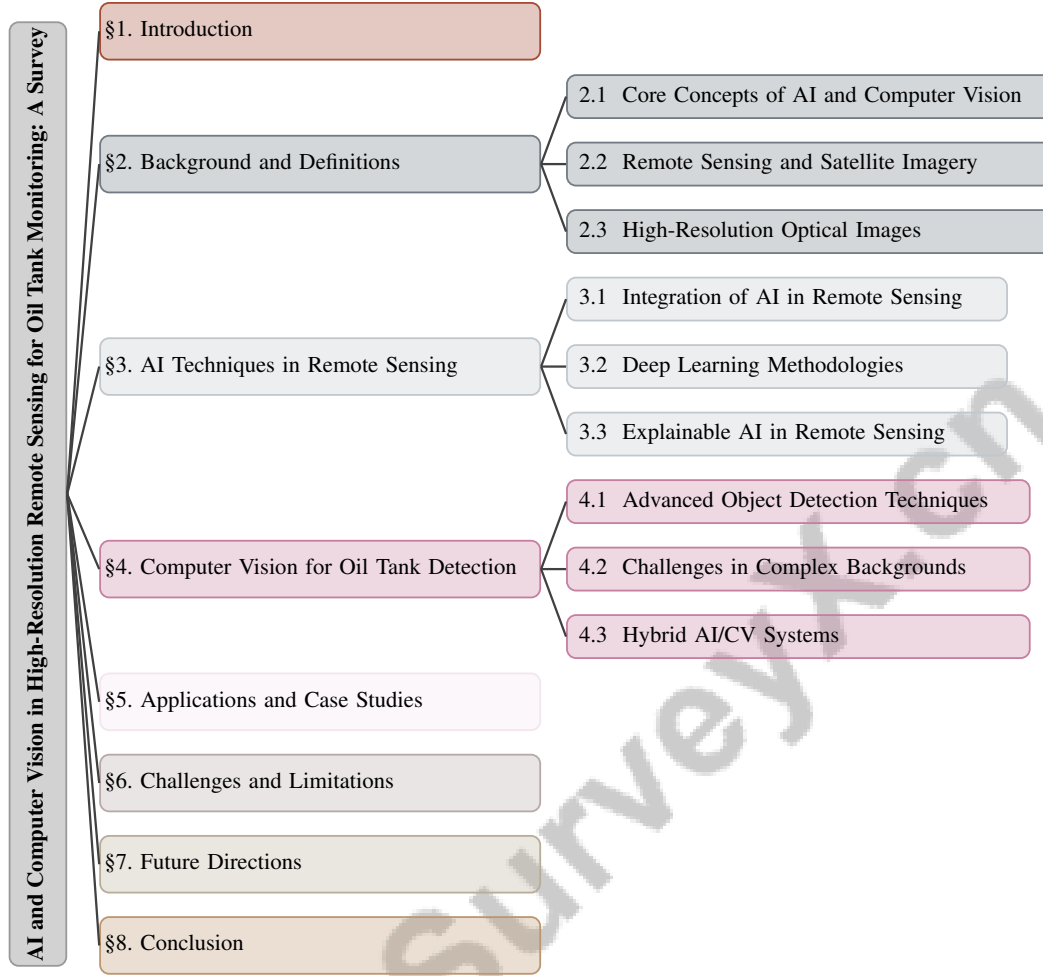


Figure 1: chapter structure

## 1.2 Importance of Satellite Imagery

Satellite imagery is essential for environmental monitoring and resource management, serving as a cornerstone for various scientific and practical applications. The integration of AI techniques with remote sensing is crucial for effective data analysis in Earth sciences, enhancing the processing and interpretation of complex datasets derived from satellite images [1]. This capability is vital for addressing challenges such as tracking deforestation, assessing climate change impacts, and managing natural resources.

In addition to terrestrial applications, satellite imagery combined with AI-enabled UAVs broadens the scope of monitoring activities across diverse fields, including agriculture, where precision farming techniques are enhanced; surveillance and disaster management, which benefit from improved response and assessment capabilities; and wildlife monitoring, where conservation efforts are supported through detailed habitat analysis [3]. This integration highlights the transformative potential of satellite imagery when paired with advanced AI methodologies, facilitating efficient and comprehensive approaches to environmental stewardship and resource management.

## 1.3 Structure of the Survey

This survey is structured to comprehensively explore the integration of AI and computer vision techniques in high-resolution remote sensing for oil tank monitoring. It begins with an introduction that emphasizes the significance of AI and computer vision in satellite imagery analysis, highlighting their transformative impact on environmental monitoring and resource management. The Background and Definitions section provides an overview of core concepts, defining key terms such as AI,

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computer vision, remote sensing, and satellite imagery, and elucidating the relevance of high-resolution optical images in oil tank monitoring.

The survey further investigates AI Techniques in Remote Sensing, examining various methodologies and their applications in image analysis and object detection. This section includes discussions on AI integration into remote sensing technologies, deep learning methodologies, and the importance of explainable AI for transparency. The subsequent section, Computer Vision for Oil Tank Detection, details techniques specifically employed for detecting and monitoring oil tanks, addressing advanced object detection methods, challenges in complex backgrounds, and hybrid AI/computer vision systems.

The Applications and Case Studies section presents real-world implementations of AI and computer vision in oil tank monitoring, discussing their impact on environmental monitoring and management, AI model performance in detection scenarios, and the EarthNets platform for model evaluation. Following this, the Challenges and Limitations section examines issues related to data quality and diversity, model interpretability, and computational constraints.

The survey concludes with Future Directions in AI, emphasizing emerging trends such as advancements in AI algorithms, integration of diverse data sources, and strategies to enhance the interpretability and robustness of AI models. It underscores the critical need for transparency and consistency in AI applications, particularly regarding model behavior and data quality, while identifying key research gaps and opportunities for innovation in explainable AI and its applications in remote sensing and UAVs, thus providing a roadmap for future exploration and methodological advancements in these domains [3, 2, 6, 1, 7]. The paper concludes by summarizing key findings and reflecting on the importance of integrating AI and computer vision in remote sensing for effective oil tank monitoring. The following sections are organized as shown in Figure 1.

## **2 Background and Definitions**

### **2.1 Core Concepts of AI and Computer Vision**

AI and computer vision are pivotal in advancing remote sensing by providing sophisticated methods for analyzing complex datasets. AI encompasses techniques like image classification, object detection, and data fusion, essential for remote sensing applications [8]. Computer vision, as a subset of AI, allows machines to interpret visual information, enabling automated analysis of images and videos. These technologies are instrumental in categorizing images into land use and land cover classes, enhancing environmental resource monitoring [9]. They address high-dimensional function estimation challenges, requiring predictive models adept at managing complex, nonlinear data [10], though issues like overfitting and high computational demands persist [11].

In oil tank monitoring, AI and computer vision are crucial due to the complexities of optical remote sensing images (ORSIs), which often feature scattered objects and complex backgrounds [12]. Advanced object detection techniques are necessary for accurate identification and monitoring. The dynamic nature of computer vision services can lead to inconsistencies, highlighting the need for benchmarks to evaluate reliability and service evolution [6]. AI is also utilized in satellite technologies for efficient pose estimation and tracking, enhancing processing capabilities through embedded systems [4]. Additionally, the integration of AI in UAVs demonstrates versatility, enabling navigation, object detection, and environmental monitoring across various domains [5]. Collectively, these concepts underscore AI and computer vision's transformative impact on remote sensing, particularly in oil tank monitoring.

### **2.2 Remote Sensing and Satellite Imagery**

Remote sensing is essential for acquiring and analyzing Earth's surface data without direct contact, utilizing sensors on platforms like satellites and UAVs for applications in environmental monitoring, resource management, and urban planning [3]. Satellite imagery provides extensive coverage and high-resolution details crucial for accurate analysis and decision-making [1]. High-resolution optical images capture fine details necessary for monitoring complex environments [1], as demonstrated by datasets like NWPU-RESISC45 and PatternNet, which offer diverse land use and land cover classes with distinct spatial patterns. These datasets advance research in scene understanding and pattern recognition, enabling robust AI models for interpreting complex visual data.

AI integration with remote sensing technologies enhances satellite imagery analysis, facilitating meaningful insights from large data volumes. This integration addresses challenges in data processing, storage, and governance, exemplified by platforms like MetaPix, which manage unstructured computer vision data [6]. AI's incorporation into UAVs expands autonomous and efficient data collection and analysis capabilities in challenging environments, broadening remote sensing applications [3]. The synergy between remote sensing and satellite imagery, bolstered by high-resolution optical images, underpins modern environmental monitoring and resource management strategies. AI and machine learning algorithms enable sophisticated data analysis techniques, improving interpretation of complex datasets and addressing data quality and model uncertainty challenges, leading to more informed decision-making across Earth sciences [1, 7].

### 2.3 High-Resolution Optical Images

High-resolution optical images are crucial in remote sensing, particularly for detecting and monitoring oil tanks. These images provide the spatial detail necessary for accurate object detection [12]. The RSSOD dataset exemplifies the utility of very high resolution (VHR) images, with a spatial resolution of approximately 0.05 meters, essential for capturing intricate details in ORSIs. Challenges in ORSIs include insufficient visual clues, low image contrast, and texture details, compounded by arbitrary orientations and large scale variations of objects [13]. Advanced methodologies, like MFPNet, enhance detection capabilities by integrating local and global features through a cascaded pyramid structure and Receptive Field Block (RFB) [14].

The complexity of backgrounds and scale-variant objects complicates salient object detection (SOD) models, affecting accuracy and completeness [9]. High-resolution optical images alleviate these issues by providing necessary detail to distinguish objects from their environments, improving SOD model performance. Datasets like PatternNet, with 38 classes and 800 images per class, highlight high-resolution imagery's importance in remote sensing image retrieval (RSIR) [15]. These datasets underpin the development of robust AI models capable of effectively interpreting complex visual data, enhancing monitoring and management of resources such as oil tanks.

As the field of remote sensing continues to evolve, the integration of artificial intelligence (AI) techniques has emerged as a pivotal development. This integration not only enhances image processing but also improves model interpretability and facilitates comprehensive environmental data analysis. To illustrate this dynamic landscape, Figure 2 presents a detailed representation of the hierarchical structure of AI techniques in remote sensing. This figure categorizes the various AI methodologies, including deep learning approaches and explainable AI (xAI) strategies, while highlighting their key methodologies, advanced techniques, and practical applications. By examining this framework, we can better understand the transformative impact of these technologies on the field, paving the way for innovative solutions and enhanced analytical capabilities.

## 3 AI Techniques in Remote Sensing

### 3.1 Integration of AI in Remote Sensing

Method Name	Methodological Approaches	Collaborative Efforts	Data Utilization
UN[16]	Deep Neural Network	AI Developers	Real Satellite Datasets
RVSA[8]	Vision Transformers	Interdisciplinary Collaboration	Data Augmentation Processes
DM-DA[17]	Diffusion Models	-	Novel Datasets
RRNet[9]	Relational Reasoning Networks	-	Novel Datasets

Table 1: Overview of AI methodologies and their applications in remote sensing, highlighting methodological approaches, collaborative efforts, and data utilization. The table provides a comparative analysis of four AI methods, illustrating their unique contributions to enhancing image processing capabilities in environmental monitoring.

The incorporation of Artificial Intelligence (AI) into remote sensing technologies has markedly improved image processing capabilities, resulting in more accurate and efficient environmental data analysis. AI methodologies, particularly computer vision (CV), are crucial for advancing remote sensing applications, exemplified by the Intel Myriad X VPU's role in hybrid AI/CV systems for real-time pose estimation and tracking [16]. This integration enhances the capture and interpretation of complex visual data, vital for environmental monitoring and resource management.

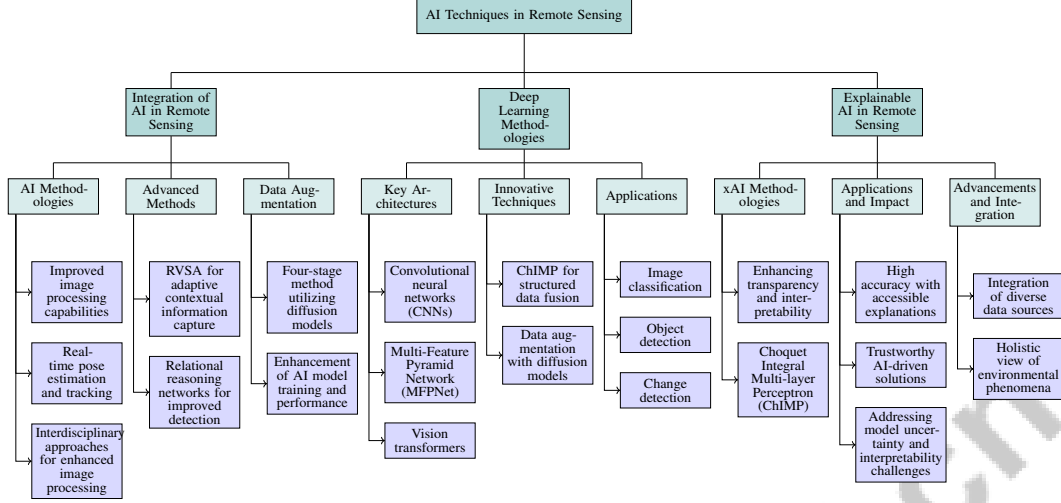


Figure 2: This figure illustrates the hierarchical structure of AI techniques in remote sensing, categorizing the integration of AI, deep learning methodologies, and explainable AI (xAI) approaches. It highlights key methodologies, advanced techniques, and their applications in remote sensing, emphasizing the transformative impact on image processing, model interpretability, and environmental data analysis.

Recent surveys categorize AI methodologies in remote sensing by emphasizing the collaboration between AI developers and domain experts, highlighting interdisciplinary approaches that enhance image processing [1]. The introduction of novel datasets, particularly for small object detection, addresses existing resource gaps and lays the groundwork for robust detection models [12]. Advanced methods like RVSA, which refines the attention mechanism of vision transformers through varied-size and rotated windows, enable adaptive contextual information capture from remote sensing images [8].

The structured analysis of Earth Observation (EO) datasets based on volume, resolution distributions, and research domains further underscores AI's role in remote sensing [4]. This categorization supports the development of AI models tailored to the diverse complexities of remote sensing data. Additionally, data augmentation processes, such as a four-stage method utilizing diffusion models, produce semantically rich EO images, enhancing AI model training and performance [17].

Moreover, relational reasoning networks like RRNet exemplify the integration of relational reasoning and multi-scale attention mechanisms, improving salient object detection in optical remote sensing images [9]. These advancements highlight the transformative impact of AI in remote sensing, particularly in enhancing image analysis accuracy and efficiency. Benchmark datasets such as PatternNet are pivotal for developing and evaluating remote sensing image retrieval (RSIR) approaches, driving further research in deep learning-based methods [15]. Table 1 presents a comprehensive comparison of AI methods employed in remote sensing, elucidating their methodological approaches, collaborative efforts, and data utilization strategies.

### 3.2 Deep Learning Methodologies

Method Name	Architectural Structures	Application Domains	Data Augmentation Techniques
MFPNet[14]	Cascaded Pyramid Structure	Object Detection	-
CAD-Net[13]	Pyramid Local Context	Object Detection	-
RVSA[8]	Vision Transformers	Scene Classification	Diffusion Models
ChIMP[18]	Multi-layer Network	Data Fusion	Synthetic Data
DM-DA[17]	Vision Transformers	Image Classification	Diffusion Models

Table 2: Overview of Deep Learning Methodologies in Remote Sensing Applications, detailing architectural structures, application domains, and data augmentation techniques. The table highlights the diversity in architectural designs and their specific applications, emphasizing the role of data augmentation in enhancing model performance.

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Deep learning methodologies have significantly transformed remote sensing by providing powerful tools for image analysis and object detection. These techniques feature hierarchical architectures categorized by layer structures and activation functions for effective feature extraction [11]. Current methods are organized into stages, including feed-forward architectures, convolutional networks, recurrent networks, and autoencoders, each demonstrating varied effectiveness in remote sensing [11].

Convolutional neural networks (CNNs) have had a profound impact on remote sensing, with architectures like AlexNet, VGGNet-16, and GoogLeNet achieving substantial accuracy improvements in image classification and object detection tasks [19]. These models leverage deep hierarchical structures to identify intricate features in high-resolution optical images, crucial for monitoring objects such as oil tanks.

Advanced models like the Multi-Feature Pyramid Network (MFPNet) enhance detection accuracy by integrating a Multi-Feature Pyramid Module (M-FPM) and Receptive Field Block (RFB), which improve feature capture across multiple scales [14]. Similarly, the Context-Aware Detection Network (CAD-Net) utilizes global and local context learning to increase sensitivity to contextual information in remote sensing images [13].

Vision transformers have also been adapted for remote sensing, employing innovations like the rotated varied-size window attention mechanism to better manage the unique characteristics of remote sensing images [8]. This approach facilitates adaptive contextual information capture, improving performance in complex image analysis tasks.

In addition to conventional deep learning methods, novel architectures such as ChIMP (Choquet Integral Multi-layer Perceptron) offer structured data fusion approaches, integrating multiple data sources for enhanced image analysis [18]. Data augmentation techniques utilizing diffusion models further bolster model performance by generating high-quality synthetic data that reflects the complexity and diversity of Earth Observation (EO) imagery [17].

Deep learning methodologies are significantly enhancing remote sensing applications by providing advanced tools for precise image analysis, including image classification, object detection, and change detection, while addressing challenges related to data quality and model interpretability. The integration of AI with remote sensing not only refines data analysis processes but also fosters new opportunities in Earth sciences, leading to more informed decision-making and innovative solutions [15, 1, 13]. Through the development of innovative architectures and data augmentation strategies, these techniques contribute to more accurate environmental resource monitoring and management.

As illustrated in ??, the integration of AI techniques, particularly deep learning methodologies, has revolutionized remote sensing data interpretation and analysis. The figure presents three examples of these methodologies, showcasing their diverse applications and architectural designs. The first subfigure highlights various neural network architectures, including the Neural Turing Machine and Auto-encoder, foundational to deep learning's data processing capabilities. The second subfigure offers a visual representation of urban and natural landscapes through aerial photography, emphasizing AI's ability to differentiate and analyze various environmental contexts. The third subfigure depicts a neural network model characterized by unit step and dot operations, illustrating fundamental input-output layer interactions within neural networks. Collectively, these examples encapsulate the transformative impact of deep learning methodologies on enhancing the precision and efficiency of remote sensing applications [11, 19, 18]. Additionally, Table 2 provides a comprehensive summary of various deep learning methodologies employed in remote sensing, illustrating their architectural structures, application domains, and data augmentation techniques.

### 3.3 Explainable AI in Remote Sensing

The integration of Explainable AI (xAI) into remote sensing is crucial for enhancing the transparency and interpretability of machine learning models in this domain. xAI methodologies address the gap between complex machine learning models and the need for interpretability, as highlighted in systematic reviews of current practices [7]. The lack of interpretability in traditional models presents challenges, particularly in high-stakes decision-making scenarios, such as environmental monitoring and resource management.

A key innovation in this field is the Choquet Integral Multi-layer Perceptron (ChIMP), which optimizes the Choquet integral using stochastic gradient descent while providing explainable AI capabilities through network introspection [18]. This approach allows stakeholders to understand the decision-making processes within the model, elucidating how various features contribute to predictions.

The application of xAI in remote sensing fosters the development of models that not only achieve high accuracy but also provide explanations accessible to domain experts and end-users. This is especially important when model outputs require validation and trust from decision-makers. By offering detailed insights into AI model behavior, xAI significantly enhances the trustworthiness and adoption of AI-driven solutions in remote sensing applications. This improvement is vital for addressing model uncertainty and interpretability challenges, facilitating the integration of AI techniques in tasks such as image classification, land cover mapping, and change detection. Furthermore, xAI aids in identifying research gaps and informing future methodologies in the evolving landscape of remote sensing technologies [17, 7, 18, 1, 4].

Moreover, advancements in xAI techniques support the integration of diverse data sources, providing a holistic view of the environmental phenomena studied. This fusion of AI techniques with remote sensing is essential for developing advanced models capable of navigating the inherent complexities and variability of remote sensing data, thereby improving applications such as image classification, land cover mapping, and object detection while addressing challenges related to data quality, model interpretability, and the necessity for domain expertise [15, 1, 8, 7]. As xAI evolves, it promises to bridge the gap between model complexity and user interpretability, ultimately leading to more informed and effective decision-making in remote sensing applications.

## 4 Computer Vision for Oil Tank Detection

### 4.1 Advanced Object Detection Techniques

Advanced object detection techniques are pivotal for identifying oil tanks in optical remote sensing images (ORSIs) with high precision. The Multi-Feature Pyramid Network (MFPNet) exemplifies such advancements, achieving mean average precision (mAP) scores of 89.8

CAD-Net further enhances detection accuracy by utilizing global and local contextual information, particularly beneficial in scenarios with subtle or obscured features [13]. This contextual awareness is essential for precise oil tank identification amidst complex backgrounds.

RRNet contributes by effectively suppressing background interference, maintaining clarity in detecting salient objects even in challenging scenarios characterized by complex backgrounds and varying object scales [9]. Its robust performance underscores its potential for reliable oil tank detection in remote sensing applications.

Additionally, a multi-model decision fusion framework significantly enhances detection performance by integrating contextual information and part-based features, leveraging the strengths of multiple detection models for comprehensive and reliable outcomes [10].

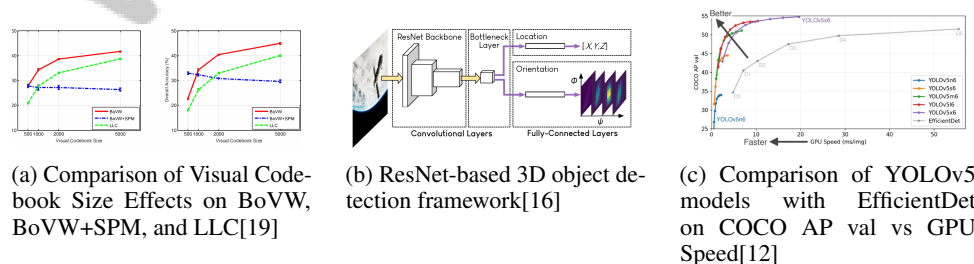


Figure 3: Examples of Advanced Object Detection Techniques

Figure 3 illustrates the challenges and advancements in oil tank detection using computer vision. The first subfigure compares the impact of visual codebook size on the accuracy of Bag of Visual Words (BoVW), BoVW with Spatial Pyramid Matching (SPM), and Locality-constrained Linear Coding

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(LLC), highlighting the influence of codebook size adjustments. The second subfigure showcases a ResNet-based 3D object detection framework, demonstrating its architecture's effectiveness in determining object location and orientation, essential for precise oil tank detection. The third subfigure contrasts YOLOv5 models and EfficientDet in terms of accuracy and processing speed on the COCO dataset, emphasizing the trade-offs between speed and accuracy crucial for real-time applications. These examples underscore the sophistication and diversity of techniques available for addressing challenges in oil tank detection.

## 4.2 Challenges in Complex Backgrounds

Detecting oil tanks in ORSIs presents challenges due to complex backgrounds and varying object scales. Cluttered environments often obscure oil tanks, complicating their differentiation from surrounding structures or natural features [13]. Arbitrary orientations and diverse scales of objects further complicate detection, as traditional models frequently struggle to maintain accuracy under such conditions [14].

Advanced models like RRNet address these issues by incorporating relational reasoning and multi-scale attention mechanisms, enhancing focus on salient features while suppressing background noise [9]. Despite these advancements, variability in object appearance and dynamic backgrounds in remote sensing images remain significant hurdles for accurate detection.

Integrating contextual information within detection networks, as seen in CAD-Net, has shown promise in improving accuracy by leveraging both global and local context [13]. This approach aids in distinguishing oil tanks from complex backgrounds by utilizing additional cues not immediately evident in raw image data. However, developing robust models capable of consistently accurate detection in diverse and cluttered environments continues to be an active research area.

The variability in scale and orientation of oil tanks necessitates highly adaptable detection models that can capture features across multiple scales and orientations [14]. Techniques such as MFPNet address this need through multi-scale feature extraction methodologies, yet the challenge of maintaining high precision amidst complex backgrounds persists.

## 4.3 Hybrid AI/CV Systems

Hybrid systems integrating Artificial Intelligence (AI) and computer vision (CV) offer a promising strategy to enhance detection capabilities in remote sensing applications, particularly for oil tank monitoring. These systems leverage AI's advanced image processing capabilities, particularly through deep learning models, while incorporating the contextual and spatial awareness provided by CV techniques. This integration facilitates the development of robust detection frameworks adept at addressing the diverse challenges posed by ORSIs, such as varying object scales, complex backgrounds, and arbitrary orientations [1, 14].

By combining AI's capacity to learn intricate patterns with CV's contextual interpretation, hybrid systems achieve superior performance in identifying and monitoring oil tanks in remote sensing imagery [13]. A notable advantage is their ability to perform real-time pose estimation and tracking, as demonstrated in applications utilizing Intel Myriad X VPU [16]. This capability is crucial for dynamic monitoring scenarios, where timely and accurate detection is vital for effective decision-making. Additionally, hybrid systems facilitate the integration of multiple data sources, enhancing the ability to capture comprehensive environmental information [3].

The implementation of hybrid AI/CV systems also supports the development of novel detection models incorporating multi-scale and multi-modal data fusion techniques. By leveraging diverse datasets and integrating various detection methodologies, these systems can achieve higher precision and recall rates, particularly in challenging environments where traditional models may falter [12]. This approach not only enhances detection accuracy but also improves the system's adaptability to different remote sensing contexts.



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## 5 Applications and Case Studies

### 5.1 Impact on Environmental Monitoring and Management

AI and computer vision have revolutionized environmental monitoring and management through remote sensing, enabling precise detection and monitoring of environmental changes via high-resolution satellite imagery. Deep learning models have surpassed traditional methods, notably enhancing oil spill detection [5]. The integration of AI with remote sensing data has led to advancements in image classification, land cover mapping, and change detection, addressing issues of data quality and model interpretability, thus enhancing decision-making in agriculture, disaster management, and climate monitoring [17, 3, 7, 1, 4]. AI models facilitate land cover classification, deforestation tracking, and climate impact assessment, providing timely and precise information for resource management.

In marine environments, computer vision aids in detecting marine pollution and biodiversity changes. Advanced AI and machine learning techniques enable real-time monitoring of environmental phenomena, improving responses to threats like oil spills [8, 1, 15, 5, 4]. AI and computer vision have also fostered predictive models forecasting environmental changes, enhancing understanding of dynamic Earth systems and informing decision-making [2, 1, 7]. These models provide insights into future scenarios, supporting proactive environmental management.

AI and computer vision are transforming environmental monitoring by enhancing the accuracy and efficiency of data analysis. This transformation is evident in remote sensing applications for land cover mapping and change detection, which leverage AI methodologies to process complex datasets from diverse sources like LiDAR and hyperspectral imaging. AI-enabled UAVs further expand monitoring capabilities through precise navigation and data collection, leading to informed decision-making for sustainable resource management. As these technologies evolve, they address challenges related to data quality and model interpretability, paving the way for innovative solutions in environmental stewardship [3, 1].

### 5.2 Performance of AI Models in Oil Tank Detection

AI models, particularly deep learning, have significantly advanced oil tank detection, excelling in predictive accuracy in high-dimensional settings by modeling complex data interactions [11]. The Multi-Channel Graph Representation (MCGR) achieves state-of-the-art performance in oil tank detection, with a mean average precision of 0.746 for five-class detection, demonstrating deep learning's efficacy in handling ORSI complexities [12]. The Rotated Varied-Size Attention (RVSA) method has enhanced plain vision transformers' performance in remote sensing tasks, achieving state-of-the-art results in detection and competitive performance in classification and segmentation [8].

The Choquet Integral Multi-layer Perceptron (iChIMP) integrates explainable AI (xAI) to enhance model performance, approximating the Choquet integral and outperforming existing methods in accuracy. This model provides insights into learned decisions through xAI indices, making it valuable in oil tank detection where understanding model decisions is crucial [18]. Datasets like PatternNet have facilitated AI model evaluation in remote sensing image retrieval, with deep learning models generally outperforming handcrafted feature-based methods in retrieval accuracy [15]. This underscores deep learning techniques' potential to revolutionize oil tank detection, offering robust solutions that enhance accuracy and interpretability.

### 5.3 EarthNets Platform for Evaluation

The EarthNets platform advances AI model evaluation for remote sensing data, providing a standardized framework for assessing deep learning methodologies. It ensures fair and consistent evaluation across remote sensing tasks, addressing the need for benchmarking in this evolving field [4]. Offering comprehensive tools and datasets, EarthNets facilitates AI model comparisons, enabling systematic analysis of their effectiveness in tackling complex remote sensing challenges. Table 3 provides an overview of key benchmarks used in the EarthNets platform to evaluate AI models across various remote sensing tasks, highlighting the diversity in dataset sizes, domains, task formats, and evaluation metrics.

Benchmark	Size	Domain	Task Format	Metric
CVS-Benchmark[2]	5,000	Computer Vision	Image Classification	Confidence Score, Consistency Rate
NWPU-RESISC45[19]	31,500	Remote Sensing	Scene Classification	Overall Accuracy, Average Accuracy
RSSOD[12]	1,759	Remote Sensing	Object Detection	mAP@0.5
PatternNet[15]	30,400	Remote Sensing	Image Retrieval	ANMRR, mAP

Table 3: Table illustrating a selection of benchmarks utilized in the evaluation of AI models for remote sensing tasks. Each benchmark is characterized by its dataset size, domain specificity, task format, and the metrics employed for performance assessment. This provides a comprehensive overview of the diverse datasets and evaluation criteria essential for advancing AI methodologies in remote sensing.

EarthNets supports evaluating explainable AI (xAI) methods, crucial in remote sensing applications. A systematic review of xAI techniques highlights local approximation methods’ prevalence, well-suited for interpretability in remote sensing tasks [7]. EarthNets incorporates these methods, allowing for assessments of AI models’ accuracy and transparency. This platform fills a critical gap by providing a reliable benchmark for deep learning model performance, essential for advancing AI technologies in remote sensing. It facilitates rigorous testing and comparison of methodologies against standards, addressing limitations in existing datasets and promoting effective AI applications across remote sensing tasks like image classification and object detection [15, 1, 19]. By fostering transparency and consistency, EarthNets enhances AI-driven solutions’ reliability and applicability in environmental monitoring and management.

## 6 Challenges and Limitations

The deployment of artificial intelligence (AI) in remote sensing encounters several significant challenges that must be systematically addressed to enhance its effectiveness. This section examines three critical issues: data quality and diversity, model interpretability and transparency, and computational constraints, each of which significantly impacts the performance and reliability of AI-driven solutions in environmental monitoring and resource management.

### 6.1 Data Quality and Diversity

The efficacy of AI models in remote sensing largely depends on the quality and diversity of datasets used for training and evaluation. Current benchmarks often lack sufficient size and diversity, which hampers the development of innovative feature representations, particularly in deep learning methods that require extensive datasets [15]. This limitation is especially problematic in small object detection, where pooling operations may obscure critical details, thus affecting detection accuracy [10]. The challenge is further compounded by difficulties in distinguishing oil spills from lookalikes and the scarcity of comprehensive training databases, complicating marine environment monitoring [5]. The absence of unified benchmarks for fair comparisons further complicates the assessment of model performance due to variability in dataset quality and size.

Models like RRNet struggle in scenarios with complex shadows and high-contrast non-salient objects, highlighting the necessity for improved data quality and diversity to enhance model robustness [9]. Addressing these data-related challenges is crucial for developing reliable AI models capable of performing effectively across diverse remote sensing scenarios.

### 6.2 Model Interpretability and Transparency

Ensuring model interpretability and transparency is vital for reliable decision-making in remote sensing applications. The complexity of remote sensing data, combined with regulatory demands for transparency, often results in a "black box" phenomenon, where AI decision-making processes remain opaque to users and domain experts [7].

Inconsistencies in computer vision services further complicate the pursuit of interpretability, as these services can vary significantly over time, undermining reliability [2]. The computational complexity of explainable AI (xAI) methods, especially those integrating multiple data sources, can hinder

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scalability and practical application [18]. As data sources multiply, computational demands increase, complicating efforts to maintain transparency without sacrificing efficiency.

Deep learning models, central to remote sensing, face challenges such as model selection, potential overfitting, and the need for substantial computational resources [11]. These challenges can limit the generalization capabilities of AI models, complicating the interpretation of their decision-making processes across various datasets and scenarios. Models like MFPNet and CAD-Net reveal limitations in detecting certain object types, underscoring the need for advanced architectures that balance high accuracy with strong interpretability. This dual focus is essential for ensuring that AI decision-making processes are both effective and comprehensible, particularly in remote sensing, where explainable AI enhances understanding of model behavior and trust in automated systems [3, 2, 8, 7].

Improving interpretability and transparency in AI models is crucial for their effective deployment in environmental monitoring and management. By addressing behavioral consistency and transparency challenges, researchers can develop systems that achieve high accuracy while providing interpretable insights into decision-making processes. This transparency fosters trust and reliability in AI-driven solutions, especially in critical applications such as environmental monitoring, precision agriculture, and disaster management [3, 2, 1, 7].

### 6.3 Computational Constraints

The processing of high-resolution remote sensing data presents significant computational constraints that affect the efficiency and scalability of AI models. These constraints are primarily due to the substantial resources required to manage the vast volumes of data generated by high-resolution optical images. The complexity of deep learning models, essential for tasks like image classification and object detection, further exacerbates these challenges [11]. The extensive computational power and memory needed for training and deploying these models can restrict their applicability, particularly in resource-constrained environments.

The high-dimensional nature of remote sensing data necessitates sophisticated models capable of managing complex, nonlinear relationships [10]. The computational demands often result in prolonged processing times and increased energy consumption, which can be prohibitive for real-time applications. Additionally, integrating multiple data sources enhances model performance but also heightens computational complexity, requiring efficient data fusion techniques to manage the additional processing load [18].

Scalability issues emerge as computational requirements increase with the size and resolution of datasets, particularly in large-scale environmental monitoring applications where timely data processing and analysis are critical [16]. While specialized hardware accelerators like GPUs and TPUs can alleviate some constraints, their high costs and energy consumption present significant barriers to widespread adoption.

To address computational bottlenecks associated with high-resolution remote sensing data, the development of efficient algorithms and data structures is essential. Techniques such as data compression, parallel processing, and distributed computing can potentially reduce processing times and resource consumption. Optimizing machine learning models, particularly in computer vision services, requires careful evaluation of trade-offs between computational efficiency and model accuracy. Overly aggressive optimization may compromise critical information, leading to inconsistencies in model behavior and evolution risks, as highlighted by recent studies emphasizing the lack of transparency and documentation regarding these risks in intelligent services. Developers must navigate these challenges to create reliable and maintainable solutions that effectively leverage advancements in AI and machine learning [2, 7].

## 7 Future Directions

### 7.1 Advancements in AI Algorithms

Emerging AI algorithms promise enhanced capabilities in remote sensing, particularly for environmental monitoring and resource management. Integrating generative augmentation with geometric transformations can enrich training datasets, improving AI model training and performance by meeting the nuanced requirements of Earth Observation (EO) datasets [17]. Enhancing detection

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performance for small and oriented objects is another key focus. Utilizing features from lower convolutional layers and designing specialized operators can achieve more accurate localization, addressing current model limitations [10]. Incorporating additional spectral information and optimizing models for challenging examples can further enhance detection accuracy in complex scenarios [9].

Advanced remote sensing technologies and automatic detection models are crucial for improving accuracy across applications. Future research should explore integrating diverse detection methods to leverage complementary strengths, leading to robust systems capable of addressing diverse remote sensing challenges [5]. Establishing comprehensive, standardized benchmarks like PatternNet is vital for advancing remote sensing image retrieval (RSIR) research, providing a consistent framework for evaluating retrieval methods and facilitating effective AI model development [15, 10].

## 7.2 Integration of Diverse Data Sources

Integrating diverse data sources is essential for improving accuracy and robustness in remote sensing applications like oil tank monitoring. Combining ground-based sensors, aerial imagery, and social media data significantly enhances classification and detection capabilities, fostering a comprehensive understanding of environmental contexts [19]. This integration refines high-resolution optical image analysis and enables sophisticated models for precise oil tank identification and monitoring, improving oil spill detection and response strategies [10, 11, 6, 18, 5]. Social media data offers real-time insights and contextual information absent in traditional methods.

The synergy of these data sources facilitates advanced machine learning models that leverage each type's strengths, achieving higher accuracy and reliability in detection and monitoring. This approach enhances remote sensing applications by integrating advanced AI techniques, improving data analysis capabilities, and enabling informed decision-making in environmental monitoring and resource management through richer datasets and insights derived from complex data patterns [17, 12, 15, 1, 7].

## 7.3 Enhancing Model Interpretability and Robustness

Enhancing AI model interpretability and robustness is crucial for reliable decision-making in remote sensing. Future research should focus on developing robust evaluation metrics tailored for explainable AI (xAI) in remote sensing, addressing the unique characteristics of the data [7]. These metrics are vital for systematically assessing xAI methodologies' effectiveness and transparency, facilitating a better understanding of model behavior. Innovative xAI methodologies tailored to remote sensing's unique features, such as high spatial resolution and diverse sensor types, are essential for addressing challenges related to data quality, model interpretability, and domain expertise integration [15, 1, 4, 7].

Improving AI model robustness is equally critical, with strategies to ensure consistent performance across diverse environments addressing generalization and adaptability issues. Enhanced techniques like data augmentation, multi-source data integration, and domain-specific knowledge incorporation bolster AI model robustness, enabling effective management of variability and complexity in remote sensing data. These methods facilitate accurate analyses in Earth sciences, advancing AI capabilities in interpreting complex remote sensing imagery [17, 10, 7, 1, 4].

A multifaceted approach combining specialized xAI methodologies with strategies to improve model consistency and adaptability is essential for enhancing interpretability and robustness. Addressing data quality, model interpretability, and domain expertise integration significantly enhances AI model capabilities in remote sensing, improving data analysis techniques and contributing to reliable applications in Earth sciences, benefiting areas like disaster monitoring, climate change assessment, and precision agriculture [3, 4, 1, 7].

## 8 Conclusion

The integration of Artificial Intelligence (AI) and computer vision into remote sensing has profoundly enhanced monitoring capabilities, particularly in the context of oil tank surveillance. Employing AI methodologies such as deep learning and explainable AI has markedly advanced image analysis and object detection, yielding improved precision in interpreting high-resolution optical remote sensing images (ORSIs). These advancements are further bolstered by computer vision techniques, which

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offer sophisticated tools for analyzing complex visual data, thereby ensuring accurate identification and continuous monitoring of oil tanks.

The significance of high-resolution satellite imagery in environmental monitoring and resource management is underscored through its application in both terrestrial and marine domains. AI and computer vision have expanded the scope of remote sensing, enabling the detection and evaluation of environmental changes with exceptional precision. This technological synergy facilitates the development of predictive models and supports real-time monitoring, thereby refining decision-making processes in environmental management.

Despite these advancements, challenges remain, including issues related to data quality, model interpretability, and computational limitations. Addressing these challenges is imperative for the sustained progress of AI-enhanced remote sensing applications. Future research endeavors should prioritize the refinement of AI algorithms, the integration of diverse data sources, and the enhancement of model interpretability and robustness, ensuring continued innovation and efficacy in this field.

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