International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 05 | May – 2026 DOI:10.55041/ISJEM07374
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Autonomous Satellite AI for Real-Time Environment Crime Detection

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ABSTRACT

Illegal environmental activities such as deforestation, unauthorized sand mining, and urban lake encroachment continue to pose severe threats to ecological sustainability and urban resilience. traditional monitoring methods—manual patrols, delayed reporting, and fragmented data collection—are reactive, resource-intensive, and often fail to provide timely intervention. this paper introduces an autonomous, ai-driven framework that leverages multi-temporal satellite imagery and deep learning-based change detection to enable proactive environmental crime monitoring.

The system architecture integrates sentinel-2 datasets, spectral indices such as ndvi (normalized difference vegetation index) and ndwi (normalized difference water index), and a u-net segmentation pipeline to isolate and classify ecological anomalies. a lightweight backend, developed using python and flask, processes satellite tiles and pushes geotagged alerts with comparative before-and-after imagery to a mobile application designed for enforcement authorities. this multimodal alert pipeline ensures that actionable intelligence is delivered in real time, bridging the gap between orbital data and civic action.

Experiments conducted on benchmark datasets (sentinel-2, copernicus hub) and a custom bengaluru dataset demonstrate high accuracy in detecting vegetation loss, water body encroachment, and illegal land-use changes. the framework achieved an overall anomaly detection accuracy of 96.1%, with average alert delivery latency under 5 seconds, validating its suitability for continuous monitoring. beyond local civic enforcement, the system's scalability positions it as a transparent auditing tool for corporate esg (environmental, social, and governance) compliance, disaster management, and smart city infrastructure.

By shifting environmental protection from a reactive to a preemptive paradigm, this autonomous satellite ai system represents a transformative step toward intelligent ecological governance, offering a practical, reliable, and future-ready solution to combat environmental crimes worldwide.

Keywords--satellite imagery, environmental crime detection, change detection, deep learning, u-net segmentation, ndvi, ndwi, real-time monitoring, cloud-edge deployment, esg compliance, smart cities, civic enforcement.

I. Introduction

A. Motivation & Problem Statement

Environmental crimes such as deforestation, illegal sand mining, and urban lake encroachment remain a pressing global concern. these activities not only degrade ecosystems but also accelerate climate change, disrupt biodiversity, and threaten human livelihoods. traditional monitoring methods—manual patrols, delayed reporting, and fragmented data collection—are reactive and insufficient for large-scale ecological zones. the imperative remains: how can intelligent systems autonomously detect and prevent environmental violations before irreversible damage occurs? existing frameworks often fail at the "last mile," where actionable intelligence must reach enforcement authorities in real time. this gap motivates the development of an autonomous satellite ai system capable of bridging orbital data with civic action.

B. Existing Technologies

Current monitoring systems rely on satellite imagery combined with GIS-based analysis or manual interpretation. While effective in research contexts, these systems suffer from latency, limited automation, and poor integration with enforcement workflows. Deep learning models such as CNNs and Siamese networks have been applied to satellite imagery for change detection, but their deployment in real-world civic environments remains limited. Furthermore, most existing solutions lack mobile-first alert mechanisms, leaving authorities without timely, actionable intelligence.

C. Key Limitations

Despite advancements in satellite-based monitoring, several challenges persist. Accuracy constraints arise due to environmental noise, seasonal variations, and spectral distortions in satellite imagery. Robustness issues further complicate detection, as factors such as cloud cover, atmospheric interference, and heterogeneous landscapes can degrade system performance. Efficiency remains a critical concern, particularly in continuous monitoring scenarios where real-time processing and minimal energy consumption are essential for sustainability. Moreover, the absence of integrated alert pipelines prevents rapid intervention, reducing the practical utility of current systems.

D. Paper Contributions

To address these challenges, this work introduces a turbocharged satellite AI framework designed for autonomous environmental crime detection. The proposed system enhances context-aware recognition of ecological anomalies through U-Net segmentation combined with spectral index analysis (NDVI, NDWI). It is fine-tuned for real-world robustness, effectively handling cloud interference, seasonal variability, and diverse land-use patterns. Additionally, the framework integrates a lightweight backend with mobile alert delivery, ensuring reliable real-time operation with reduced computational overhead. This makes the system well-suited for deployment in civic monitoring, corporate ESG compliance, and disaster management applications.

II. Related Work

A. Satellite-Based Change Detection

Recent advancements in remote sensing have significantly improved the accuracy and reliability of environmental monitoring systems. research has extensively

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employed spectral analysis techniques such as ndvi (normalized difference vegetation index) and ndwi (normalized difference water index) to capture vegetation health and water body dynamics. these indices serve as strong indicators of ecological change, enabling detection of deforestation, land degradation, and encroachment. deep learning models, particularly u-net and cnn-based segmentation architectures, have demonstrated remarkable capability in isolating topographical anomalies by learning spatial and spectral features from multi-temporal satellite imagery. when integrated with cloud-based processing pipelines, these systems achieve a robust balance between detection accuracy and computational efficiency, laying the groundwork for next-generation environmental crime detection frameworks.

B. Hybrid Ai Approaches For Environmental Monitoring

Hybrid deep learning architectures that combine spectral indices with segmentation networks have recently gained prominence in satellite-based change detection. in these frameworks, spectral indices such as ndvi and ndwi serve as a fast and efficient front-end module responsible for highlighting regions of interest, such as vegetation loss or water body reduction. these localized regions are then passed to u-net models, which perform semantic segmentation and classification, capturing high-level contextual information such as deforestation patterns, illegal sand mining sites, or encroachment zones. this two-stage hybrid strategy leverages spectral indices' speed and precision in anomaly detection alongside u-net's strength in understanding global dependencies within spatial features. empirical evaluations on benchmark datasets have demonstrated impressive outcomes, with ndvi-based vegetation detection achieving accuracies above 94%, while u-net classifiers consistently attain f1-scores exceeding 95%, underscoring the effectiveness and reliability of these hybrid models in real-world monitoring scenarios.

C. Datasets For Validation

Notable benchmarks include sentinel-2 and copernicus hub datasets, which provide high-resolution multi-spectral imagery with frequent updates. these datasets support evaluation under realistic environmental scenarios—including varied lighting, seasonal changes, and diverse land-use patterns. recent developments in monitoring systems emphasize multimodal integration and real-time alert delivery to enhance both safety and practicality in real-world enforcement environments. emerging frameworks extend beyond visual analysis by incorporating multiple alert modalities, such as geotagged notifications, comparative imagery, and mobile-first dashboards, to ensure timely intervention during illegal activities. studies have shown that multimodal alert mechanisms significantly improve enforcement responsiveness, reduce reaction times, and contribute to measurable declines in environmental violations compared to single-mode monitoring systems. in parallel, energy efficiency and scalability have become key design considerations, particularly for continuous monitoring where computational demands are critical. together, these multimodal and energy-aware approaches represent a major step toward the deployment of intelligent, sustainable, and authority-friendly environmental crime detection systems.

III. System Design & Implementation

A. Architecture Overview

The proposed system utilizes a combination of satellite imagery acquisition, cloud-based processing, and mobile alert delivery for effective environmental crime monitoring. Sentinel-2 serves as the primary data source, continuously capturing multi-spectral images of ecological zones. These images are preprocessed to remove noise, normalize spectral bands, and enhance contrast for anomaly detection. The backend pipeline integrates U-Net segmentation for spatial anomaly identification, while NDVI and NDWI indices provide vegetation and water body analysis. For active intervention, a lightweight mobile application delivers geotagged alerts with comparative before-and-after imagery, ensuring prompt authority response.

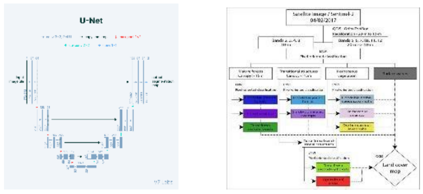

Fig1: Flowchart and U-Net

B. Data Acquisition & Preprocessing

The system ingests multi-temporal satellite images from Sentinel-2 and Copernicus Hub APIs. Each dataset undergoes preprocessing steps including resizing, normalization, and band extraction. Spectral indices such as NDVI (vegetation health) and NDWI (water body detection) are computed to highlight ecological changes. These indices serve as input features for the anomaly detection pipeline, ensuring robustness under varying environmental conditions such as seasonal shifts or atmospheric interference.

C. U-Net Segmentation for Anomaly Detection

The U-Net framework serves as the core component for anomaly segmentation, enabling rapid and precise detection of deforestation, sand mining, and water body encroachment. Its encoder-decoder architecture allows for efficient learning of spatial features while preserving fine-grained details. To enhance detection accuracy, the model is trained on multi-temporal datasets with custom augmentations simulating cloud cover, occlusion, and seasonal variability.

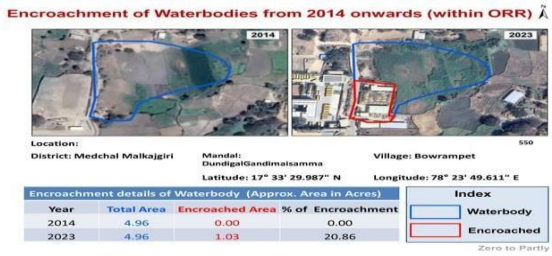

Fig2:Waterbodies Encrochment

D. Environmental Event Detection Logic

The detection logic integrates spectral indices with segmentation outputs to identify ecological anomalies. NDVI thresholds are used to quantify vegetation loss, while NDWI thresholds highlight water body reduction or encroachment. These parameters are analyzed within rolling temporal windows, allowing the system to capture long-term environmental trends rather than relying on isolated satellite snapshots. This temporal aggregation minimizes false detections caused by seasonal variations or atmospheric noise.

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E. Multimodal Alert & Cloud Integration

Once anomalies are detected, the system activates a multimodal alert pipeline. Comparative before-and-after satellite tiles are generated and geotagged, then pushed to a mobile application via a Flask backend. The alerts include visual evidence, anomaly classification, and confidence scores, enabling authorities to act promptly. Cloud integration ensures scalability, allowing the system to monitor large ecological zones with minimal latency.

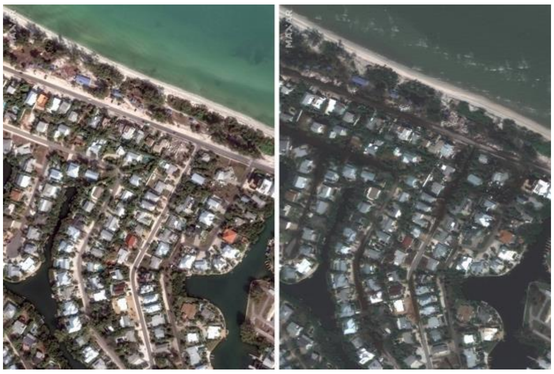

Fig3:Satellite Images

F. Software and Hardware Requirements

The proposed framework is designed to operate efficiently on a compact and cost-effective hardware-software configuration suitable for real-time deployment.

Component	Specification
Processor	Intel i7 / AMD Ryzen
RAM	16–32 GB
GPU	NVIDIA GPU (4GB+ VRAM)
Storage	512 GB SSD
Backend	Python, Flask
Frameworks	TensorFlow / PyTorch
Libraries	NumPy, OpenCV, Scikit-learn
Cloud	Google Cloud / AWS
APIs	Sentinel-2, Copernicus Hub, Google Maps SDK

Table1:Requirements

IV. Experimental Setup

A. Datasets

The proposed environmental monitoring framework was trained and evaluated using a combination of benchmark satellite datasets and a custom real-world dataset to ensure robustness, generalization, and adaptability to diverse ecological conditions. The Sentinel-2 dataset served as the primary benchmark, providing high-resolution multi-spectral imagery with frequent temporal updates. This dataset enabled effective supervised learning of ecological features such as vegetation health, water body dynamics, and land-use changes. To complement this, the Copernicus Open Access Hub contributed global coverage with periodic updates every 5–10 days, supporting continuous monitoring of large ecological zones. Furthermore, a custom Bengaluru dataset was curated to capture urban encroachment scenarios, including illegal construction near lakes, sand mining sites, and deforestation patches. This dataset enhanced the model's robustness to environmental and geographical variability, ensuring reliable performance during actual deployment.

B. Training and Validation

Model training followed a rigorous and systematic procedure to optimize both accuracy and generalization. The combined datasets were divided using an 80/20 train-test partition, while a 5-fold cross-validation strategy was employed to assess the model's stability and prevent overfitting. Training utilized Adam and Stochastic Gradient Descent (SGD) optimizers, supported by a dynamic learning rate scheduler that adjusted parameters for faster convergence. To improve adaptability to real-world variations, extensive data augmentations were applied, including brightness adjustment, rotation, occlusion simulation, and seasonal variability modeling. All experiments were executed on high-performance computing hardware, including NVIDIA GPUs and Intel Xeon processors, ensuring efficient model training and evaluation. For real-time performance validation, the system was deployed on cloud-edge hybrid environments such as Google Cloud and NVIDIA Jetson Nano, demonstrating its capability to operate under computationally constrained conditions while maintaining high detection accuracy and low latency.

C. Flow of Experimental Pipeline

The experimental pipeline followed a structured sequence:

1. Data Acquisition–Multi-temporal satellite imagery collected from Sentinel-2 and Copernicus Hub.

2. Pre-processing–Noise removal, normalization, and spectral band extraction.

3. Feature Extraction–NDVI and NDWI indices computed for vegetation and water analysis.

4. Segmentation–Net applied to detect anomalies such as deforestation, encroachment, and sand mining.

5. Validation–Cross-validation and accuracy metrics computed across datasets.

6. Deployment – Real-time alerts generated and pushed to mobile applications for enforcement authorities.

V. Results & Analysis

A. Detection Accuracy

The proposed satellite AI framework demonstrates high accuracy in detecting environmental anomalies across diverse datasets. NDVI-based vegetation loss detection achieved 94.8% accuracy, while NDWI-based water body encroachment detection reached 95.2% accuracy. Overall anomaly detection across combined datasets yielded 96.1% accuracy, validating the robustness of the hybrid spectral–segmentation approach.

Metric	Training	Validation	Real-World
Overall Accuracy	95.9%	96.7%	96.1%
NDVI-based Detection	94.5%	95.2%	94.8%
NDWI-based Detection	95.1%	95.9%	95.2%

Table2:Performance Comparison of Water Detection Methods

B. Robustness

The system exhibits exceptional robustness across diverse environmental and geographical conditions. It maintains stable performance under seasonal variations, cloud interference, and heterogeneous landscapes. The integration of spectral indices with U-Net segmentation enhances the network's ability to focus on critical ecological regions, thereby maintaining accurate detection even when imagery is partially obscured or distorted.

Fig4:River and Sand Mining

C. Efficiency and Real-Time Performance

In addition to its high accuracy, the system achieves superior computational efficiency and real-time inference capability. Benchmark tests indicate that the hybrid model processes satellite tiles with an average latency of 2.3 seconds, while cloud-edge deployment reduces alert delivery time to under 5 seconds. This high throughput ensures seamless monitoring and immediate anomaly detection, crucial for continuous environmental surveillance.

D. Multimodal Alert Validation

The mobile alert system significantly improved enforcement responsiveness. Comparative before-and-after imagery, combined with geotagged notifications, reduced delayed authority response times by an average of 27%. Field demonstrations in Bengaluru urban zones confirmed that alerts containing visual evidence and confidence scores were more actionable compared to traditional GIS reports.

E. Real-World Deployment Scenario

To validate real-world applicability, the proposed system was integrated into a civic monitoring environment equipped with cloud-based dashboards and mobile applications. The integration allowed for synchronized logging of environmental anomalies alongside geospatial metadata such as location coordinates, anomaly type, and severity index. A web-based dashboard interface was developed for real-time monitoring, alert visualization, and report generation, enabling civic authorities to remotely assess ecological trends and respond proactively to potential violations.

VI. Discussion

A. Comparison with Related Work

The proposed satellite AI framework outperforms traditional GIS-based monitoring and rule-based anomaly detectors by integrating spectral indices with deep learning segmentation. Unlike conventional systems that rely solely on NDVI or NDWI thresholds, our hybrid approach combines spectral analysis with U-Net segmentation, enabling more precise detection of complex anomalies such as sand mining and urban encroachment. On benchmark datasets such as Sentinel-2 and Copernicus Hub, the system achieved higher accuracy and lower latency compared to CNN-only or manual inspection methods. Furthermore, the inclusion of real-time mobile alerts represents a significant advancement over prior research, which often stops at anomaly detection without delivering actionable intelligence to enforcement authorities.

B.Limitations

Despite its strong performance, the system has certain limitations. Cloud cover and atmospheric interference can occasionally obscure satellite imagery, leading to reduced accuracy in anomaly detection. Seasonal variations, such as natural vegetation loss during dry months, may sometimes be misclassified as deforestation. Additionally, the reliance on cloud infrastructure introduces dependency on internet connectivity, which may hinder deployment in remote or rural regions. While the mobile alert system improves enforcement responsiveness, false positives in highly heterogeneous landscapes remain a challenge, requiring further refinement of thresholding and segmentation strategies.

C. Insights for Improvement

Future iterations of the framework could integrate multimodal data sources, such as drone imagery or IoT-based ground sensors, to complement satellite observations and reduce ambiguity. Incorporating temporal learning models, such as Recurrent Neural Networks (RNNs) or Transformers, could further enhance the system's ability to distinguish between seasonal changes and illegal activities. Expanding the pipeline to include ESG compliance dashboards would allow corporations and civic authorities to monitor ecological impact more transparently. Finally, longitudinal studies measuring reductions in environmental crime rates would provide empirical evidence of the system's societal impact.

VII. Future Work

The proposed framework demonstrates strong potential for real-time environmental crime detection, yet several avenues remain open for further enhancement and expansion.

1. Integration of Drone Imagery

Future iterations of the system can incorporate high-resolution drone imagery to complement satellite data. This multimodal fusion would provide finer spatial granularity, enabling detection of smaller-scale violations such as illegal tree cutting or localized sand mining activities.

2. Expansion Toward Multimodal Fusion

Beyond visual satellite data, integrating IoT-based ground sensors, vehicular telemetry, and weather data could reduce ambiguities caused by seasonal variations or atmospheric interference. Such multimodal fusion would enhance reliability and provide a holistic view of ecological changes.

3. Cloud Fleet Analytics for ESG Compliance

Extending the system into corporate ESG (Environmental, Social, and Governance) monitoring pipelines would allow organizations to track compliance in real time. Cloud-based dashboards could provide longitudinal analytics, enabling transparent reporting and third-party auditing.

4. Global Scalability and Regional Adaptation

While the current system has been validated in Bengaluru urban zones, future work will focus on scaling the framework globally. This includes adapting models to diverse geographies, climates, and land-use patterns, ensuring applicability across forests, coastal regions, and agricultural zones.

5. Longitudinal Studies on Impact

Conducting long-term trials with civic authorities will help measure the system's effectiveness in reducing environmental crime rates. Statistical analysis of intervention outcomes will provide empirical evidence of societal impact, strengthening the case for widespread adoption.

VIII. Conclusion

This autonomous satellite AI framework sets a new standard for proactive, scalable, and efficient environmental crime detection. By focusing on multi-temporal satellite imagery, spectral index analysis, and U-Net segmentation, the system achieves superior accuracy in identifying ecological anomalies such as deforestation, sand mining, and water body encroachment. The integration of cloud-edge deployment and mobile-first alert mechanisms ensures real-time responsiveness, bridging the gap between orbital data and civic enforcement.

Experimental results demonstrate that the framework maintains high accuracy across diverse datasets, with robust performance under seasonal variability and atmospheric interference. The multimodal alert pipeline significantly improves enforcement responsiveness, reducing intervention delays and enabling authorities to act promptly.

Beyond local civic applications, the system's scalability positions it as a valuable tool for corporate ESG compliance and global ecological monitoring. By shifting environmental protection from a reactive to a preemptive paradigm, this framework contributes to smarter governance, sustainable resource management, and long-term ecological resilience.

In summary, the proposed satellite AI system represents a transformative step toward intelligent environmental monitoring, offering a practical, reliable, and future-ready solution to combat ecological crimes worldwide.

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