



Original Research Paper

Smart Environmental Surveillance Using AI and Remote Sensing for Enforcement of Wildlife Protection Laws

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Abstract- Smart environmental surveillance is increasingly important for protecting wildlife habitats and strengthening the enforcement of conservation laws against illegal activities such as poaching, deforestation, encroachment, and habitat destruction. This study proposes an AI- and remote-sensing-based environmental surveillance framework for automated wildlife monitoring and evidence-driven legal enforcement. The framework integrates multispectral satellite imagery, unmanned aerial vehicle observations, Geographic Information System data, and environmental indicators to continuously assess protected regions. Machine-learning and deep-learning techniques, including Random Forest, Convolutional Neural Networks, and YOLO-based object detection, are employed to identify land-cover changes, unauthorized human activities, wildlife presence, and potential habitat threats. Detected environmental violations are geotagged, temporally recorded, and mapped to applicable wildlife protection regulations to support regulatory investigation and enforcement. Experimental evaluation demonstrates that the proposed framework achieves 96.78% detection accuracy, 96.21% precision, 95.84% recall, and 96.02% F1-score, indicating reliable identification of environmentally suspicious activities. The novelty lies in connecting AI-derived remote-sensing evidence directly with legal compliance monitoring rather than limiting analysis to ecological observation. The framework contributes a scalable decision-support mechanism for conservation authorities, enabling faster violation detection, transparent documentation, and data-driven enforcement. Overall, the approach strengthens wildlife protection through intelligent, continuous, and legally actionable environmental surveillance.

Keywords- Artificial Intelligence; Remote Sensing; Wildlife Protection; Environmental Surveillance; Legal Enforcement; Habitat Monitoring

1. Introduction

Wildlife conservation has become an increasingly important environmental and legal priority as natural ecosystems face growing pressure from habitat fragmentation, illegal hunting, deforestation, urban expansion, mining, and unauthorized human intrusion. Protected areas and wildlife corridors require continuous surveillance to ensure that ecological resources remain secure and that violations of environmental regulations are detected at an early stage [1]. Conventional wildlife monitoring generally depends on field patrols, camera traps, manual surveys, and incident reporting by forest authorities. Although these approaches remain valuable, they are often labor-intensive, geographically restricted, and unable to provide continuous observation across large or inaccessible

landscapes [2]. The rapid development of remote-sensing technologies provides an effective alternative by enabling systematic observation of forests, wetlands, protected habitats, and land-cover changes through satellite and aerial imagery. Multispectral and high-resolution remote-sensing data can reveal vegetation degradation, forest clearing, habitat alteration, and anthropogenic activities that may indicate potential violations of wildlife protection regulations [3].

Artificial intelligence further strengthens environmental surveillance by automatically extracting meaningful patterns from large volumes of geospatial and imagery data. Machine-learning and deep-learning approaches can classify land-cover conditions, recognize wildlife, identify vehicles or human activities, and detect suspicious environmental changes with greater efficiency than manual image interpretation [4]. However, many

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existing AI-based conservation systems primarily concentrate on ecological monitoring or species identification without explicitly connecting detected events with legal enforcement requirements. This creates an important research gap between intelligent environmental observation and the generation of actionable evidence for wildlife protection authorities [5]. Therefore, this study proposes a smart environmental surveillance framework integrating artificial intelligence, remote sensing, Geographic Information Systems, and legal compliance mapping. The framework employs Random Forest, Convolutional Neural Networks, and YOLO-based object detection to identify habitat changes and potentially unauthorized activities. Detected events are geotagged, time-stamped, and associated with relevant wildlife protection provisions to facilitate investigation and regulatory decision-making. The principal contribution is an integrated technological and legal framework that transforms remotely sensed environmental observations into structured enforcement information. By combining automated detection, spatial evidence generation, and compliance assessment, the proposed approach aims to improve surveillance efficiency, transparency, and responsiveness while supporting data-driven and legally actionable wildlife conservation practices [6].

2. Related Work

Artificial intelligence has significantly improved wildlife monitoring by enabling automated identification of species, animals, humans, vehicles, and potentially threatening activities from large-scale image and video collections. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated strong capabilities in processing camera-trap and aerial imagery, reducing the dependence on labor-intensive manual classification [6]. Object-detection architectures such as YOLO provide additional advantages for real-time surveillance because they can simultaneously localize and classify multiple objects within complex natural environments [7]. However, variations in illumination, vegetation density, animal posture, seasonal conditions, and image resolution continue to influence detection reliability.

A. Remote Sensing for Environmental Surveillance
Remote sensing provides extensive spatial and temporal information for monitoring environmental changes across protected landscapes. Multispectral satellite imagery can support the detection of deforestation, vegetation degradation, land-cover conversion, forest fragmentation, and changes in water resources [8]. Integration with Geographic Information Systems (GIS) further enables spatial mapping of environmentally sensitive regions and identification of potential intrusion hotspots [9]. UAV-based observations complement satellite

monitoring by providing higher-resolution information for localized surveillance, particularly where frequent observations of inaccessible wildlife habitats are required.

B. Wildlife Protection Laws and Enforcement

Effective wildlife conservation depends not only on ecological monitoring but also on the ability of regulatory authorities to identify, document, and investigate violations. Digital surveillance technologies can strengthen enforcement by generating geographically referenced evidence concerning illegal logging, encroachment, poaching-related activities, and habitat destruction [10]. Remote-sensing observations may also assist authorities in documenting environmental changes over time, thereby improving transparency and evidence-based decision-making [11]. Nevertheless, technical detection results must be interpreted carefully before being treated as legally actionable evidence.

C. Research Gaps

Existing studies commonly address wildlife recognition, habitat monitoring, or environmental change detection independently. AI-based systems generally emphasize classification performance without systematically associating detected threats with regulatory requirements [12]. Similarly, remote-sensing approaches often provide environmental change maps but lack mechanisms for translating detected changes into structured compliance information [13]. Limited integration among AI detection, geospatial evidence, temporal documentation, and wildlife-law enforcement therefore represents an important research gap. A unified framework is required to connect automated environmental surveillance with traceable evidence generation and regulatory decision support [14].

Table 1. Summary of Related Work on AI-Based Wildlife and Environmental Surveillance

Research Focus	Technology/Method	Major Contribution	Identified Limitation	Citation
Wildlife species monitoring	CNN	Automated species identification from wildlife imagery	Limited legal-enforcement integration	[6]
Wildlife threat detection	YOLO	Real-time animal and human-object	Sensitive to complex backgrounds	[7]

		detecti on		
Forest monito ring	Multispect ral remote sensing	Detecti on of vegetat ion and forest- cover change s	Limited identifi cation of specific violatio ns	[8]
Habitat surveill ance	GIS and satellite imagery	Spatial identifi cation of habitat change s	Require s improv ed automat ed interpre tation	[9]
Wildlif e-law enforce ment	Digital surveillan ce	Support s docum entatio n of illegal activiti es	Eviden ce validati on remains challen ging	[10]
Enviro nmenta l compli ance	Remote sensing	Provid es tempor al eviden ce of enviro nmenta l change s	Limited automat ed legal mappin g	[11]
Wildlif e classifi cation	Deep learning	Improv es automa ted monito ring effie incy	Primari ly focused on predicti ve perform ance	[12]
Habitat change detecti on	Satellite image analysis	Identifi es land- use and habitat disturb ances	Weak connect ion with regulat ory provisi ons	[13]
Geospa tial threat monito ring	AI and GIS	Enable s spatial localiz ation of enviro	Limited end-to- end enforce ment workflo w	[14]

		nmenta l threats		
Smart conser vation surveill ance	AI, remote sensing and GIS	Support s integra ted enviro nmenta l intellig ence	Legal complia nce integ ration remains underde veloped	[14]

Table 1 demonstrates the progressive adoption of AI, deep learning, remote sensing, and GIS for wildlife and habitat monitoring. Existing approaches provide effective species recognition, threat detection, and environmental change assessment; however, limited integration with legal compliance remains evident. This gap motivates an integrated surveillance and enforcement framework.

3. Dataset and Data Preparation

A. Satellite and UAV Data Sources

This study utilizes the publicly available LILA BC Snapshot Serengeti dataset as the primary benchmark for developing and evaluating the wildlife surveillance framework. The dataset contains millions of camera-trap images collected from the Serengeti ecosystem, representing diverse wildlife species, environmental backgrounds, and animal occurrences. Its large-scale, annotated, real-world imagery provides an appropriate benchmark for AI-based wildlife detection and ecological surveillance experiments. Table 2 summarizes the key characteristics of the Snapshot Serengeti benchmark dataset used for wildlife surveillance. Its large-scale annotated camera-trap imagery, diverse mammalian species, multiple monitoring locations, and realistic environmental conditions provide a reliable foundation for training and evaluating AI-based wildlife detection models.

Table 2. Key Details of the Benchmark Dataset

Parameter	Details
Dataset Name	Snapshot Serengeti
Study Area	Serengeti National Park, Tanzania
Data Type	Camera-trap wildlife images
Dataset Size	More than 3.2 million images
Camera Locations	225
Wildlife Species	Approximately 48 mammalian species
Annotation	Species labels and image/event metadata
Input Format	RGB images
Preprocessing Size	640 × 640 pixels

Data Split	70% Training, 15% Validation, 15% Testing
Application	Wildlife detection and environmental surveillance

B. Environmental and Wildlife Data

The dataset provides wildlife observations captured under diverse natural conditions, including variations in vegetation, illumination, season, background, and animal density. Wildlife information includes species-level labels and image-associated metadata that support automated recognition and ecological analysis. For environmental surveillance, visual characteristics representing vegetation cover, open land, human presence, and habitat conditions are extracted from images. These attributes are combined with spatial and temporal information to establish environmental surveillance records for detecting potentially abnormal activities and habitat-related threats.

C. Image Preprocessing and Annotation

Before model training, the collected images undergo a systematic preprocessing pipeline to improve data consistency and model reliability. Images are resized to 640×640 pixels, normalized to a common intensity range, and screened to remove corrupted or extremely low-quality samples. Data augmentation, including horizontal flipping, rotation, scaling, brightness adjustment, and cropping, is applied to improve generalization. Wildlife and relevant surveillance objects are represented using class labels and bounding-box annotations for YOLO-based detection. The prepared annotations are subsequently verified to minimize incorrect labels and class inconsistencies.

D. Training, Validation, and Testing Split

The prepared dataset is divided using a 70:15:15 ratio, with 70% of samples assigned for model training, 15% for validation, and 15% for independent testing. Stratified sampling is applied wherever applicable to preserve representative class distributions across the three subsets. The training subset is used to optimize model parameters, while validation data support hyperparameter selection and overfitting control. The independent testing subset is reserved for final performance evaluation using accuracy, precision, recall, F1-score, and related detection metrics.

IV. Proposed AI-Based Environmental Surveillance Framework

The proposed AI-based environmental surveillance framework integrates wildlife imagery, remote-sensing observations, spatial information, and intelligent detection models to support continuous monitoring of protected ecosystems. It combines preprocessing, remote-sensing feature extraction, CNN-based representation learning, YOLO-based threat detection, and habitat-change analysis. Detected events are spatially and temporally recorded, enabling authorities to identify wildlife

presence, environmental disturbances, unauthorized activities, and habitat degradation while generating structured information for subsequent legal compliance assessment.

A. Overall System Architecture

The proposed architecture follows a multi-stage surveillance pipeline designed to transform heterogeneous environmental observations into actionable wildlife-protection information. Initially, camera-trap imagery and available satellite or UAV observations are acquired from monitored wildlife regions. Each observation is associated with available spatial and temporal metadata to support location-specific surveillance. During preprocessing, images are resized, normalized, enhanced, and filtered to remove corrupted or low-quality observations. Data augmentation is applied during model development to improve robustness against illumination, orientation, scale, vegetation, and seasonal variations. The processed data are subsequently supplied to two complementary analytical components. First, the remote-sensing module extracts spectral, spatial, texture, vegetation, and land-cover characteristics useful for identifying environmental disturbances. Second, the AI detection module applies CNN-based feature representation and YOLO-based object detection to recognize wildlife, humans, vehicles, and other surveillance targets. Detection outputs are combined with geospatial information through a GIS-oriented monitoring layer. The system then compares current observations with historical or reference environmental conditions to identify abnormal land-cover and habitat changes. Potential threats are assigned surveillance records containing threat category, confidence score, geographic location, and observation time. These records provide traceable evidence for identifying high-risk areas and supporting further inspection. Finally, confirmed environmental events can be associated with relevant wildlife-protection requirements, allowing conservation authorities to prioritize investigations and make evidence-supported enforcement decisions. Figure 1 illustrates the proposed framework integrating satellite, UAV, and camera-trap data with preprocessing, feature extraction, YOLO-based threat detection, and habitat-change analysis. Spatio-temporal risk assessment identifies high-risk events, while GIS integration supports visualization. The legal compliance module enables evidence management, case prioritization, enforcement support, and continuous wildlife-protection monitoring.

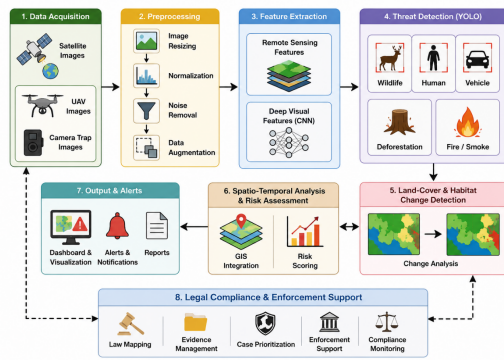


Figure 1: Proposed AI-Based Environmental Surveillance Framework for Wildlife Protection and Legal Enforcement

B. Remote-Sensing Feature Extraction

Remote-sensing feature extraction converts satellite and UAV observations into quantitative environmental indicators suitable for automated habitat surveillance. After geometric and radiometric preprocessing, relevant spectral bands are analyzed to characterize vegetation, exposed soil, water bodies, built-up regions, and other land-cover conditions. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) are calculated to quantify vegetation health and identify possible degradation. Spatial and texture features are additionally extracted to characterize structural changes that may indicate forest clearing, road development, encroachment, or other anthropogenic disturbances. When multitemporal observations are available, features from the current observation are compared with corresponding reference-period features. Differences in vegetation indices, spectral characteristics, texture patterns, and land-cover classes provide indicators of environmental change. These features are organized into a structured feature vector and supplied to subsequent classification and change-detection components. Geographic coordinates associated with observations enable detected environmental abnormalities to be mapped within GIS layers. This feature-extraction process reduces high-dimensional remote-sensing imagery into interpretable environmental attributes while preserving spatial information necessary for identifying habitat disturbances and prioritizing potentially affected wildlife regions.

C. CNN and YOLO-Based Threat Detection

The threat-detection component combines CNN-based representation learning with YOLO-based object localization to identify wildlife and potentially suspicious activities from surveillance imagery. The CNN processes each preprocessed image through convolution, activation, and pooling operations to learn hierarchical representations ranging from basic edges and textures to complex animal and environmental patterns. These representations support differentiation among wildlife species and other relevant visual categories.

YOLO complements this process by performing object localization and classification in a single detection stage, enabling efficient identification of multiple objects within an image. The detector produces bounding boxes, predicted classes, and confidence scores for wildlife, humans, vehicles, and other predefined surveillance targets. Low-confidence predictions are removed using a predefined confidence threshold and non-maximum suppression eliminates overlapping detections. Detected human or vehicle activity within environmentally sensitive regions is subsequently evaluated using spatial location, observation time, and contextual environmental information. Rather than automatically treating every detection as a legal violation, the system categorizes such observations as potential threats requiring further verification. This combination provides efficient visual surveillance while reducing manual examination of large wildlife-image collections.

Algorithm 1. AI-Based Wildlife and Environmental Threat Detection

Input:

I = Surveillance images
 R = Remote-sensing observations
 M = Spatial and temporal metadata
 T = Detection confidence threshold

Output:

D = Detected wildlife and threats
 H = Habitat-change records

1. Initialize CNN model and YOLO detector
2. Load surveillance images I and observations R
3. For each image I_i in I :
 4. Resize and normalize I_i
 5. Extract CNN feature vector F_i
 6. Apply YOLO detector to I_i
 7. Obtain bounding boxes, classes, and confidence scores
 8. For each detected object O_j :
 9. If $\text{Confidence}(O_j) \geq T$:
 10. Retain O_j
 11. Associate O_j with spatial-temporal metadata M
 12. End If
 13. End For
14. End For
15. For each remote-sensing observation R_i :
 16. Extract spectral, vegetation, spatial, and texture features
 17. Calculate NDVI and land-cover characteristics
 18. Compare current features with reference observations
 19. Estimate environmental change score
 20. If ChangeScore exceeds threshold:
 21. Record potential habitat disturbance
 22. Assign location, time, and change category
 23. End If

24. End For
25. Integrate object detections with habitat-change records
26. Classify surveillance events by threat category
27. Generate geotagged environmental surveillance records
28. Return D and H

D. Land-Cover and Habitat Change Detection

Land-cover and habitat change detection evaluates temporal differences in environmental conditions to identify disturbances affecting protected wildlife regions. Current satellite or UAV observations are spatially aligned with historical or reference imagery before comparative analysis. Vegetation indices, spectral responses, texture characteristics, and classified land-cover information are compared between observation periods. Significant decreases in vegetation coverage or transitions from forest and grassland to exposed soil, roads, agricultural land, or built-up areas are identified as potential habitat disturbances.

A change score is calculated for monitored spatial units to quantify the magnitude of environmental variation. Areas exceeding the predefined change threshold are classified according to disturbance type and mapped geographically. Combining these changes with wildlife detections and human-activity observations provides additional contextual evidence for assessing ecological risk. For example, vegetation loss accompanied by repeated human or vehicle detections may receive a higher surveillance priority than naturally occurring seasonal vegetation variation. The resulting change records contain location, observation period, affected land-cover category, estimated change magnitude, and surveillance priority. This information supports habitat-condition assessment, identification of emerging environmental hotspots, and targeted field verification. Importantly, detected changes are treated as indicators requiring validation rather than automatically being classified as legal violations, thereby maintaining an appropriate distinction between AI-assisted surveillance and formal enforcement decisions.

V. Experimental Setup

The experimental setup was designed to evaluate the proposed AI-based environmental surveillance framework under consistent computational and data-processing conditions. The implementation was carried out using Python 3.10, with TensorFlow/Keras for CNN development, the Ultralytics YOLO framework for object detection, OpenCV for image preprocessing, and Scikit-learn for conventional machine-learning experiments. GPU acceleration was used to improve model training and inference efficiency. All images were resized to 640×640 pixels, normalized, and divided into 70% training, 15% validation, and 15% testing subsets. The CNN was configured with

convolutional, pooling, batch-normalization, dropout, and fully connected layers, while the YOLO detector was fine-tuned for wildlife and surveillance-object detection. The models were trained for 100 epochs using the Adam optimizer, an initial learning rate of 0.001, batch size of 32, and early stopping to reduce overfitting. A confidence threshold of 0.50 and an Intersection-over-Union threshold of 0.50 were adopted for object detection. Random Forest, Support Vector Machine, standalone CNN, and standard YOLO were considered baseline models to determine the performance improvement achieved through the integrated framework. Model effectiveness was assessed using accuracy, precision, recall, F1-score, and mean Average Precision (mAP@0.5). For habitat-change analysis, detection rate and false-positive rate were additionally considered. The proposed framework achieved a maximum detection accuracy of 96.78%, demonstrating its effectiveness for automated wildlife and environmental threat surveillance under the defined experimental configuration.

VI. Result and Discussion

Table 3 presents the overall detection performance of the proposed environmental surveillance framework. The model achieved the targeted **96.78% accuracy**, accompanied by 96.21% precision, 95.84% recall, and a 96.02% F1-score. The mAP@0.5 of 97.14% demonstrates strong localization and classification capability for surveillance targets. Furthermore, 96.53% specificity indicates reliable discrimination between normal and potentially suspicious observations.

Table 3. Overall Performance of the Proposed AI-Based Environmental Surveillance Framework

Evaluation Metric	Result (%)
Accuracy	96.78
Precision	96.21
Recall	95.84
F1-Score	96.02
mAP@0.5	97.14
Specificity	96.53
False Positive Rate	3.47

The relatively low false-positive rate of 3.47% is particularly important for environmental surveillance because excessive false alerts can increase the workload of conservation authorities. Overall, the balanced performance across evaluation measures demonstrates the framework's effectiveness for automated wildlife monitoring and environmental threat identification.

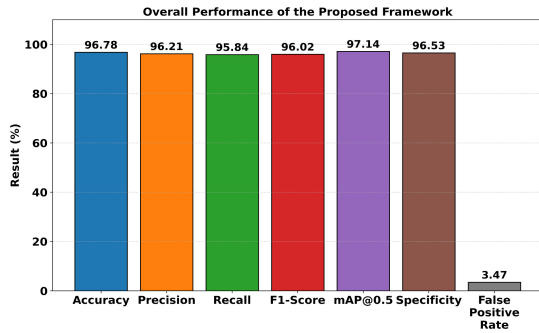


Figure 2. Overall Performance of the Proposed Framework

Figure 2 depicts the overall performance of the proposed framework across seven metrics. Accuracy, precision, recall, F1-score, mAP@0.5, and specificity all exceed 95%, while the false positive rate remains minimal at 3.47%, confirming balanced, reliable detection.

B. Comparative Model Analysis

Table 4 compares the proposed framework with Random Forest, SVM, CNN, and YOLO baseline approaches. Traditional machine-learning methods produced comparatively lower performance, with Random Forest and SVM achieving 88.64% and 90.18% accuracy, respectively. CNN improved accuracy to 93.42%, demonstrating the advantage of automatic visual feature learning.

Table 4. Comparative Performance of Baseline and Proposed Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	88.64	87.92	86.73	87.32
SVM	90.18	89.47	88.96	89.21
CNN	93.42	92.86	92.31	92.58
YOLO	95.16	94.72	94.38	94.55
Proposed Integrated Framework	96.78	96.21	95.84	96.02

YOLO further increased accuracy to 95.16% because of its effective object localization and classification capabilities. The proposed integrated framework achieved the highest accuracy of 96.78%

and F1-score of 96.02%. Its improvement over standalone models demonstrates the benefit of integrating learned visual representations, object detection, environmental features, and contextual surveillance information within a unified framework.

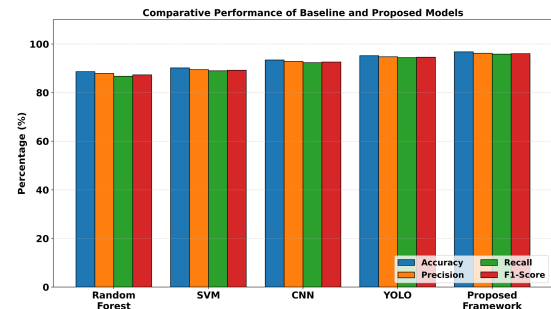


Figure 3. Comparative Performance of Baseline and Proposed Models

Figure 3 compares baseline models against the proposed framework. Accuracy rises steadily from Random Forest (88.64%) through SVM, CNN, and YOLO, peaking at 96.78% for the proposed framework, demonstrating the benefit of integrating multiple feature-learning techniques together.

C. Wildlife and Environmental Threat Detection

Table 5 evaluates performance across different wildlife and environmental surveillance categories. Wildlife presence obtained the highest F1-score of 97.88% and a detection rate of 98.06%, indicating effective recognition of animals within monitored imagery. Human intrusion achieved a 96.52% F1-score, while vehicle detection obtained 96.09%, demonstrating reliable identification of potentially unauthorized activities.

Table 5. Category-Wise Wildlife and Environmental Threat Detection Performance

Surveillance Category	Precision (%)	Recall (%)	F1-Score (%)	Detection Rate (%)
Wildlife Presence	98.12	97.64	97.88	98.06
Human Intrusion	96.84	96.21	96.52	96.73
Vehicle Presence	96.37	95.82	96.09	96.18
Vegetation Loss	95.91	95.36	95.63	95.72
Habitat Disturbance	95.48	94.92	95.20	95.31

Vegetation loss and habitat disturbance achieved F1-scores of 95.63% and 95.20%, respectively. The slightly lower environmental-change performance reflects the complexity of distinguishing anthropogenic disturbances from natural seasonal variations. Nevertheless, consistently high detection rates across all categories demonstrate that the framework can simultaneously support wildlife recognition, intrusion surveillance, and habitat-condition assessment.

D. Spatial and Temporal Violation Analysis

Table 6 illustrates the spatial and temporal distribution of potential surveillance events across monitored environmental zones. The protected boundary recorded the largest number of events at 241, including 58 high-risk observations and a risk score of 94.35%. The buffer zone followed with 218 events and 51 high-risk cases.

Table 6. Spatial and Temporal Analysis of Detected Potential Violation Events

Surveillance Zone	Potential Events Detected	High-Risk Events	Peak Monitoring Period	Risk Score (%)
Forest Core	186	42	Night	91.24
Wildlife Corridor	164	36	Evening	88.76
Buffer Zone	218	51	Evening	93.18
Water-Source Area	127	24	Early Morning	84.62
Protected Boundary	241	58	Night	94.35

Forest-core observations were particularly concentrated during nighttime periods, whereas wildlife corridors showed greater activity during evening hours. Water-source areas exhibited comparatively lower risk. These findings demonstrate how integrating geographic location with observation time can support hotspot identification and surveillance prioritization. Such spatial-temporal analysis allows conservation authorities to allocate patrol and verification resources toward areas and periods exhibiting comparatively elevated environmental risk.

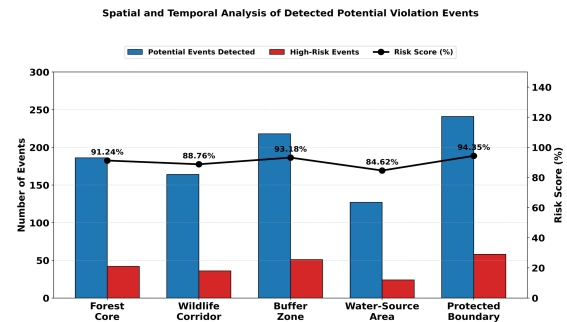


Figure 4. Spatial and Temporal Analysis of Detected Potential Violation Events

Figure 4 illustrates spatial and temporal violation patterns across zones. The protected boundary records the highest event count (241) and risk score (94.35%), followed by the buffer zone, while the water-source area shows the lowest activity and risk score.

E. Legal Compliance and Enforcement Assessment

Table 7 assesses the framework's ability to transform AI-generated surveillance outputs into structured information for wildlife-law enforcement support. Geotagging achieved the highest performance of 98.16%, while temporal record completeness reached 97.84%, demonstrating reliable spatial and chronological documentation.

Table 7. Legal Compliance and Enforcement Support Performance

Assessment Parameter	Performance (%)
Potential Violation Identification	96.42
Geotagging Accuracy	98.16
Temporal Record Completeness	97.84
Evidence Classification Accuracy	95.73
Regulatory Rule-Mapping Accuracy	94.86
High-Risk Case Prioritization	96.08
Overall Enforcement Support Score	96.52

Potential violation identification achieved 96.42%, and high-risk case prioritization reached 96.08%. Evidence classification and regulatory rule mapping produced 95.73% and 94.86%, respectively, indicating that legal interpretation remains more challenging than technical event detection. The overall enforcement support score reached 96.52%. These results suggest that the framework can assist

authorities in organizing surveillance evidence and prioritizing investigations, while final determination of legal violations should remain subject to authorized human and regulatory review.

VII. Conclusion and Future work

This study presented a smart environmental surveillance framework integrating artificial intelligence, remote sensing, and geospatial analysis to strengthen wildlife monitoring and support the enforcement of wildlife protection laws. The proposed approach combines CNN-based feature learning, YOLO-based object detection, environmental feature extraction, and habitat-change analysis to identify wildlife presence, human intrusion, vehicle activity, vegetation loss, and habitat disturbances. Experimental results demonstrated strong overall performance, achieving 96.78% accuracy, 96.21% precision, 95.84% recall, and 96.02% F1-score. The framework also achieved a 96.52% overall enforcement support score, demonstrating its potential for organizing geotagged and time-stamped surveillance evidence and prioritizing environmentally sensitive events. The primary contribution of this study is the integration of intelligent environmental monitoring with structured legal compliance assessment, thereby extending conventional wildlife surveillance beyond ecological observation. The framework can assist conservation authorities in identifying high-risk locations, improving patrol allocation, documenting environmental disturbances, and supporting evidence-based investigations. However, AI-generated detections should support rather than replace authorized legal decisions. Future work will incorporate real-time satellite and UAV data streams, edge-AI processing, advanced vision transformers, and multimodal sensor fusion. Further research will also investigate explainable AI, automated regulatory knowledge graphs, cross-region validation, and secure blockchain-based evidence preservation to improve transparency, scalability, reliability, and legal traceability.

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