# A Systematic Review of Lightweight Anomaly Detection Techniques for UAV Video Surveillance

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**Abstract**
Recent advancements in aerial surveillance have intensified interest in UAV-based anomaly detection, particularly as real-time monitoring becomes increasingly critical in dynamic environments. This systematic review synthesizes sixteen peer-reviewed studies published in 2025 that investigate deep learning techniques tailored for UAV anomaly detection. The search process, conducted through the Web of Science Core Collection and augmented with snowballing, yielded three dominant research themes: lightweight real-time detection models, spatiotemporal and self-supervised anomaly learning, and robustness under challenging environmental conditions. The findings highlight a clear shift toward computational efficiency through compact CNN architectures and hardware-accelerated designs, alongside improved temporal reasoning via LSTM-based and prediction-driven frameworks. Additionally, several studies emphasize enhancing visibility and structural clarity under low-light, noisy, or variable-scale conditions through multimodal fusion and multi-scale refinement. Despite these advancements, limitations remain concerning dataset diversity, standardized evaluation, and real-world experimentation. The review concludes by outlining future directions that include expanding UAV anomaly datasets, strengthening temporal modeling, and validating models through practical deployments.
***Keywords:***
*UAV anomaly detection; lightweight deep learning; spatiotemporal modeling; self-supervised learning; multimodal fusion; multi-scale refinement; aerial surveillance; systematic review.*

## 1. Introduction

Unmanned Aerial Vehicles (UAVs) have become an essential component in modern surveillance due to their ability to provide wide-area coverage, rapid mobility, and flexible deployment in dynamic environments. This shift has increased the need for reliable anomaly detection techniques that can identify unsafe or unusual events from aerial video streams. However, detecting anomalies from UAV footage remains challenging because of continuous camera motion, unstable backgrounds, and significant variations in scale and illumination factors that degrade the performance of traditional vision-based methods [1] [2].

Recent research trends show increasing interest in lightweight deep-learning models that can run directly on UAV hardware with limited computational resources [3] [4], as well as spatiotemporal approaches that leverage motion patterns and prediction-based frameworks to improve anomaly understanding in dynamic aerial scenes [1] [5]. Despite these advancements, existing studies differ widely in model type, evaluation metrics, datasets, and problem focus, making it difficult to obtain a unified understanding of the landscape or compare methods effectively.

Therefore, this systematic literature review aims to synthesize current research in UAV-based anomaly detection by analyzing lightweight models, spatiotemporal learning approaches, and robustness-oriented techniques designed for challenging environmental conditions. Through structured screening and thematic analysis, the review identifies dominant techniques, highlights persistent challenges, and evaluates the performance and applicability of existing methods in real-time UAV scenarios. The findings provide a consolidated foundation for understanding the state of the field and guiding future development toward more scalable and resource-efficient UAV anomaly detection solutions.

To guide this systematic review, the following research questions were formulated:

- RQ1: What are the existing anomaly detection techniques in video surveillance, and how have they been adapted for drone-based systems?
- RQ2: What are the main challenges and limitations of current anomaly detection approaches when applied to drone video data?
- RQ3: How do lightweight anomaly detection models (e.g., EfficientAD, FastFlow, ConvLSTM) perform on drone-specific datasets in terms of accuracy, efficiency, and adaptability?

Manuscript received February 5, 2026
Manuscript revised February 20, 2026
https://doi.org/10.22937/IJCSNS.2026.26.2.7

## 2. Methodology

### A. Search Term

A structured search strategy was developed to identify relevant studies on UAV-based anomaly detection. The search was conducted exclusively through the Web of Science (WoS) Core Collection, following the systematic approach used in the reference study. ("anomaly detection" OR "abnormal behavior" OR "unusual activity") AND ("UAV" OR "drone" OR "aerial video" OR "aerial surveillance") AND ("deep learning" OR "CNN" OR "LSTM" OR "autoencoder") AND ("real-time" OR "lightweight") NOT ("cybersecurity" OR "sensor network" OR "audio")

### B. Inclusion/Exclusion Criteria

The following criteria guided the selection of papers:

- Inclusion Criteria:
- Published in 2025
- Written in English
- Peer-reviewed journal or conference papers
- Focused on UAV/drone-based anomaly detection and provided experimental evaluation

Exclusion Criteria:

- Published before 2025
- Not written in English
- Hardware-/sensor-only studies
- Review papers or conceptual-only papers
- No experiments or no evaluation
- Not related to UAV imagery

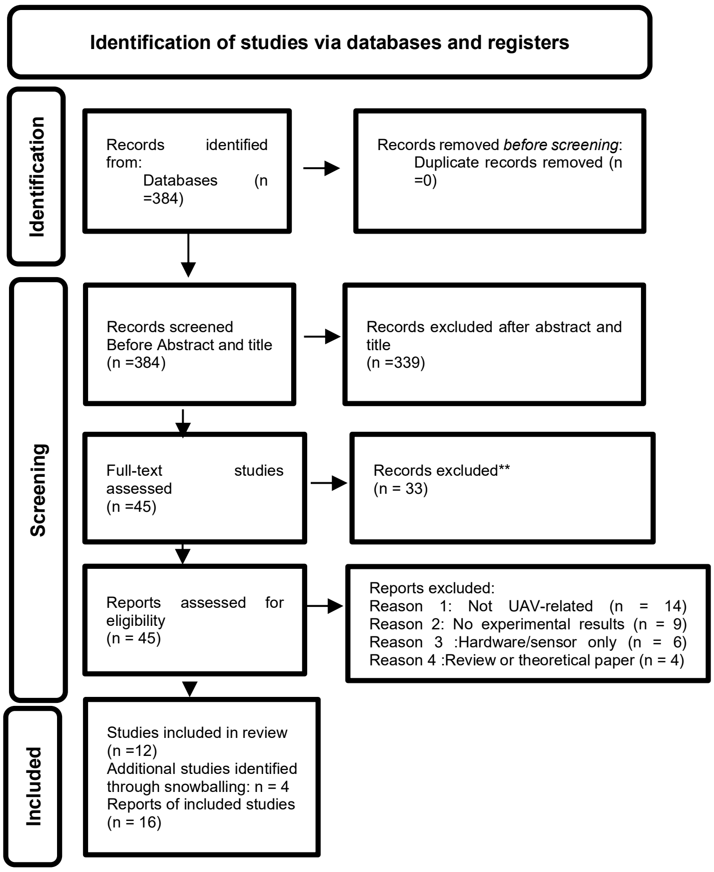


**Figure 1:** PRISMA workflow of paper identification, screening, eligibility, and inclusion.

### C. Filtering Stages

Following the initial search, all retrieved records were imported into Zotero, which automatically detected and removed duplicate entries. The remaining papers were then exported to Rayyan, where additional duplicates were identified and removed. Rayyan was also used to manage the screening process and apply the inclusion and exclusion criteria.After duplicate removal, the screening proceeded in three stages:

1. **Title and Abstract Screening**
   The filtering applied in Web of Science reduced the results to 384 studies. These were screened in Rayyan based on relevance to UAV anomaly detection, resulting in the exclusion of 339 papers.
2. **Full-Text Screening**
   A total of 45 studies were examined in full. Using Rayyan's labeling tools, 33 papers were excluded for reasons such as lacking UAV focus, missing experiments, or being hardware-/review-only.
3. **Snowballing**
   Backward and forward reference checking identified 4 additional papers that met the criteria. In total, 16 studies were included for synthesis in this review.

## 3. Results

In this review, anomaly detection is interpreted in a broader operational context, including the identification of rare, hazardous, or abnormal events such as wildfires, infrastructure defects, and structural anomalies captured in UAV imagery.

### A. Summary of Search Results

The systematic search conducted through the Web of Science Core Collection yielded a total of 384 records after applying filters restricting the query to the year 2025 and the Computer Science, Artificial Intelligence category. These records underwent a multi-stage screening process summarized in Figure 1 (PRISMA Flow Diagram), which provides an overview of the identification, screening, eligibility assessment, and final inclusion stages. Following the title and abstract screening, 339 articles were excluded for not meeting the relevance criteria for UAV-based anomaly detection. The remaining 45 studies proceeded to full-text evaluation, during which 33 papers were excluded due to reasons such as lack of UAV experimentation, insufficient methodological detail, or a primary focus on hardware-oriented or non-visual analysis. This resulted in 12 studies meeting the eligibility criteria. To ensure completeness, snowballing was conducted through backward reference checking and citation tracing, identifying four additional studies, bringing the final number of included papers to 16. Studies retrieved directly from the database were labeled with the prefix S, while those identified through snowballing were labeled SB, indicating only the retrieval pathway rather than methodological difference

### B. Extracted Themes from the 16 Studies

#### 1. Lightweight Real-Time UAV Detection Models

Several studies focused on developing lightweight and computationally efficient architectures capable of running directly on UAV platforms. These works commonly employed compact convolutional neural networks (CNNs), which reduce the number of parameters and operations to support real-time inference on resource-limited aerial hardware [3][4]. Some models incorporated feature-fusion mechanisms that combine information from multiple levels of representation to enhance detection accuracy while maintaining computational efficiency [6]. Other studies explored hardware-accelerated designs, where specialized embedded processors enable faster execution and reduced energy consumption during flight [7]. Together, these approaches highlight a growing emphasis on balancing speed, accuracy, and energy efficiency to enable real-time onboard anomaly detection.

#### 2. Spatiotemporal and Self-Supervised Anomaly Learning

A second major research direction centers on capturing temporal dynamics in drone-captured video. UAV footage often includes continuous motion, viewpoint changes, and unstable backgrounds, making temporal reasoning essential for anomaly detection. Several studies utilized Long Short-Term Memory (LSTM) components to model temporal dependencies and evolving behavior across sequential frames, thereby enhancing detection robustness [1][5]. Other studies adopted prediction-driven architectures in which the model predicts future frames or segmentation masks and identifies anomalies by comparing predicted and observed outputs. Because these methods rely on temporal consistency rather than manual annotation, they function as a form of self-supervised learning that reduces the need for large, labeled datasets [1]. This theme reflects a broader shift toward models capable of understanding motion patterns and structural transitions in aerial video.

### 3. Robustness Under Challenging Environmental Conditions

The third theme addresses techniques designed to maintain reliable performance under adverse or unpredictable outdoor environments. UAV surveillance frequently encounters low-light conditions, occlusions, environmental noise, and significant variations in object scale. To address these challenges, several studies proposed multimodal fusion strategies that integrate enhanced versions of the visual signal to improve target visibility in degraded scenes [2]. Others implemented adaptive feature-enhancement modules that highlight informative structures when raw imagery is weak, while additional works applied multi-scale refinement approaches to improve detection of thin or small objects such as power lines [8]. Collectively, these studies underscore the importance of designing UAV anomaly detection models that perform effectively despite environmental variability.

**Table 1**:Summary Table of the 16 Included Studies.

| ID | Theme | Method / Model | Challenge | Key Findings |
|---|---|---|---|---|
| S1[3] | Lightweight UAV detection | Edge-deployed CNN | Computation limits | Achieves real-time detection with reduced computation cost. |
| S2[1] | Spatiotemporal anomaly detection | Self-supervised CNN-LSTM | Motion & unstable background | Handles motion variations and unstable backgrounds effectively. |
| S3[6] | Lightweight oriented detection | Dynamic Smooth Feature Fusion | Balancing speed & precision | Balances precision and speed in aerial imagery. |
| S4[4] | Energy-efficient UAV inference | TakuNet (CNN) | Power constraints | 32% reduced power with comparable accuracy. |
| S5[7] | Hardware acceleration | DL accelerator | Throughput constraints | Improves real-time throughput on UAV hardware. |
| S6[9] | Crowd anomaly detection | YOLOv8 adaptation | Dense crowd complexity | Effective for dense aerial crowds under real-time constraints. |
| S7[2] | Low-light target detection | RMF-ED fusion | Low-light detection | Boosts detection in poor lighting conditions. |
| S8[10] | Wildfire detection | Teacher–student segmentation | Wildfire visibility limits | High recall for early fire detection in UAV images. |
| S9[8] | Power line segmentation | PL-UNet | Thin structures + scale variation | Real-time aerial segmentation using adaptive fusion. |
| S10[11] | Pavement crack segmentation | GLoU-MiT Transformer | Need for global & local modeling | Enhances crack detection with global–local modeling. |
| S11[12] | 3D tower asset classification | DF-3DNet | Efficient 3D classification | Lightweight 3D classification suitable for UAV scans. |
| S12[13] | Cooperative UAV tracking | Adaptive Coordination Net | Multi-drone clutter | Improves multi-drone coordination in cluttered scenes. |
| SB1[5] | Spatiotemporal prediction | Future segmentation + relational modeling | Spatiotemporal prediction | Strong for anomaly prediction with motion understanding. |
| SB2[14] | Traffic anomaly dataset | UAV dataset | Lack of benchmarks | Provides benchmark dataset for anomaly detection in aerial traffic scenes. |
| SB3[15] | Real-time anomaly pipeline | Vision-based detection system | Real-time UAV surveillance | Demonstrates feasibility of real-time UAV anomaly surveillance. |
| SB4[16] | Crowd anomaly detection | Hybrid aerial & ground features | Multi-view complexity | Handles complex crowd behaviors using UAV perspectives. |

## 4. Summary Table of the 16 Included Studies

Table 1 provides an overview of the sixteen studies included in this review. Each study is summarized based on its primary theme, methodological approach, identified challenge, and key findings. The table highlights the diversity of techniques used in UAV-based anomaly detection and provides a consolidated view of how these studies map onto the three dominant themes identified in the literature.

### 4.1 Discussion

The synthesis of the sixteen studies reveals clear patterns that define contemporary approaches to UAV-based anomaly detection. A recurring trend across the literature is the prioritization of lightweight model design, motivated by the inherent computational and energy constraints of UAV platforms. Instead of relying on deep or highly complex architectures, researchers increasingly favor compact CNN-based models, feature-fusion mechanisms, and hardware-accelerated implementations that can sustain real-time inference during flight [3][4][7]. This movement reflects a shift toward practicality, where operational feasibility is considered as important as detection accuracy. Temporal reasoning emerges as a second major trend. UAV video presents substantial challenges due to motion, unstable backgrounds, and dynamic event progression. Studies employing LSTM-based temporal modeling demonstrate improved capacity to interpret evolving patterns, while prediction-driven frameworks further advance anomaly detection by learning temporal structure directly from unlabeled aerial video [1][5]. These designs reduce the dependency on annotated datasets and indicate a clear trajectory toward self-supervised and spatiotemporal learning methods. A third prominent direction centers on robustness to environmental challenges. Real-world aerial surveillance rarely occurs under ideal conditions; thus, studies employing multimodal fusion, adaptive enhancement, and multi-scale refinement demonstrate efforts to maintain performance despite low illumination, occlusions, or noise [2][8]. These approaches highlight an increasing awareness of the need to bridge the gap between controlled experimental settings and practical UAV deployments. Together, these trends address the research questions guiding this review. The diverse array of models demonstrates how traditional anomaly-detection methods are being adapted to meet UAV-specific constraints. Identified challenges including motion instability, annotation scarcity, and hardware limitations justify the integration of temporal learning and efficiency-driven designs. Furthermore, the emergence of energy-efficient and lightweight architectures supports the need for benchmarking advanced temporal and flow-based models such as EfficientAD, FastFlow, and ConvLSTM in future stages of this research. Although direct quantitative comparison is limited due to differences in datasets, evaluation metrics, and experimental settings, lightweight anomaly detection models consistently demonstrate favorable trade-offs between detection accuracy, inference speed, and computational efficiency when applied to UAV-based scenarios.

### 4.2 Limitations

Despite notable advancements, the existing literature exhibits several limitations. Many studies rely on small or domain-specific datasets, restricting generalizability and complicating direct comparison across methods. Variability in evaluation protocols and performance metrics further limits the ability to establish consistent baselines. Additionally, although datasets such as UIT-ADrone have contributed valuable resources, the scarcity of comprehensive and publicly available UAV anomaly datasets remains a significant barrier to progress [14]. These limitations underscore the need for standardized evaluation frameworks and more diverse aerial anomaly datasets.

### 4.3 Implications

The findings of this review indicate several implications for future research. Expanding the availability of UAV anomaly datasets and developing unified evaluation protocols would significantly enhance methodological rigor. Integrating lightweight architectures with advanced temporal modeling offers a promising pathway for improving robustness in complex aerial environments. Moreover, real-world deployment studies that examine performance under varying motion, weather, and illumination conditions are essential for validating the practical reliability of UAV-based anomaly detection systems. Addressing these gaps will contribute to the development of more effective and operationally viable solutions for aerial surveillance.

## 5. Conclusion

This systematic review demonstrates how recent research in UAV-based anomaly detection is converging toward three core directions: lightweight model design, spatiotemporal learning, and environmental robustness. Collectively, the reviewed studies show a clear move toward practical, real-time solutions that balance accuracy with computational and energy constraints. Temporal modeling techniques, including LSTM-based frameworks and prediction-driven architectures, address challenges inherent to aerial video such as motion instability and limited annotated data. At the same time, robustness-focused methods underscore the importance of maintaining detection reliability under low-light, noisy, or structurally complex conditions. However, the field continues to face limitations related to dataset scarcity, inconsistent evaluation metrics, and limited real-world validation. Addressing these gaps will be essential for enabling UAV anomaly detection systems that perform reliably in operational settings. Future research should prioritize developing more comprehensive datasets, integrating efficient architectures with richer temporal reasoning, and conducting deployment-focused evaluations to assess practicality beyond controlled experimental scenarios.

## Acknowledgment
The author would like to acknowledge the support received during the completion of this research

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