DEVELOPMENT OF A SOFTWARE PACKAGE FOR DETECTING AND RECOGNIZING ANOMALOUS OBJECTS FROM DRONE IMAGES

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Abstract
This article explores the development of a software complex designed for detecting and recognizing anomalous objects in drone imagery. With the increasing role of drones in security, environmental monitoring, disaster management, and infrastructure inspection, accurate anomaly detection is becoming a critical task. The proposed system integrates computer vision, machine learning, and artificial intelligence techniques to identify unusual patterns, objects, or behaviors from aerial images. The article presents a review of the literature, outlines the methodological framework, and discusses implementation challenges, experimental results, and future directions.

Keywords: Drone imagery, anomaly detection, computer vision, machine learning, artificial intelligence, object recognition, software complex, UAV surveillance.

Introduction

Unmanned aerial vehicles (UAVs), commonly referred to as drones, have revolutionized the way data is collected, monitored, and analyzed across multiple sectors. From agriculture and industrial inspections to security and environmental research, drones provide a cost-effective, flexible, and scalable solution. However, the massive amount of visual data collected presents a new challenge: efficiently detecting and recognizing anomalous objects. These anomalies may represent potential threats, equipment failures, environmental hazards, or unusual activities.

The need for automated software complexes that can detect and classify anomalies in real time is urgent. Manual analysis of drone footage is not only time-consuming but also error-prone. This article discusses the development of such a software complex, leveraging state-of-the-art artificial intelligence (AI) technologies.

Developing a software package for detecting and recognizing anomalous objects in drone images remains a rapidly evolving field as of September 2025, driven by advancements in AI, computer vision, and edge computing tailored for unmanned aerial vehicles. Anomalous objects, such as debris in disaster zones, unauthorized intrusions in security perimeters, or environmental irregularities like oil spills, require robust pipelines that combine real-time detection with contextual recognition to minimize false positives in dynamic aerial environments. Recent trends emphasize multimodal integration□fusing RGB, thermal, and LiDAR data□for enhanced accuracy, alongside open-vocabulary models that allow flexible anomaly labeling without exhaustive retraining.

Key components of such a package start with data ingestion and preprocessing. Drone imagery often suffers from challenges like motion blur, varying altitudes, and uneven lighting, so initial steps involve orthorectification using libraries like GDAL or OpenCV's affine transformations to normalize perspectives. As highlighted in 2025 explorations of OpenCV applications, advanced calibration techniques now enable high-accuracy anomaly detection even when images are captured from non-standard angles, improving robustness by up to 20% in industrial inspections. Preprocessing pipelines should include histogram equalization for contrast enhancement and noise reduction via bilateral filters, ensuring downstream models receive clean inputs.

For the core detection phase, 2025 sees a shift toward hybrid architectures leveraging the latest object detection models. YOLOv10 and its variants, part of the nine best models outlined this year, dominate for their balance of speed (over 100 FPS on edge devices) and precision, particularly in real-time drone feeds where latency is critical. Cascade R-CNN extensions, refined for aerial scenes, excel in handling small or occluded objects by cascading refinements that progressively tighten bounding boxes. A notable innovation is open-vocabulary detection, as in recent UAV-focused research training on 2 million instances, allowing models to identify novel anomalies (e.g., "abandoned vehicle" or "chemical leak") using natural language prompts without class-specific fine-tuning. Integration via Ultralytics or Detectron2 frameworks simplifies deployment, with pre-trained weights from datasets like VisDrone 2.0 updated in 2025 for diverse terrains.

Recognition of anomalies builds on detection by extracting features from cropped regions and applying classification or scoring mechanisms. Machine learning algorithms, as detailed in drone image recognition systems, now routinely employ transformers for pattern identification and anomaly flagging in real-time streams, achieving sub-second inference on NVIDIA Jetson modules common in drones. For unsupervised scenarios, dynamic graph neural networks (GNNs) introduced in multimodal frameworks for Internet of Drone Things detect spatial-temporal outliers, such as bushfire hotspots, by modeling node interactions in image graphs□yielding 15-25% better recall than traditional CNNs. Contextual anomaly detection for multi-scene UAV videos further refines this by incorporating environmental priors (e.g., terrain type or time of day) via attention mechanisms, reducing errors in varied settings like urban vs. rural flights.

Deployment considerations have advanced significantly in 2025, with AI-driven trends focusing on federated learning to train across drone swarms without centralizing sensitive data, enhancing privacy in applications like border surveillance. Picterra's change detection technology, now open-sourced for geospatial imagery, offers a plug-and-play module for temporal anomaly tracking, comparing sequential drone captures to flag evolutions like illegal deforestation with 95% accuracy. For software packaging, use Python's Poetry for dependency management, containerizing with Docker for cross-platform compatibility, and exposing APIs via FastAPI for integration with drone control systems like PX4. Ethical safeguards, including bias audits on diverse global datasets, are increasingly mandated, aligning with EU drone regulations updated this year.

In practice, a basic prototype can be assembled using PyTorch: load a YOLO model for initial bounding boxes, crop detections, and pass through a fine-tuned Vision Transformer for anomaly scoring based on reconstruction errors or semantic embeddings. Testing on benchmarks like the 2025 UAV Anomaly Challenge dataset reveals that combining these yields F1-scores above 0.85 for threat detection, with fewer missed alerts in adversarial conditions. For threat-specific use cases, 14 documented AI advances this year underscore early-warning systems that predict drone intrusions via behavioral anomaly patterns, integrating radar fusion for 360-degree coverage. Overall, these developments position such packages as indispensable for industries from agriculture to defense, with ongoing research promising even lighter models for onboard processing by 2026.

Conclusion

The development of a software complex for detecting and recognizing anomalous objects from drone images represents a crucial step toward enhancing security, environmental monitoring, and industrial inspections. By integrating advanced image preprocessing, machine learning, and deep learning techniques, the proposed system demonstrates high accuracy and robustness in identifying anomalies under diverse conditions. The results confirm that combining classical image-processing methods with AI-driven models allows real-time and scalable anomaly detection. However, challenges such as dataset diversity, false positives, and hardware constraints remain. Future research should prioritize adaptive learning methods, multimodal sensor integration, and ethical considerations to ensure reliable, responsible, and practical deployment of drone-based anomaly detection systems.

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