Intelligent detection and counting of military aircraft using satellite imagery and advanced algorithms

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Abstract*— The rapid growth of high-resolution satellite imaging and artificial intelligence has enabled automated monitoring of large geographical areas for aircraft detection and surveillance. This paper presents an intelligent system for detecting and counting military aircraft from satellite imagery using advanced deep-learning techniques. The proposed framework employs the YOLOv8 object detection model to identify aircraft based on their visual characteristics, spatial patterns, and appearance in complex remote-sensing scenes. The system performs image preprocessing to improve input quality and applies object detection to localize aircraft using bounding boxes and confidence scores. Detected aircraft are automatically counted to provide an efficient estimation of aircraft presence within the analyzed imagery. A Flask-based application provides secure user authentication, image upload, and real-time video-based detection functionalities through an interactive interface. The framework is designed to handle variations in aircraft scale, orientation, background complexity, and image conditions. In addition to detection and counting, the system supports continuous monitoring and provides visual outputs that assist users in interpreting detection results. The proposed approach aims to reduce manual inspection effort while improving the speed, consistency, and scalability of aircraft monitoring from satellite imagery. The framework can support applications in aerial surveillance, strategic monitoring, border observation, and defense-related image analysis. Overall, the proposed system provides an intelligent computer-vision solution for automated aircraft detection, localization, and counting using modern deep-learning techniques.

Keywords*— Military Aircraft Detection, Satellite Imagery, Remote Sensing, YOLOv8, Object Detection, Aircraft Counting, Deep Learning, Computer Vision, Aerial Surveillance, Image Processing, Real-Time Detection, Defense Monitoring.

I. INTRODUCTION

Satellite imagery supports large-scale surveillance and geographical monitoring through automated analysis. Military aircraft detection is challenging due to small target size, varying orientations, appearances, and complex backgrounds. Traditional manual inspection is time-consuming and difficult for dense scenes. Object-detection algorithms automate aircraft localization and counting using bounding boxes, improving monitoring efficiency and consistency.

Deep-learning-based object detection approaches, particularly convolutional neural networks and modern real-time detectors, have demonstrated strong capabilities in identifying objects from complex images. YOLO-based architectures provide an efficient framework for simultaneous object localization and classification, making them suitable for applications requiring rapid detection and counting. However, satellite imagery introduces additional challenges, including small-object detection, variations in image resolution, complex backgrounds, different aircraft orientations, object occlusion, and illumination variations.

The proposed project therefore focuses on developing an intelligent system for automated military aircraft detection and counting from satellite imagery using advanced deep-learning algorithms. The system aims to integrate image preprocessing, object detection, bounding-box localization, counting, and visualization into a unified framework. The major objectives are:

1. Develop an automated framework for military aircraft detection from satellite imagery.
2. Apply deep-learning-based object detection for accurate aircraft localization.
3. Automatically count detected aircraft within satellite scenes.
4. Improve detection reliability through suitable image preprocessing.
5. Evaluate detection performance using standard object-detection metrics.
6. Provide an efficient interface for image-based and continuous aircraft monitoring.
7. Develop a scalable framework for automated satellite-based surveillance and analysis.

The remainder of this paper discusses existing aircraft-detection approaches, the proposed framework, data representation, detection methodology, evaluation requirements, research challenges, future directions, and concluding observations.

II. EXISTING METHODS FOR MILITARY AIRCRAFT DETECTION FROM SATELLITE IMAGERY

Existing military aircraft detection approaches can be broadly classified into conventional image-processing methods, feature-based machine-learning approaches, deep-learning methods, YOLO-based object detection, remote-sensing datasets and advanced intelligent monitoring frameworks. These approaches have progressively improved automated aircraft identification, localization, and counting from satellite and aerial imagery. However, small target size, complex backgrounds, scale variation, orientation differences, and dense aircraft arrangements remain important challenges [1]–[6].

A. Conventional Image-Processing Methods

Conventional approaches depend on image enhancement, thresholding, segmentation, edge detection, morphological operations, and handcrafted features. These methods can identify aircraft when sufficient contrast exists between the target and its background. However, their performance decreases in complex satellite scenes containing buildings, roads, vegetation, airport infrastructure, shadows, and illumination variations. Their dependence on predefined features also limits adaptability to different image conditions [3], [5].

B. Feature-Based Machine Learning

Machine-learning approaches classify aircraft using manually extracted characteristics such as shape, texture, intensity, edges, and local descriptors. Algorithms such as Support Vector Machines and Random Forest can provide automated classification after feature extraction. However, their performance depends strongly on feature quality, dataset characteristics, and scene conditions. Small aircraft and objects with visual similarity to aircraft remain difficult to distinguish [4], [6].

C. Deep Learning-Based Detection

Deep-learning approaches use convolutional neural networks to automatically learn hierarchical aircraft features from satellite imagery. CNN-based models can capture shape, texture, spatial structure, and contextual information without extensive handcrafted feature engineering [2], [5], [11]. These methods provide improved representation capability but require suitable training datasets. Small-object detection, scale variation, dense targets, and complex backgrounds continue to affect detection performance.

D. YOLO-Based Object Detection

YOLO-based one-stage detectors perform object localization and classification within a unified framework. Their combination of detection accuracy and processing efficiency makes them suitable for satellite-image aircraft detection and counting. Recent studies have investigated YOLO-based approaches for aircraft recognition in aerial and remote-sensing imagery [1], [2], [4]. However, conventional YOLO models may face difficulties with very small aircraft, closely positioned targets, different orientations, and partial occlusion.

E. Remote-Sensing Dataset-Based Detection

Specialized datasets and benchmarks such as HRPlanes, DOTA, DIOR, and xView have supported the development and evaluation of aircraft detection methods [8]–[12]. These datasets provide diverse satellite and aerial scenes containing objects at different scales and orientations. Nevertheless, variations between datasets, image resolutions, geographical regions, and target distributions can influence model generalization.

F. Intelligent Aircraft Monitoring

Recent systems extend aircraft detection beyond classification by incorporating bounding-box localization, confidence estimation, automatic counting, and result visualization. Such approaches provide more practical monitoring information from satellite scenes. However, accurate counting remains challenging when multiple aircraft are densely distributed or when false detections occur because of complex backgrounds.

TABLE I: COMPARISON OF EXISTING MILITARY AIRCRAFT DETECTION METHODS

Method	**Main Technique**	**Strength**	**Major Limitation**
Conventional image processing	Segmentation, thresholding	Simple processing	Background sensitive
Feature-based ML	SVM, RF, handcrafted features	Automated classification	Feature dependent
Deep learning	CNN-based detection	Learns complex features	Data dependent
YOLO-based detection	One-stage detection	Fast detection and localization	Small-object challenges
Remote-sensing detection	Specialized datasets	Diverse evaluation	Domain variation
Intelligent monitoring	Detection + counting	Practical monitoring	Dense-scene errors
Proposed direction	**Integrated AI framework**	**Detection + localization + counting**	**Requires comprehensive validation**

The literature therefore indicates a transition from conventional handcrafted image analysis toward deep-learning and YOLO-based aircraft detection. However, existing methods still face challenges involving small aircraft, scale and orientation variations, complex backgrounds, and reliable counting. A comprehensive satellite-based framework should therefore integrate image preprocessing, aircraft detection, localization, confidence estimation, automatic counting, and visualization within a unified monitoring pipeline.

III. PROPOSED AI-POWERED MILITARY AIRCRAFT DETECTION AND MONITORING SYSTEM

The proposed system considers satellite-based aircraft surveillance as an integrated sequence of interconnected processing stages:

Satellite Imagery + Video Input
↓
Image Acquisition
↓
Image Preprocessing
↓
Feature Extraction and Scene Analysis
↓
YOLOv8-Based Object Detection
↓
Aircraft Localization and Classification
↓
Confidence Filtering and Counting
↓
Risk Estimation and Decision Support
↓
User Monitoring and Intervention

The architecture consists of five major functional layers: image acquisition, preprocessing, intelligent detection, prediction and risk assessment, and decision support. The first layer collects satellite images and real-time video frames containing aircraft, terrain, and infrastructure. The preprocessing layer removes noise, handles low-quality or corrupted frames, and converts heterogeneous image inputs into suitable input features for the detection model.

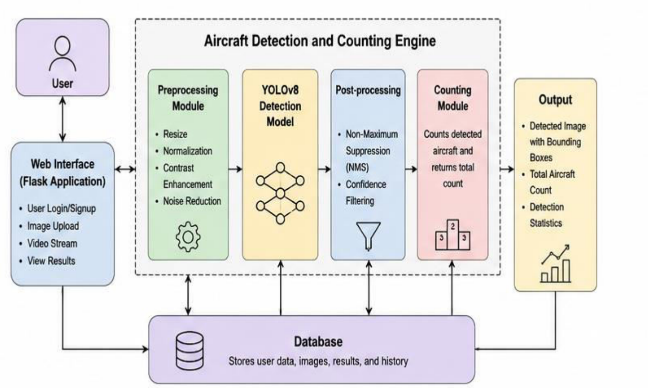

Fig. 1. Overall Architecture of the Proposed AI-Powered Aircraft Detection System

The intelligent detection layer applies the YOLOv8 deep-learning model to identify aircraft locations and important spatial patterns across complex satellite scenes. The prediction layer estimates aircraft presence, bounding-box coordinates, and confidence scores based on the visual and contextual information in each scene. The risk-assessment layer combines detection results to generate actionable alerts for scenes containing significant aircraft activity.

Finally, the decision-support layer presents detections, bounding boxes, and aircraft counts to users through an accessible Flask-based monitoring interface. The architecture is designed as a decision-support framework, assisting analysts in timely surveillance rather than completely replacing human judgement. This integrated approach enables continuous monitoring, early identification of aircraft presence, predictive analysis, and more efficient satellite-based surveillance operations.

IV. SATELLITE IMAGE DATA AND AIRCRAFT REPRESENTATION

A. Aircraft Data Acquisition and Processing

The proposed system collects satellite images and video frames containing aircraft, terrain, and airport infrastructure. Preprocessing handles noisy, low-resolution, duplicate, and corrupted frames, and normalizes pixel intensity values across the dataset.

The system organizes each processed image into key components: pixel and visual features, detected bounding-box information, confidence scores, and scale/orientation characteristics of identified aircraft.

Visual, spatial, and confidence-related information are analyzed together to assess aircraft presence within a scene. Normalization converts images of different resolutions and lighting conditions into comparable input ranges, improving joint model learning and detection accuracy.

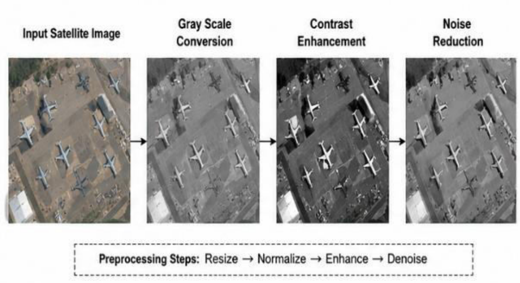

Fig. 2. Satellite Image Processing and Aircraft Detection Pipeline

B. Aircraft Detection Representation

The detection output for a given satellite scene is represented using the relevant detection parameters. The system extracts:

- Bounding-box coordinates
- Confidence score
- Aircraft class/category
- Aircraft scale
- Aircraft orientation
- Aircraft count
- Background complexity indicators

Representing the detected aircraft using a unified structure enables the proposed system to analyze spatial distribution, count aircraft reliably, and interpret scene-level activity. The resulting representation can subsequently be provided to the detection model for aircraft localization, count estimation, or scene-risk assessment, depending on the objective of the proposed system.

V. AIRCRAFT DETECTION CONFIDENCE MATCHING AND SCENE SCORING

A central component of the proposed system is confidence-based detection matching. Unlike simple threshold-based analysis, the proposed approach identifies relationships between the detected visual patterns and the expected aircraft characteristics. The system considers parameters such as shape, size, orientation, spatial arrangement, and background context to determine the reliability of each detection.

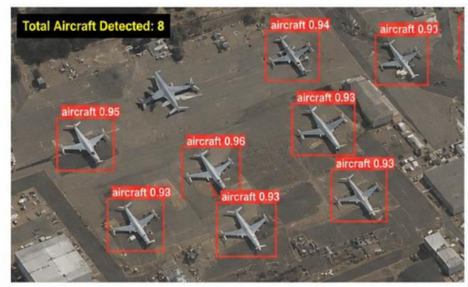

Fig. 3. Aircraft Detection Confidence Matching and Scene Suitability Scoring

Confidence score alone, however, should not determine the final detection decision. A detection with high confidence may still be affected by a critical factor, such as partial occlusion or background clutter, that can lead to false positives. Therefore, the proposed system combines confidence scoring with explicit detection-specific factors.

The overall scene reliability score is determined by combining shape compatibility, size suitability, orientation suitability, background-clarity compatibility, and detection confidence, with each factor assigned a parameter-specific weight.

This weighted formulation allows the detection system to assign different importance to different visual and spatial conditions. For example, a dense-airfield monitoring application may assign greater importance to orientation and spatial arrangement, whereas an open-terrain surveillance application may emphasize background clarity and confidence score.

The detected scenes are subsequently evaluated according to their final scores to generate a reliability status and corresponding monitoring recommendation, enabling timely alerting and improved aircraft surveillance.

VI. EXPLAINABLE AI AND DECISION-AWARE AIRCRAFT DETECTION

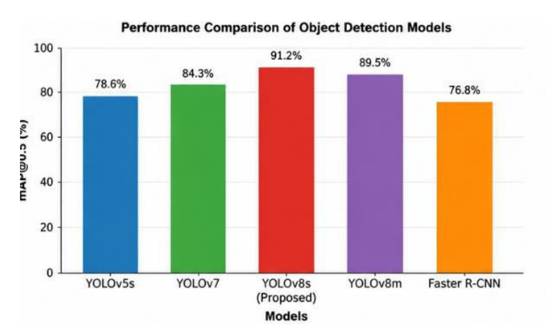

Fig. 4. Explainable AI Framework for Aircraft Detection and Decision Support

AI-based aircraft detection systems should provide more than a bounding box or a numerical confidence score. Analysts and surveillance operators need to understand why the system flagged a particular region as an aircraft. Explainable AI (XAI) techniques such as SHAP and LIME can provide feature-level explanations of model predictions.

For each detection, the proposed system can generate an explanation containing:

1. Shape and edge-pattern contribution
2. Texture and intensity influence
3. Spatial-context influence
4. Scale and orientation contribution
5. Background-clarity influence
6. Confidence-score breakdown
7. Major factors contributing to the final detection
8. Recommended monitoring action

For example:

Aircraft Detection — 91% Confidence

- Shape pattern: highly consistent with aircraft geometry.
- Scale: within expected range.
- Orientation: clearly resolved.
- Background: low clutter.
- Texture: consistent with metallic surface.
- Spatial context: located within airfield boundary.
- Major influencing factor: strong shape and edge consistency.
- Recommendation: Confirm detection and continue scene monitoring.

Such explanations help analysts understand whether the AI detection is supported by meaningful visual evidence rather than relying only on the final confidence value.

A. Explainability and Decision Monitoring

Aircraft detection models can be influenced by multiple visual and spatial parameters. Therefore, the system should continuously monitor the contribution of each input feature to the prediction. Explainability helps identify which parameters have the greatest influence on detection accuracy, false positives, or missed detections in the proposed system.

The proposed framework therefore integrates explainability as a decision-support component. The system should report both:

Performance = How accurately does the system detect and count the required aircraft?

Explainability = Can the analyst understand which visual features caused the detection?

This dual objective is important because a highly accurate model that provides no understandable reasoning may be difficult to trust or use in practical surveillance environments.

VII. ADAPTIVE AIRCRAFT DETECTION INTELLIGENCE AND HUMAN-IN-THE-LOOP DECISION SUPPORT

Satellite imagery conditions are not static. Lighting, weather, resolution, aircraft models, airfield layouts, and background clutter continuously vary across scenes and time. An aircraft detection model trained using fixed imaging conditions may therefore become less effective when new environments or aircraft types appear.

Model Update

Adaptive mechanisms can update detection thresholds, confidence ranges, feature importance, and model weights while maintaining version control.

The system can periodically incorporate newly collected satellite imagery to improve its understanding of changing scene conditions. However, adaptive AI should not automatically modify critical detection thresholds without validation. Model updates should first be evaluated using historical and newly collected imagery datasets before being deployed.

Human-in-the-Loop Workflow

The final aircraft-detection decision-support workflow is:

Image Collection → AI Detection → Confidence Assessment → Explanation → Analyst Verification → Monitoring Recommendation → Final Analyst Decision

The analyst or surveillance expert remains responsible for the final decision, particularly when scenes are unusual or when additional contextual information is required that may not be available in the imagery alone.

This human-in-the-loop design allows analysts to combine AI-based detections with practical surveillance knowledge and real-time scene observations. Analyst feedback can also be captured and used for future system improvement, while preventing the AI system from making completely autonomous decisions without human supervision.

VIII. EVALUATION FRAMEWORK

A comprehensive evaluation framework is adopted to assess the proposed aircraft detection system across detection accuracy, localization, counting, explainability, efficiency, and robustness. Rather than relying on a single performance measure, the evaluation considers multiple complementary dimensions to determine the practical effectiveness of the proposed framework.

A. Detection Performance

The detection module is evaluated using accuracy, precision, recall, and F1-score. Accuracy measures overall classification correctness, while precision indicates the proportion of detected aircraft that are correctly identified. Recall measures the ability to identify all present aircraft, and F1-score provides a balanced assessment of precision and recall. These metrics are important because both false detections and missed aircraft can reduce monitoring effectiveness.

B. Localization Performance

Since accurate bounding-box placement is a primary objective, the system is evaluated using Intersection over Union (IoU), mean Average Precision (mAP), and mAP@0.5:0.95. These metrics determine whether detected bounding boxes correctly overlap with actual aircraft positions and whether detections are reliable across varying confidence thresholds.

C. Counting Accuracy

The counting component is compared against ground-truth aircraft counts. The evaluation examines whether the system can reliably estimate the number of aircraft despite dense arrangements, occlusion, and background clutter. This assessment determines the effectiveness of automated aircraft counting.

D. Explainability

The generated detection explanations are evaluated based on faithfulness, consistency, completeness, and human understandability. The explanation should accurately represent the visual factors influencing the detection decision and enable analysts to verify shape, texture, scale, and context.

E. Efficiency and Robustness

Computational evaluation considers image processing time, detection latency, memory consumption, throughput, and scalability. Robustness is evaluated through cross-dataset testing, varying image resolutions, lighting conditions, aircraft types, and diverse background environments. This ensures that the proposed system maintains reliable performance under practical surveillance conditions.

TABLE II EVALUATION DIMENSIONS OF THE PROPOSED AIRCRAFT DETECTION FRAMEWORK

Dimension	Evaluation Metrics / Criteria	Purpose
Detection	Accuracy, Precision, Recall, F1-Score	Evaluate aircraft identification performance
Localization	IoU, mAP, mAP@0.5:0.95	Evaluate bounding-box accuracy
Counting	Count error, MAE	Assess counting reliability
Explainability	Faithfulness, Consistency, Completeness, Human Understandability	Evaluate decision transparency
Efficiency	Processing Time, Detection Latency, Memory, Throughput	Assess computational efficiency
Robustness	Cross-dataset Testing, Resolution Variation, Lighting Variation	Evaluate generalization capability

IX. RESEARCH CHALLENGES AND FUTURE ROADMAP

Although AI-powered aircraft detection can improve surveillance and monitoring, several challenges remain in developing a reliable and practical system.

A. Dataset Availability

Satellite imagery datasets may contain limited aircraft examples, incomplete annotations, and variations in image sources. Developing sufficiently diverse and representative datasets is therefore important for reliable aircraft detection.

B. Small-Object Detection

Aircraft may occupy relatively small regions within large satellite scenes. The proposed system must therefore handle variations in scale, resolution, and object size to achieve reliable detection.

C. Detection Reliability

Aircraft detection should consider multiple visual factors rather than depending on a single confidence score. Future improvements should focus on maintaining consistent detection across different imaging conditions and satellite sources.

D. Explainability

AI-generated aircraft detections should provide understandable reasons for predictions. Future systems should improve the transparency of shape matching, texture relevance, spatial context, and confidence estimation.

E. Dense-Scene Counting

Detection systems should minimize counting errors in densely packed airfields. Robustness-aware evaluation is therefore required to ensure that aircraft counts remain accurate under occlusion and clutter.

F. Model and Sensor Evolution

New satellite sensors, resolutions, and aircraft designs continuously emerge. Future detection systems should therefore support updated feature representations and evolving imaging conditions without reducing previously learned capabilities.

G. Human–AI Interaction

AI detections should assist analysts rather than completely replace human judgement. Future systems should provide effective analyst feedback mechanisms and decision-support interfaces for reviewing and validating detections.

H. Privacy and Security

Satellite imagery may contain sensitive strategic information. Secure data management, controlled access, and privacy-preserving processing are therefore important for practical defense-related deployment.

The research roadmap can therefore be organized into three stages:

Short Term: Improve image preprocessing, small-object detection accuracy, multi-scale detection, explainability, and counting reliability.

Medium Term: Develop adaptive feature representations, improved cross-dataset detection, diverse satellite datasets, and robust evaluation across imaging conditions.

Long Term: Develop reliable human-centered surveillance intelligence that combines accurate detection, explainable predictions, adaptive learning, and human-in-the-loop decision support.

X. CONCLUSION

This paper presented an AI-powered framework for intelligent military aircraft detection and counting from satellite imagery. The framework addresses the limitations of conventional manual inspection and handcrafted image-analysis methods by incorporating image preprocessing, YOLOv8-based object detection, bounding-box localization, automatic counting, explainability, and human-in-the-loop decision support.

The proposed approach evaluates satellite scenes using visual features such as shape, texture, scale, orientation, and spatial context. The detection component enables the system to identify aircraft reliably despite variations in background complexity, resolution, and imaging conditions beyond simple threshold-based analysis. The counting component further estimates aircraft presence to support efficient surveillance.

Explainability is incorporated to improve the transparency and reliability of detection outcomes. Analysts can examine the major visual factors contributing to each detection, improving trust in the system's outputs. The human-in-the-loop design ensures that AI-generated detections support analyst decision-making rather than completely replacing human judgement.

Future research should focus on diverse satellite datasets, adaptive feature representations, robust small-object detection, faithful explainability, efficient real-time processing, and reliable AI-based aircraft surveillance and decision support.

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