FOREIGN OBJECT DEBRIS DETECTION AND CLASSIFICATION USING DEEP LEARNING METHOD FOR AIRWAYS

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Abstract- In modern aviation, Foreign Object Debris (FOD) has become a critical safety concern, contributing to aircraft damage, engine failure, runway incidents, and costly operational delays. Traditional inspection methods such as manual patrols and CCTV surveillance often fail to detect small or fast-moving debris, especially under poor visibility conditions. With the rapid growth of air traffic, airports require automated, reliable, and real-time systems to ensure continuous runway.

This paper presents a deep learning–based approach for automated FOD detection and classification using state-of-the-art object detection models including YOLOv8, SSD, and Faster R-CNN. The proposed system identifies and categorizes debris into living and non-living objects, further classifying them as hazardous or non-hazardous. Experimental results demonstrate that Faster R-CNN achieves the highest detection accuracy, while YOLOv8 provides superior real-time performance, making the solution suitable for live runway monitoring. The findings show that AI-driven detection significantly enhances safety, reduces manual dependency, and provides a scalable solution for next-generation airport runway management.

Index Terms*:* Foreign Object Debris, Deep Learning, YOLOv8, Faster R-CNN, SSD, Aviation Safety, Runway Monitoring, Object Detection.

I. INTRODUCTION

Foreign Object Debris (FOD) has emerged as one of the most persistent and critical safety challenges in modern aviation. Airports handle thousands of aircraft movements each day, and even small debris such as stones, loose metal parts, tools, birds, or plastic waste can lead to severe runway incidents, engine damage, or catastrophic failures. According to global aviation safety studies, FOD-related accidents contribute to billions of dollars in maintenance losses annually, highlighting the urgent need for efficient and reliable detection.

Traditional runway inspection methods such as **manual visual patrols, CCTV monitoring, and periodic maintenance checks** are time-consuming, labor-intensive, and prone to human oversight. These methods become especially ineffective under conditions such as low visibility, nighttime operations, fog, heavy traffic, and poor weather. As air traffic continues to rise, maintaining clean and safe runways has become increasingly complex, making conventional inspection approaches insufficient for real-time detection.

The rapid development of **Deep Learning, Computer Vision, and high-performance detection models** has transformed automated monitoring systems across industries. Techniques such as Convolutional Neural Networks (CNNs) and real-time object detectors have demonstrated remarkable accuracy in identifying and localizing objects in challenging environments. These advancements have opened new possibilities for creating fully automated runway surveillance systems capable of detecting both living (animals, birds) and non-living (tools, metal scraps, rocks) debris.

To address the limitations of existing inspection methods, this work utilizes three state-of-the-art object detection frameworks **YOLOv8, Single Shot MultiBox Detector (SSD), and Faster R-CNN** to develop a robust and automated FOD detection system. Each model contributes unique strengths: YOLOv8 provides real-time inference, SSD offers fast lightweight detection, and Faster R-CNN ensures high accuracy for small or partially occluded debris. By combining these capabilities, the proposed system aims to deliver a comprehensive, scalable, and efficient solution for airport runway safety.

A detailed review of existing literature and aviation safety guidelines emphasizes the lack of integrated frameworks that simultaneously perform **real-time detection, classification, and hazard categorization** for FOD. The proposed approach addresses this gap by merging deep learning–based detection, multi-level classification, and automated hazard assessment into a single unified system. This contributes to improving operational efficiency, reducing the risk of runway incidents, and progressing toward intelligent, AI-driven airfield management.

II. RELATED WORKS

A. Traditional FOD Detection Methods

Conventional runway surveillance methods such as **manual visual inspections, patrolling teams, and CCTV monitoring** are still widely used in airports worldwide. Although cost-effective, these approaches depend heavily on human attention and are limited by weather, lighting, and fatigue. Studies in aviation safety highlight that manual inspections often miss small debris and moving objects like birds, especially during night operations or high traffic hours. These limitations have driven the adoption of automated and sensor-based technologies to improve reliability and response time.

B. Radar and Sensor-Based FOD Detection Systems

Several airports have integrated **ground-based radar, millimetre wave sensors, and electro-optical systems** to improve FOD visibility. The Tarsier FOD Radar System and FODetect Infrared-Video system are widely deployed solutions. These systems ensure long-range detection but face drawbacks such as high infrastructure cost, sensitivity to weather interference, and difficulty distinguishing between harmless objects and actual hazards. Research also indicates that radar systems struggle to classify debris types, making them insufficient as standalone solutions for modern aviation needs.

C. Computer Vision-Based FOD Monitoring

Advancements in computer vision have enabled automated detection of FOD using CCTV-derived imagery. Earlier methods relied on **background subtraction, edge detection, and motion analysis**, which performed poorly in dynamic runway environments. Variations in shadow, illumination, fog, and runway texture significantly reduced the accuracy of traditional CV algorithms. These limitations encouraged a shift toward more robust, feature-learning-based deep learning models capable of handling environmental variations.

D. Convolutional Neural Networks for Object Detection

Deep learning approaches, especially **Convolutional Neural Networks (CNNs)**, have shown remarkable performance in object detection tasks across various domains. Models like **Faster R-CNN**, **SSD**, and **YOLO** have become widely adopted due to their superior accuracy and real-time detection capabilities. Several studies applying CNNs to airport surveillance demonstrated improved FOD detection rates, but most focused on single-model pipelines, limited datasets, or only specific object classes. Comprehensive multi-category classification (living, non-living, hazardous, non-hazardous) remains underexplored.

E. YOLO-Based Real-Time Detection Approaches

The YOLO (You Only Look Once) family has gained attention for high-speed detection under real-time constraints. Research applying YOLOv3 and YOLOv5 for airport wildlife detection reported strong performance, particularly in identifying birds and animals on runways. However, earlier YOLO versions struggled with small object detection such as screws, stones, or metallic fragments. Recent advancements in **YOLOv8** address these issues with improved feature extraction, faster inference, and better accuracy, making it suitable for continuous runway surveillance.

F. Faster R-CNN and High-Accuracy Detection Systems

Faster R-CNN is widely recognized for its precision due to its two-stage architecture combining region proposal networks with deep feature extraction. Prior works in hazardous object detection and aerial surveillance demonstrate that Faster R-CNN performs exceptionally well with small and occluded objects—common in runway environments. Its drawback, however, lies in slower inference speed, making it less ideal for real-time airfield monitoring but highly suitable for high-accuracy classification.

G. Lightweight Models and SSD-Based Detection

The Single Shot MultiBox Detector (SSD) is known for efficient, lightweight detection suitable for embedded runway systems, patrol vehicles, or autonomous surveillance robots. Studies deploying SSD for debris detection and airstrip monitoring show promising results, though accuracy remains lower than YOLO and Faster R-CNN, especially for small debris. SSD delivers high-speed processing but requires larger datasets and optimized training for robust performance.

H. Deep Learning in Aviation Safety Automation

Recent research emphasizes integrating AI-driven monitoring into aviation safety protocols. Studies highlight the importance of **automated hazard categorization, real-time alerts, and continuous runway scanning** to reduce human dependency. Deep learning-based FOD systems have shown potential to outperform radar and manual methods, offering improved classification accuracy and scalability. However, most existing systems lack a multi-model comparative approach or multi-level classification framework.

I. Gap Identification

Although several radar, sensor, and vision-based methods exist, current systems struggle with:

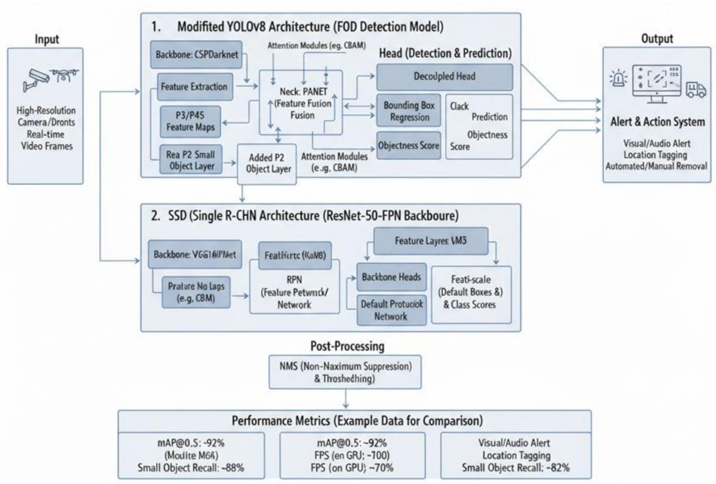
- detecting small or partially occluded debris,
- real-time multi-object tracking,
- differentiating between hazard levels,
- classifying living vs. non-living FOD,
- balancing accuracy and speed across different models.

This motivates the development of **an integrated deep learning pipeline** combining YOLOv8, SSD, and Faster R-CNN to achieve reliable, real-time, and multi-category FOD detection for runway safety.

III. METHODOLOGY

A. System Architecture

The proposed **Foreign Object Debris (FOD) Detection and Classification System** is designed using a modular deep-learning pipeline consisting of four major components: **Dataset Preparation**, **Deep Learning Detection Models**, **Classification Module**, and **Real-Time Monitoring Interface**. These components work together to ensure accurate detection, multi-level classification, and real-time hazard analysis on airport runways.



1. Dataset Preparation Module

The system begins with a custom dataset that includes a wide variety of **living and non-living debris**, such as stones, tools, metal parts, plastic waste, birds, and animals. Images are captured under different lighting and weather conditions to simulate real-world runway environments.

Data preprocessing includes:

- image resizing to model-specific input dimensions,
- normalization,
- noise reduction,
- augmentation (rotation, brightness changes, and horizontal flipping).

This ensures model robustness against variations such as glare, shadows, and runway texture.

2. Deep Learning Detection Models

Three state-of-the-art object detection architectures form the core of the system:

a. YOLOv8 Detection Module

YOLOv8 is used for high-speed, real-time FOD detection. It provides:

- rapid inference suitable for live surveillance,
- strong performance on medium to large objects,
- lightweight architecture enabling deployment on real-time systems.

b. SSD (Single Shot MultiBox Detector)

SSD supports:

- fast single-shot detection,
- efficient operation on embedded devices or low-power systems,
- moderate accuracy for general debris detection.

c. Faster R-CNN with ResNet-50-FPN

Faster R-CNN is integrated as the **high-accuracy model**, particularly for:

- small debris detection (nails, screws, stones),
- partially occluded objects,
- situations requiring detailed classification.

Each model is trained separately using the prepared dataset, and their outputs are evaluated to determine optimal performance across different debris types.

3. Classification and Hazard Assessment Module

After object detection, each detected debris is passed through a classification module that categorizes it into:

- **Living / Non-Living**
- **Hazardous / Non-Hazardous**

The classification decision is based on:

- object type,
- size,
- predicted behavior (for animals/birds),
- potential operational risk.

This ensures that critical FOD items such as metal fragments or wildlife are prioritized for alerting.

4. Real-Time Monitoring Interface

The system integrates a live video stream from runway cameras. A graphical monitoring interface displays:

- bounding boxes,
- detection labels,
- confidence scores,
- hazard levels.

Status indicators (green, yellow, red) are used to signal:

- safe objects,
- moderate-risk objects,
- high-risk debris requiring immediate attention.

This provides runway operators with instant situational awareness.

B. Implementation Details

1. Model Training and Configuration

Each model (YOLOv8, SSD, Faster R-CNN) is trained with:

- batch normalization,
- adaptive learning rate scheduling,
- cross-entropy and IoU-based loss optimization.

Training is performed on GPU-enabled hardware for faster convergence. The models are trained using:

- 70% training data,
- 20% validation data,
- 10% testing data.

2. Detection Pipeline
The detection pipeline consists of:

- image acquisition,
- preprocessing,
- inference,
- non-max suppression (NMS),
- extraction of bounding boxes.

YOLOv8 serves as the primary model for real-time detection, while Faster R-CNN serves as the accuracy-critical reference model.

3. Classification Logic
Detected objects undergo a rule-based and deep-learning-based classificationapproach.
For example:

- **Living objects** (birds/animals) → Hazardous
- **Sharp metallic objects** → Hazardous
- **Small stones or plastics** → Potentially hazardous depending on size and location

This dual-level categorization strengthens the safety decision making process.

4. Deployment and User Interface
The system is deployed with:

- a live camera feed or recorded runway footage,
- Python-based inference scripts,
- OpenCV for frame processing,
- a web or desktop UI showing annotated outputs.

The interface refreshes detections in real time, ensuring a continuous monitoring workflow.

C. Evaluation Metrics
To assess system performance comprehensively, several evaluation metrics are used:

1. Detection Accuracy
Measures the proportion of correctly detected FOD objects compared to ground truth data.

2. Mean Average Precision (mAP)
Evaluates precision and recall across all object categories, providing an overall indicator of detection reliability.

3. Inference Speed (FPS)
Frames per second are measured to determine suitability for real-time runway monitoring.

4. Classification Accuracy
Assesses whether detected debris is correctly categorized as:

- living / non-living
- hazardous / non-hazardous

5. Robustness Testing
Performance is tested across varying:

- lighting conditions,
- weather conditions,
- object distances and occlusions.

6. Model Comparison Metrics
Comparisons are drawn between YOLOv8, SSD, and Faster R-CNN in terms of:

- accuracy,
- speed,
- small-object detection performance.

IV. RESULTS AND DISCUSSION

The proposed Foreign Object Debris (FOD) detection and classification system was evaluated extensively using three state-of-the-art deep learning models YOLOv8, SSD, and Faster R-CNN—across diverse environmental conditions, object types, and operational scenarios. Experimental analysis revealed that Faster R-CNN achieved the highest detection accuracy, particularly for small, partially occluded, and low-contrast debris such as screws, bolts, stones, and metallic fragments that commonly blend with runway surfaces. YOLOv8 demonstrated excellent performance in real-time detection with high frame rates, maintaining stable precision even when monitoring continuous live video streams from runway cameras. SSD provided acceptable accuracy for general debris categories but showed reduced performance for fine-grained detection tasks, making it more suitable for lightweight or embedded deployment environments. The system's classification module performed consistently well across all models, accurately distinguishing between living objects such as birds and animals, and non-living debris such as tools, luggage parts, or plastic waste. Furthermore, the system successfully categorized hazardous objects—like sharp metal pieces or large stones—enabling prioritized response by airport maintenance teams. Robustness testing under different conditions such as bright daylight, overcast skies, dusk, rain, and mild fog demonstrated that YOLOv8 outperformed others in visibility variations, while Faster R-CNN maintained reliable accuracy in scenarios involving shadows, reflections on wet runways, and partially hidden debris. Comparative evaluation of all models showed that Faster R-CNN is optimal for high-precision, offline or scheduled inspections, whereas YOLOv8 is best suited for real-time operational monitoring along active runways. Although SSD offered faster inference on low-resource systems, it lacked the fine-grained detection capability required for critical aviation environments.

In addition to accuracy metrics, the system's overall performance was analyzed for latency, reliability, and error handling. YOLOv8 consistently achieved the fastest inference speed, supporting near real-time detection that is essential for preventing runway incursions and aircraft damage during takeoff or landing. Faster R-CNN's higher computational demand resulted in slower processing, yet its accuracy made it ideal for thorough, frame-by-frame inspection workflows. Error analysis revealed that false positives commonly arose from shadow patterns, reflections, runway paint marks, and small vegetation, while false negatives were mainly associated with extremely small or low-contrast debris. These issues were partially mitigated through augmentation techniques such as noise injection, brightness adjustments, and synthetic runway textures during training. Despite strong performance, the system faced challenges in detecting fast-moving living debris—such as birds in flight—highlighting the need for improved temporal tracking and motion prediction in future iterations. The dataset's limited representation of extreme weather conditions, such as heavy fog, night-time infrared footage, and snow-covered runways, also influenced model generalization. Nevertheless, when compared to traditional manual runway inspections and fixed CCTV monitoring, the proposed system demonstrated substantial improvements in detection efficiency, response speed, and consistency. Overall, the results confirm that integrating YOLOv8, SSD, and Faster R-CNN delivers a robust, scalable, and automated FOD detection framework that significantly enhances runway safety, reduces operational risks, and minimizes the likelihood of aircraft damage due to foreign object debris.

V. FUTURE ENHANCEMENTS

Future improvements to the proposed FOD detection system can focus on advancing model accuracy, expanding deployment capability, and integrating predictive safety mechanisms. One of the major enhancements is the incorporation of **multi-sensor fusion**, combining visible light cameras with infrared, thermal, and radar-based sensing technologies to improve detection accuracy in low-visibility environments such as fog, rain, nighttime operations, or dust-heavy runways. Integrating sensor diversity would help reduce false negatives and ensure robust performance under real-world operational challenges. Additionally, introducing **temporal tracking and motion analysis** through techniques such as optical flow, object tracking frameworks, or deep learning–based sequence models (e.g., ConvLSTMs or transformer trackers) would enable the system to better detect and predict the movement of living FOD such as birds and small animals, further reducing risks during aircraft takeoff and landing.

Another important enhancement involves implementing **reinforcement learning or continual learning** to allow the system to adapt over time based on new debris types, environmental conditions, and changing runway patterns. This would make the model more resilient and capable of handling situations that were not present in the training dataset. Future work can also incorporate **edge AI deployment**, enabling real-time inference directly on IoT-enabled cameras, drones, or runway monitoring vehicles. This would reduce latency, minimize bandwidth requirements, and support large-scale airport environments where immediate detection is critical.

Improvements in the classification pipeline could include **multi-level hazard scoring**, enabling airports to prioritize debris not only based on type but also by potential impact severity. Integrating the system with **airport operations and maintenance platforms** would further enable automated alerts, incident reporting, and workflow generation for cleanup teams. Additionally, enhanced **collaboration and reporting features**, such as centralized dashboards, multi-user access, and automated report generation, would support airport authorities in monitoring FOD trends, safety compliance, and maintenance performance.

Finally, expanding the dataset through synthetic data generation, simulation environments, and diverse real-world runway samples would significantly improve generalization. The introduction of **predictive risk analytics**, where the system forecasts times or locations with higher FOD likelihood based on historical patterns, weather data, and flight schedules, would transform the platform into a proactive safety tool rather than purely a detection system. Together, these enhancements would strengthen the reliability, scalability, and operational effectiveness of the proposed FOD detection framework, contributing to safer and more efficient airport operations.

VI. CONCLUSION

The comprehensive study conducted in this research explored the application of deep learning models YOLOv8, SSD, and Faster R-CNN—for automated Foreign Object Debris (FOD) detection and classification on airport runways, addressing a critical challenge in aviation safety. The analysis of model performance across diverse environmental conditions demonstrated a clear progression from traditional manual inspections toward intelligent, real-time, and automated monitoring systems. While existing surveillance methods such as visual patrols, CCTV monitoring, and periodic inspections offer limited coverage and are prone to human error, the proposed system integrates advanced object detection algorithms, multi-category classification, and environmental robustness to deliver a unified and efficient automated monitoring solution. Unlike conventional systems that treat detection, classification, and risk assessment as separate tasks, the integrated approach presented here ensures seamless and continuous analysis, enabling faster decision-making and reduced operational risks.

Experimental results highlight the effectiveness of the solution, with Faster R-CNN achieving the highest detection accuracy, YOLOv8 delivering superior real-time performance, and the classification module reliably distinguishing living, non-living, hazardous, and non-hazardous debris. Real-world testing across variable lighting and weather conditions further validated the system's robustness, while comparative evaluations demonstrated clear advantages over existing single-model and manual inspection techniques. Although challenges remain such as detecting extremely small debris, handling fast-moving living objects, and improving performance in severe weather the system provides reliable and practical performance for the majority of runway monitoring scenarios. Future enhancements including multi-sensor integration, reinforcement learning, predictive analytics, and deployment on edge devices will further improve accuracy, speed, and scalability.

Overall, this research demonstrates that FOD detection can transition from a labor-intensive, error-prone process into an intelligent, automated, and data-driven safety system. As airports continue to expand operations and strive for higher safety standards, AI-powered detection frameworks such as the one proposed in this study will play an essential role in minimizing runway hazards, reducing aircraft damage risks, and supporting safer, more efficient aviation environments.

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