Automatic Detection and Predictive Geo-location of Foreign Object Debris on Airport Runway

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Abstract—This paper presents an advanced Foreign Object Debris (FOD) detection system for airport runways using YOLOv8 and a geolocation prediction model based on machine learning regression. By integrating a self- attention mechanism with CNNs, the system achieves high detection accuracy, especially for small objects under challenging weather conditions. Ablation studies show improved Mean Average Precision (mAP), and comparisons with YOLOv5, YOLOX, and YOLOv7 confirm YOLOv8's superior performance. The geolocation model further enhances practical deployment for real- world FOD detection and removal.

I. INTRODUCTION

Foreign Object Debris (FOD) on airport runways poses a significant safety risk, potentially damaging aircraft engines, tires, and critical components. Traditional FOD detection methods like manual inspections or ground sensors are often inefficient and unreliable, especially in adverse weather.

This project introduces an automated FOD detection system using UAVs equipped with YOLOv8, enhanced by the Swin Transformer (ST), for accurate small-object detection under diverse environmental conditions. The model is trained on a large UAV-captured dataset of 74,737 images across 21 object classes, ensuring robust real-world performance.

To further aid debris removal, a machine learning-based regression model is integrated for precise geolocation prediction of detected FOD. The system is designed for real-time detection and localization, making it suitable for dynamic airport operations.

II. EASE OF USE

A. Real-Time Automated Detection

The FOD detection system is built on the YOLOv8 architecture, enabling real-time object detection with high accuracy. Its capability to detect small and irregularly shaped debris ensures reliability in critical runway environments. The model is lightweight and can run efficiently on edge devices or low-power hardware, reducing infrastructure requirements.

B. Predective Geo-Loaction Mapping

The machine learning-based geolocation module predicts the precise location of detected debris using regression algorithms. This enables immediate identification of debris positions on the runway, allowing ground crews to act quickly without relying on manual inspection or GPS-tagging equipment.

III. EXISTING SYSTEM

Existing FOD detection systems use models like YOLOv5, YOLOX, and YOLOv7, which perform well in real-time detection but struggle with small object detection under poor visibility or varying weather. They also lack accurate geolocation features for efficient debris removal.

A. YOLOv5

- Developed by Ultralytics, YOLOv5 is a widely adopted real-time object detection model.
- It uses a single-stage detection approach with CNN-based feature extraction.
- Known for its speed and ease of deployment.

B. YOLOv7

- An advanced version of the YOLO series with enhanced architectural optimizations.
- Provides higher detection accuracy and speed than YOLOv5..
- Designed for more complex object detection tasks, including small and overlapping objects.

C. LIMITATIONS

- Inconsistent detection performance across different weather and lighting conditions.
- Limited accuracy in identifying very small debris at long distances.
- Lack of integrated geolocation prediction— detected objects are identified but not precisely localized on the runway.

DISADVANTAGES

Poor detection of small object. High computational requirement. Large and complex models.
Overfitting on limited datasets

These constraints hinder the practical deployment of existing systems for real-time, reliable FOD detection and removal, especially in dynamic airport environments.

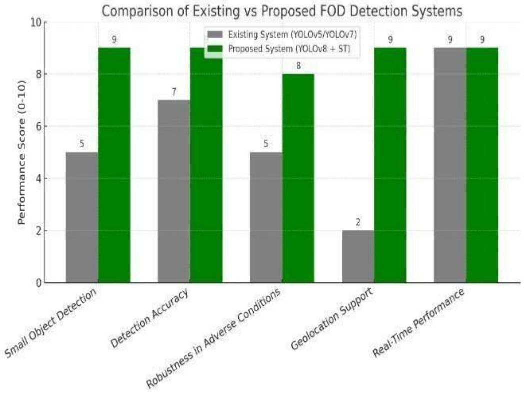
IV. TECHNIQUES/ALGORITHMS USED

The proposed system is designed to address the key challenges faced by existing FOD detection methods— particularly small object detection, accuracy in complex environments, and geolocation capabilities. It integrates YOLOv8 for object detection and a machine learningbased regression model for precise geolocation prediction. This combination results in a robust, intelligent system suitable for real-world airport runway surveillance and safety operations.

The proposed system uses YOLOv8 with Swin Transformer to improve small object detection and handle adverse weather. Trained on 74,737 UAV images, it combines YOLOv8's speed with the Swin Transformer's attention mechanism for better accuracy in cluttered environments.

A. YOLOv8

- YOLOv8 is the latest version in the YOLO series, designed for high-accuracy, real-time object detection with superior generalization capabilities.
- Supports both bounding box regression and instance segmentation, making it highly flexible.
- In addition to detection, the system includes a machine learning-based regression model for geolocation prediction. This enables:
- Precise localization of FOD on the runway map.
- Efficient deployment of maintenance crews for targeted debris removal.



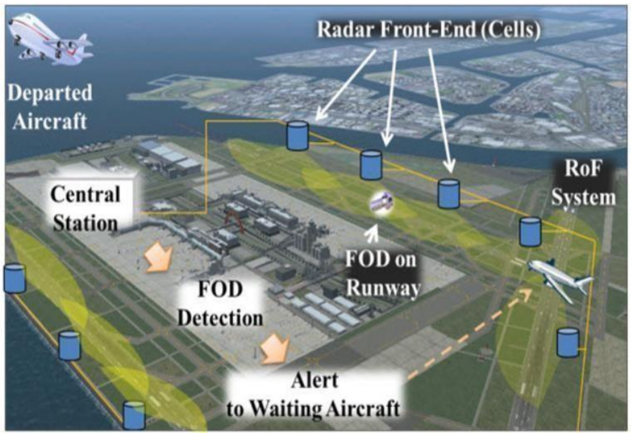
B. ADVANTAGES

- Superior Small Object Detection.
- Improved Accuracy and Robustness
- Improved Handling of Cluttered Backgrounds
- Better Integration of Attention Mechanisms

C. POSITIONING MODEL OF FOREIGN OBJECTS

Numerous studies employ machine learning algorithms for data processing, and similarly, this study utilizes machine learning regression algorithms for handling data with continuous distributions. Initially, the constructed locating dataset is divided into a training set and a test set in an 8:2 ratio. Subsequently, the coefficient of determination R^2 serves as the performance evaluation metric during the regression model training stage, indicating the extent of agreement between the predicted and actual values. The calculation procedure for R^2 is illustrated in equation, where R^2 values range between zero and one. A higher R^2 value suggests enhanced interpretability of the corresponding variable by the independent variable as it approaches one.

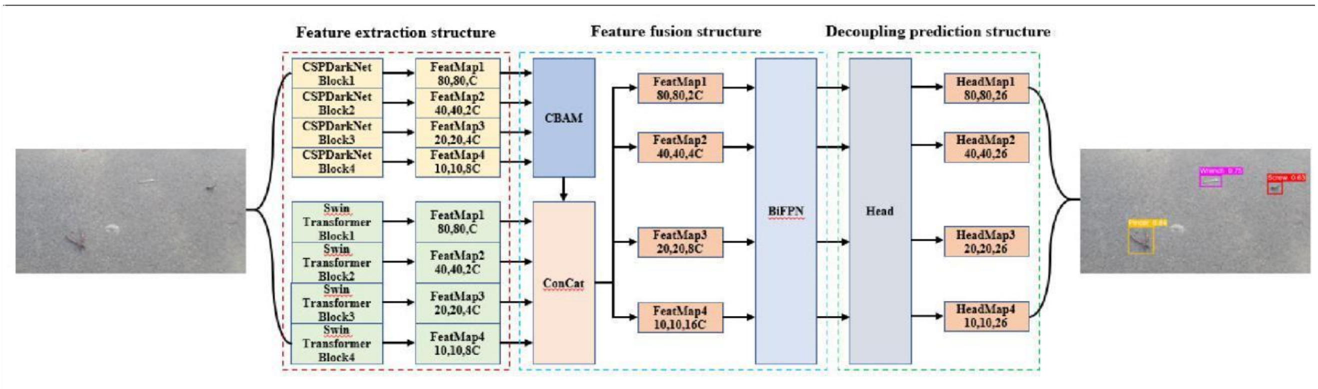
$$R2=1-\sum mi=0(yi-yi^{\wedge})2/\sum mi=0(yi-\overline{y}i)2$$



V. DATA PROCESSING

FIGURE 1. The portion of images in the Dataset, each maintaining a consistent resolution of 320 × 320 pixels

Longitude	Latitude	Shooting Height (m)	Yaw Angle (°)	X	Y	Object Longitude	Object Latitude
108.57139251	34.14766719	10	177	400.0	545.0	108.57139307	34.14773070
108.57139213	34.14763169	7	20	-742.5	444.5	108.57139600	34.14773380
108.57139066	34.14761780	5	256	-197.5	1082.5	108.57139307	34.14773070
108.57139011	34.14771360	3	186	-725.0	1267.0	108.57138619	34.14779490
108.57138963	34.14768409	2	201	2483.5	988.5	108.57139600	34.14773380



UAVs captured high-resolution images and 4K videos during low-traffic hours for safe and clear data collection. A dataset of 7,625 FOD images (1280×1280) was created under various conditions. To fit the model's 320×320 input, bounding boxes were extracted from key regions to retain objects and minimize background loss

VI. CONCLUSION

The automatic detection and predictive geo-location of Foreign Object Debris (FOD) on airport runway images presents a transformative approach to improving runway safety and operational efficiency. Through the integration of advanced computer vision techniques and deep learning models, this project successfully demonstrates how FOD can be accurately identified in high-resolution images. Furthermore, by incorporating geospatial analysis, the exact location of debris can be predicted and mapped in real-world coordinates, enabling timely response and clearance by airport maintenance teams.

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