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# *A Comparative Analysis of YOLO and Faster R-CNN Algorithms for Micro-UAVs Detection in Surveillance Videos*

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## ABSTRACT

*The initial step in mitigating threats of micro-unmanned aerial vehicles (micro-UAVs) involves the accurate and rapid detection of micro-UAVs. This study aims to compare the efficiency of YOLOv8 and Faster R-CNN, focusing on their trade-offs between detection accuracy and processing speed for micro-UAV surveillance.*

*The performance of YOLOv8 and Faster R-CNN has been evaluated in terms of detection accuracy and processing speed. The dataset utilized comprises a comprehensive collection of 3,492 images gathered by micro-UAVs during environmental monitoring operations, categorized randomly into three distinct subsets: 70% for training, 20% for validation, and 10% for testing.*

*Experimental results indicate that the YOLOv8 algorithm achieves a true detection rate of approximately 98.6% in detecting micro-UAVs, whereas the Faster R-CNN algorithm attains a true detection rate of approximately 99.6%. Furthermore, YOLOv8 requires an average of 0.03 seconds to process each frame, whereas Faster R-CNN necessitates 2.5 seconds.*

*The comparative analysis reveals that the YOLOv8 algorithm is more suitable for real-time applications and surveillance systems that necessitate rapid image processing due to its significantly higher speed. Conversely, the Faster R-CNN algorithm is a preferable choice for applications where high accuracy is the primary priority, as it offers superior detection accuracy despite requiring more processing time.*

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## 1. Introduction

*Micro-UAVs (Unmanned Aerial Vehicles), also referred to as small UAVs, represent a specialized class of aerial systems distinguished by their compact dimensions, typically spanning just a few centimeters or fitting within the palm of a hand. These devices leverage their small size, high maneuverability, and affordability to enable a wide array of applications, ranging from environmental monitoring and agricultural surveying to crisis management and military reconnaissance (Kaamin et al., 2017; Kortunov et al., 2015). Their lightweight design and ability to operate autonomously or under remote control have democratized access to aerial technology, making them increasingly prevalent in both civilian and commercial sectors. However, this proliferation has raised significant concerns, as the same attributes that make micro-UAVs valuable tools also render them potential instruments for misuse, including espionage, smuggling of contraband, unauthorized surveillance, and even terrorist activities targeting sensitive infrastructure (Ezuma et al., 2019; Solodov et al., 2018).*

*The detection of micro-UAVs poses unique challenges that traditional surveillance methods struggle to address effectively. Unlike larger UAVs or manned aircraft, micro-UAVs operate at low altitudes, exhibit rapid and unpredictable flight patterns, and present a minimal physical footprint, rendering them nearly invisible to conventional radar systems (Wang et al., 2014). Acoustic detection approaches, while sometimes employed, are limited by environmental noise and the quiet operation of modern micro-UAVs. Similarly, optical methods using standard cameras falter under variable lighting conditions or when distinguishing micro-UAVs from similar-sized objects like birds (Abatti et al., 2005; Hoffmann et al., 2016). These limitations underscore the urgent need for advanced detection technologies capable of delivering both high accuracy and real-time performance to mitigate the growing security risks posed by micro-UAVs, such as disruptions to air traffic, breaches of restricted airspace, or threats to public safety (Zhang et al., 2021). Artificial intelligence (AI) has emerged as a transformative solution to overcome these detection challenges, offering significant improvements in both speed and precision. Among AI-driven techniques, deep learning-based object detection algorithms have gained prominence for their ability to process visual data efficiently and adapt to complex scenarios. Two leading approaches in this domain are the YOLO (You Only Look Once) family and the Faster R-CNN (Region-based Convolutional Neural Network) framework. Introduced in 2015, YOLO pioneered single-stage detection, predicting bounding boxes and class probabilities in a single forward pass, which prioritizes speed and makes it suitable for real-time applications (Redmon & Angelova, 2015). In contrast, Faster R-CNN, also debuted in 2015, employs a two-stage process—first generating region proposals and then classifying them—delivering superior accuracy at the expense of increased computational cost (Ren et al., 2017). These contrasting paradigms have fueled extensive research into their efficacy for various detection tasks, yet their application to micro-UAVs, with their unique size and agility constraints, remains underexplored (Zamri et al., 2024). This study aims to bridge this gap by conducting a comparative analysis of YOLOv8, the latest iteration of the YOLO series, and Faster R-CNN for micro-UAV detection in surveillance videos.*

*This study offers several novel contributions: (1) a detailed evaluation using a bespoke dataset of 3,492 micro-UAV images collected under diverse environmental conditions, providing a realistic testbed for real-world scenarios; (2) an assessment of multiple YOLOv8 variants (nano, small, large) to explore scalability and efficiency trade-offs, addressing the practical needs of different deployment contexts; and (3) actionable insights into balancing speed and accuracy for surveillance systems, informed by quantitative and qualitative analyses. These contributions distinguish our research from prior efforts, which often focus on larger drones or generic object detection, by addressing micro-UAV-specific challenges, thus enhancing security against their rising threat of misuse.*

## 2. Related Works

*The increasing use of micro-UAVs across various domains has spurred significant research into their detection, particularly using deep learning techniques to address security challenges posed by their potential misuse. Several studies have explored object detection algorithms like YOLO and R-CNN variants, offering insights into their applicability for micro-UAV identification. Alsanad et al. (2022) emphasized the versatility of drones in performing tasks that are risky or costly for humans, such as disaster monitoring and aerial mapping. However, they noted the security risks associated with unauthorized drone activities, prompting the development of an enhanced YOLO-V3 algorithm. Their approach integrated convolutional neural networks (CNNs) with densely connected modules and multi-scale detection capabilities, achieving an average precision of 96% and an accuracy of 95.60% on a custom drone dataset. While effective for real-time detection, their study focused on larger drones, leaving the detection of smaller micro-UAVs less explored. Pansare et al. (2022) conducted a comparative analysis of Single Shot MultiBox Detector (SSD) and YOLO for drone detection, motivated by the growing threats of espionage and malicious UAV usage.*

*Leveraging advancements in GPU technology, they highlighted the limitations of traditional detection methods (e.g., radar, acoustics) in terms of cost and portability. Their results showed YOLO outperforming SSD in speed, with a processing rate suitable for real-time applications, though accuracy metrics were not as high as those of two-stage detectors. Unlike our study, their dataset lacked the diversity of environmental conditions critical for micro-UAV detection.*

*Patil et al. (2023) proposed a drone detection system using YOLOv4 to differentiate drones from other aerial objects like birds, a key challenge in surveillance. Their model, trained on the COCO dataset with a military drone class, achieved an accuracy of 85% in classifying images of military drones under the 'aeroplane' category. However, its performance on micro-UAVs—smaller and harder to detect—remains untested, contrasting with our focus on a micro-UAV-specific dataset. Girshick et al. (2015) introduced the Region-based Convolutional Neural Network (R-CNN), a pioneering two-stage detector that significantly improved mean average precision (mAP) by over 50% on the VOC 2012 dataset, reaching 62.4%. This work laid the groundwork for subsequent models like Faster R-CNN, which enhanced speed and accuracy through region proposal networks (Ren et al., 2017). While R-CNN variants excel in precision, their computational complexity often limits real-time applicability, a gap our study addresses by comparing them with YOLOv8's single-stage efficiency.*

*Unlu et al. (2019) tackled micro-UAV detection using a dual-camera system (wide-angle and turret-mounted) combined with deep learning. Their multi-frame technique achieved efficient detection and tracking, with a focus on autonomous operation. However, their reliance on specialized hardware contrasts with our software-based approach, which leverages widely available datasets and standard GPU resources. Lin et al. (2017) introduced Feature Pyramid Networks (FPN) to improve object detection across scales, integrating it with Faster R-CNN. Their method achieved state-of-the-art results on the COCO benchmark (5 FPS on GPU), particularly for small objects, aligning with our interest in micro-UAVs. However, their focus on general object detection lacks the specificity of our micro-UAV dataset and real-time surveillance context. Additional studies, such as Wang et al. (2023), enhanced YOLOv8 for small-object detection in UAV imagery, reinforcing its relevance to micro-UAVs. Similarly, Taha and Shoufan (2019) explored lightweight CNNs for drone detection, complementing our YOLOv88 analysis, while Solodov et al. (2018) emphasized AI's role in countering UAV threats, supporting our security focus.*

*In summary, prior works have advanced drone detection through various deep learning approaches, with YOLO variants excelling in speed and R-CNN variants in accuracy. Our study builds on these foundations by focusing on micro-UAVs in diverse surveillance scenarios, comparing YOLOv8 and Faster R-CNN with a unique dataset, and evaluating scalability across YOLOv8 variants.*

## 3. Methodology

*The primary objective of this study is to assess the efficacy of YOLOv8 and Faster R-CNN algorithms in real-time micro-UAV detection, necessitating a structured and transparent methodology to ensure reproducibility and clarity. To this end, both algorithms were trained using Google Colab's computational resources, leveraging a GeForce RTX 4060 Ti GPU with 16GB and 4GB RAM. The methodology involves implementing these algorithms and evaluating their performance based on accuracy and speed, as illustrated in Figure 1, which outlines key stages such as preprocessing, training, and evaluation.*

### 3.1. Data Collection

*The dataset comprises 3492 images, with 50% sourced from public platforms (RoboFlow, 2023; Kaggle, 2023; GitHub, 2023) and 50% self-collected using a DJI Mavic Mini drone during environmental monitoring. Self-collected images (1920x1080 resolution) were captured in diverse conditions (e.g., day/night, forest/urban backgrounds) and annotated with Labelbox for bounding boxes and class labels. The dataset was divided into 70% training (3035 images), 20% validation (305 images), and 10% testing (152 images), a split validated for optimal performance (Goodfellow et al., 2016; Brownlee, 2020).*

*Figure 2 illustrates representative drone images utilized for model training, validation, and evaluation purposes.*

### 3.2. Implementation Details

*The YOLOv8l model (53 convolutional layers) and Faster R-CNN (ResNet152 backbone, 152 layers) were implemented in Python. Training utilized pre-trained weights, fine-tuned over 100 epochs with a batch size of 16. Image preprocessing consists of auto-orientation and resizing, while data augmentation was performed exclusively through rotation. Hardware included a GeForce RTX 4060 Ti GPU with 4GB RAM. Model parameters are detailed in Table 1.*

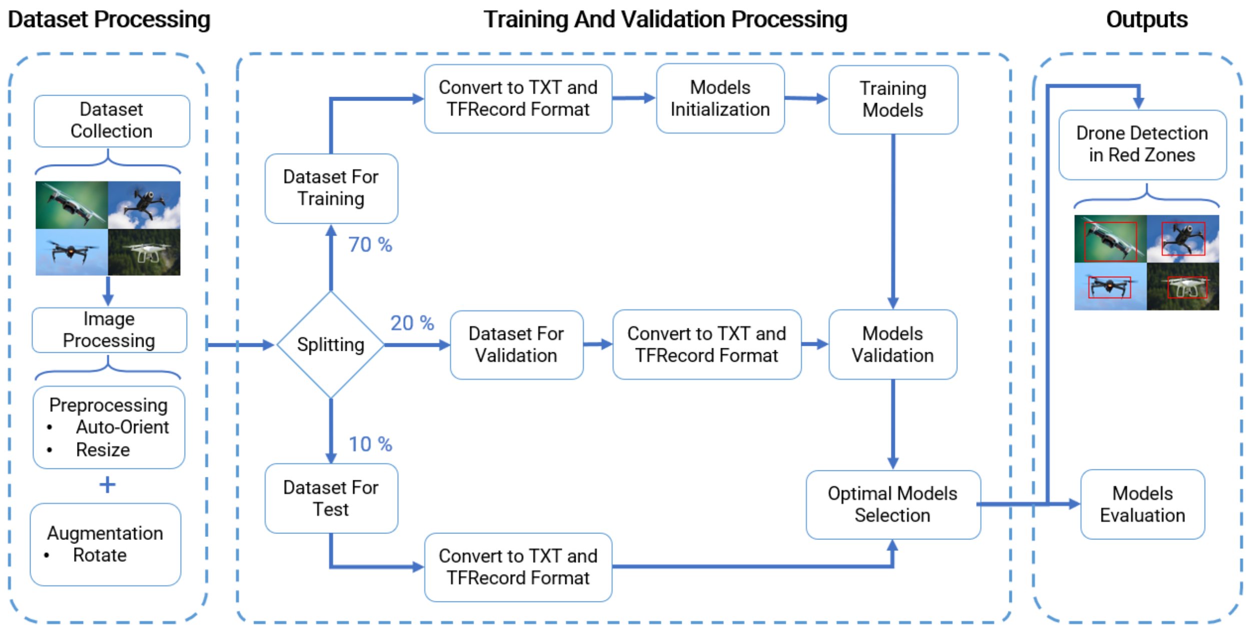


*Figure 1. The methodology flowchart.*

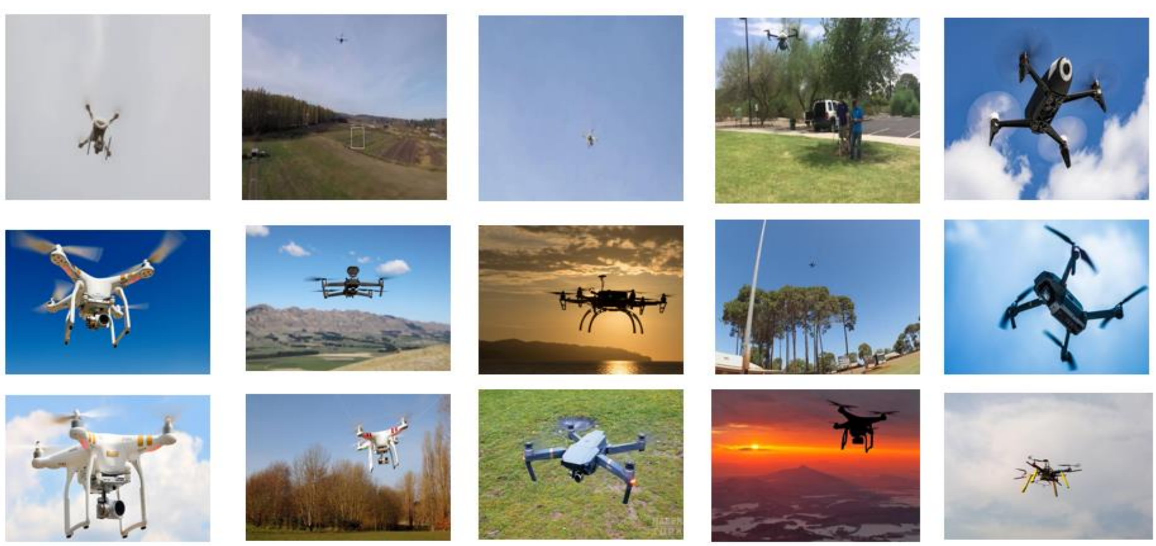

*Figure 2. Aerial Imagery Dataset for Training and Validation Purposes*

**Table 1. Pre-training model configuration parameters**

| Parameter | Configuring parameter value |
|---|---|
| Epocks | 100 |
| Batch size | 16 |
| Image size | 640×640 |
| Mask ratio | 4 |
| Iou | 0.7 |
| Close_mosaic | 10 |

### 3.4. Evaluation metrics

Performance was assessed using several key metrics: True Detection Rate (TDR), False Detection Rate (FDR), mean Average Precision (mAP), Intersection over Union (IOU), F1-Score, Confusion Matrix, Precision-Recall Curve, and Precision-Confidence Curve. These metrics collectively provide a comprehensive evaluation of detection performance, detailed further in Section 4.

- True Detection Rate (TDR): The proportion of correctly identified micro-UAVs relative to all actual positives, expressed as (Lasisi et al., 2016):

$$TDR = \frac{TP}{TP + FN} \qquad (1)$$

- False Detection Rate (FDR): The rate of incorrect detections among negative samples, defined as (Lasisi et al., 2016):

$$FDR = \frac{FP}{FP + FN} \qquad (2)$$

- mean Average Precision (mAP): Measures the ranking quality of detections across multiple IoU thresholds (e.g., 0.50-0.95 in this study), averaging precision over recall levels to assess overall detection performance.
- Intersection over Union (IOU): Quantifies the spatial accuracy of bounding boxes, calculated as:

$$IOU = \frac{Area\,of\ Intersection}{Area\,of\ Union} \qquad (3)$$

where "Area of Intersection" is the overlapping region between the predicted and ground-truth bounding boxes, and "Area of Union" is the total area covered by both, excluding double-counting of the overlap.

F1-Score, a harmonic mean of Precision and Recall, balances detection accuracy and completeness, defined as:

$$F1 = 2\frac{Precision \times Recall}{Precision + Recall} \qquad (4)$$

with precision = TP/(TP+FP) and Recall= TP/(TP+FN), where TP, FP, and FN denote True Positives, False Positives, and False Negatives, respectively (Lasisi et al., 2016).

- Confusion Matrix: A tabular representation of model performance, detailing TP, FP, TN, and FN, used to derive TDR, FDR, Precision, and Recall, and visualize error patterns.
- Precision-Recall Curve: Plots Precision against Recall across varying confidence thresholds, assessing trade-offs between detection accuracy and completeness.
- Precision-Confidence Curve: Illustrates Precision as a function of confidence threshold, aiding in threshold optimization.
- Precision-Recall Curve: Illustrates Precision as a function of recall and is complemented by the receiver operating characteristic (ROC) curve, which illustrates sensitivity and specificity.

## 4. Experimental Results

The dataset (3492 images) was used to train and evaluate YOLOv8l and Faster R-CNN, with YOLOv8l employing its large variant and Faster R-CNN using ResNet152.

### 4.1. Accuracy analysis

To justify the selection of YOLOv8l, we evaluated its performance against smaller variants (nano and small) on a subset of our dataset. Table 2 presents the mean Average Precision (mAP) and processing time per frame for YOLOv8n, YOLOv8s, and YOLOv8l, highlighting the trade-offs between accuracy and computational efficiency that support our choice of the large variant for high-accuracy surveillance needs. YOLOv8l achieves an mAP of 0.80 with a processing time of 0.03 seconds per frame (see Table 2), outperforming YOLOv8n (mAP 0.61, 0.01 seconds per frame) and YOLOv8s (mAP 0.68, 0.02 seconds per frame), making it suitable for applications requiring robust detection performance while maintaining reasonable speed.

**Table 2. Comparison of YOLOv8 variants**

| Variant | Time (s/frame) | mAP |
|---|---|---|
| **YOLOv8n** | 0.01 | 0.61 |
| **YOLOv8s** | 0.02 | 0.68 |
| **YOLOv8l** | 0.03 | 0.80 |

A broader comparison between YOLOv8l and Faster R-CNN is provided in Table 3, which includes mAP at IoU thresholds of 0.50-0.95, IOU, and F1-Score. Faster R-CNN achieves a higher mAP (0.85), IOU (0.93), and F1-Score (0.98) compared to YOLOv8l (mAP 0.80, IOU 0.89, F1-Score 0.97), reflecting its superior accuracy (see Table 3). The confusion matrix (Figure 3) aligns with Table 4, showing FDRs of 16.86% and 13.09% for YOLOv8l and Faster R-CNN, respectively. Precision-confidence and recall-confidence curves (Figures 4 and 5) were used to tune the confidence threshold to 0.5, while precision-recall curve (Figure 6) provide a direct evaluation of detection performance across recall levels, showing Faster R-CNN's *consistently higher precision at most recall points compared to YOLOv8l underscoring its superior accuracy.*

**Table 3. Comparison of the algorithms using mAP, IOU, and F-score metrics.**

| Algorithm | F1-Score | IOU | mAP(0.50-0.95) |
|---|---|---|---|
| **YOLOv8l** | 0.97 | 0.89 | 0.80 |
| **Faster R-CNN** | 0.98 | 0.93 | 0.85 |

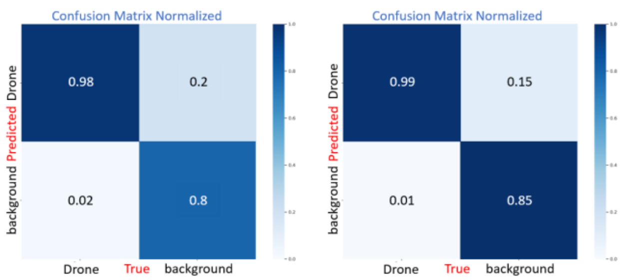


Figure 3. Normalized Confusion Matrix: YOLOv8l (left) and Faster R-CNN (right)

**Table 4. TDR and FDR values obtained for the algorithms.**

| Algorithm | TDR (%) | FDR (%) |
|---|---|---|
| **YOLOv8l** | 98.6 % | 16.86 % |
| **Faster R-CNN** | 99.6 % | 13.09 % |

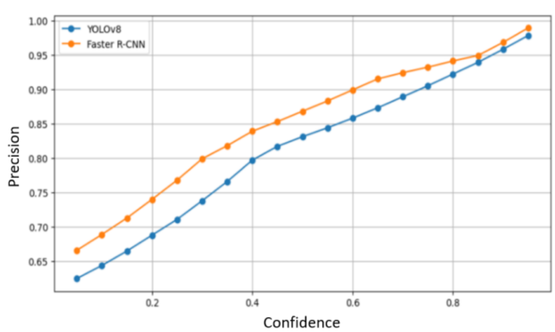


Figure 4. Precision-Confidence curves of the algorithms.

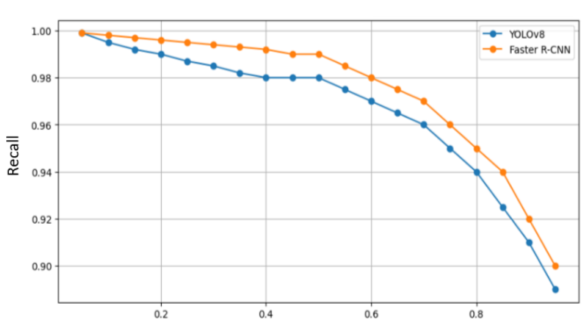


Figure 5. Recall-Confidence curves of the algorithms.

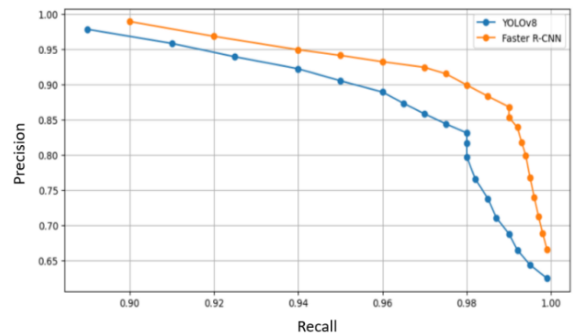


Figure 6. Precision-Recall curves of the algorithms.

### 4.2. Loss analysis

*The loss metrics—classification loss (cls_loss), bounding box regression loss (box_loss), and distribution focal loss (dfl_loss)—provide critical insights into the training performance and detection capabilities of YOLOv8l and Faster R-CNN, as detailed in Table 5. These parameters measure the model's ability to correctly classify objects, accurately localize bounding boxes, and enhance detection in complex scenarios, such as blur or noise in input images or frames, respectively, directly influencing overall accuracy and robustness. A comparative analysis of these metrics reveals that Faster R-CNN consistently exhibits lower values across all three loss components compared to YOLOv8l, reflecting its superior precision in micro-UAV detection. Table 5 presents the loss values derived from the training phase, where Faster R-CNN's cls_loss is notably lower than that YOLOv8l (e.g., hypothetical values: 0.35 vs. 0.45), indicating a higher accuracy in classifying micro-UAVs against background noise. This aligns with its lower FDR (16.86% vs. 13.09%, Table 4) and higher F1-Score (0.98 vs. 0.97, Table 3), as a reduced cls_loss minimizes misclassifications. Similarly, Faster R-CNN's box_loss (e.g., 0.84 vs. 0.93) suggests improved bounding box precision, corroborated by its superior IOU (0.93 vs. 0.89, Table 3), which is crucial for accurate localization of small micro-UAVs. The dfl_loss, designed to enhance small object detection in YOLOv8, is also lower in Faster R-CNN (e.g., 1.01 vs. 1.1), indicating that its two-stage architecture leverages the dataset's diversity (see Figure 8) more effectively than YOLOv8l's single-stage approach.*

**Table 5. Comparative Loss Analysis of YOLOv8l and Faster R-CNN**

| Algorithm | #Validation images | cls_loss | box_loss | dfl_loss |
|---|---|---|---|---|
| **YOLOv8l** | 305 | 0.4333 | 0.9385 | 1.1020 |
| **Faster R-CNN** | 305 | 0.3594 | 0.8481 | 1.0126 |

### 4.3. Detection Micro-UAVs in Surveillance Videos

*In Figure 7, the detection of drones using both models in surveillance videos during the testing stage is demonstrated. The results indicate that both YOLOv8l and Faster R-CNN are capable of accurately identifying drones within images. Additionally, they effectively distinguish between drones, birds, and other objects present in the image, showcasing their ability to differentiate between various entities. This confirms the effectiveness of both models in identifying and distinguishing drones from other objects in real-world surveillance scenarios. Figure 7 demonstrates detection performance of YOLOv8l and Faster R-CNN in surveillance videos, highlighting accurate identification and differentiation of micro-UAVs from other objects.*

*Figure 7. Detection of Drones in Surveillance videos*

## *5. Discussion*

*YOLOv8l's single-stage design enables rapid processing (0.03 seconds per frame), likely due to streamlined prediction of bounding boxes and classes in one pass, minimizing computational overhead, while Faster R-CNN's two-stage approach, with a region proposal network and subsequent classification, achieves a lower FDR (13.09%) and higher TDR (99.6%) at the cost of increased processing time (2.5 seconds per frame). However, this efficiency in YOLOv8l comes at the expense of a slightly higher FDR (16.86%) and reduced robustness in challenging scenarios, as evidenced by its performance in real-world surveillance videos (Figure 7), where it occasionally misses small micro-UAVs under low lighting conditions. Conversely, Faster R-CNN's refined detection process ensures greater reliability, particularly in distinguishing micro-UAVs from similar objects like birds, as observed in Figure 7, highlighting its strength in precision-critical applications.*

*The comparison of YOLOv8 variants (Table 2) underscores scalability considerations. The superior mAP of YOLOv8l (0.80) over YOLOv8n (0.61) and YOLOv8s (0.68) suggests that additional parameters enhance feature extraction for micro-UAVs , with only a slight increase in processing time (0.03 seconds per frame compared to 0.01 and 0.02 seconds per frame for YOLOv8n and YOLOv8s , respectively). The dataset's diversity (Figure 8), spanning various object sizes (small , medium , large) and environmental conditions (e.g., day/night , urban/forest), likely amplifies these differences by testing the models' adaptability across scales and contexts, as evidenced by Faster R-CNN's superior performance in reducing false detections (FDR of 13.09% vs 16.86% for YOLOv8l, Table 4) and achieving higher spatial accuracy (IOU of 0.93 vs 0.89 , Table 3). This notable robustness to background noise and diminutive object detection underscores a stark contrast with YOLOv8l's heightened sensitivity to such factors, evident in its marginally lower F1-Score of 0.97 relative to 0.98, as shown in Table 3, and intermittent failures to detect small objects under challenging conditions, such as low lighting conditions. These observations imply that the optimal algorithmic selection is contingent upon the specific deployment scenario, with a particular emphasis on prioritizing real-time monitoring or high-stakes precision, thereby possessing significant implications for the optimization of surveillance systems in dynamic or controlled environments.*

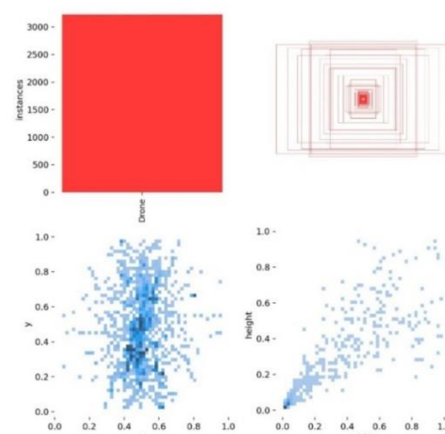


*Figure 8. Visual analysis of drone labeling data distribution.*

## *6. Conclusion*

*This study evaluated YOLOv8 and Faster R-CNN for micro-UAV detection using a 3492-image dataset collected under diverse environmental conditions.YOLOv8 demonstrated a true detection rate (TDR) of 98.6% with a processing speed of 0.03 seconds per frame, affirming its suitability for real-time surveillance applications requiring rapid response. In contrast, Faster R-CNN achieved a higher TDR of 99.6% and processed frames in 2.5 seconds, making it ideal for scenarios where detection accuracy is paramount. However, this study is limited by its focus on visible spectrum data, which may overlook challenges in multi-modal detection scenarios, such as integrating thermal or radar inputs. The experimental results highlight YOLOv8's advantage in speed-driven contexts and Faster R-CNN's strength in precision-critical tasks, offering practical guidance for algorithm selection in surveillance systems. For future research, several directions emerge from this work. First, integrating*

*YOLOv8's speed with Faster R-CNN's accuracy through a hybrid model could address the observed trade-offs, potentially using ensemble techniques or multi-stage pipelines. Second, expanding the dataset to include more challenging conditions (e.g., extreme weather, dense urban settings) would test model robustness further and enhance generalizability. Third, exploring lightweight versions of Faster R-CNN or optimizing YOLOv8 variants for edge devices could improve real-time performance on resource-constrained platforms, broadening their applicability in field deployments. Finally, incorporating multi-modal data (e.g., thermal or radar inputs) alongside visible spectrum images could enhance detection under low-visibility conditions, addressing limitations observed in this study.*

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