Drone Classification and Identification Using Computer Vision, Machine Learning and YOLO V8 Algorithm

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Abstract: Drones have increasingly been exploited by adversaries in border regions to transport contraband such as drugs and weapons. The widespread adoption of drone technology across various sectors has brought significant advantages, but also raised critical concerns involving security, privacy, and regulatory oversight. With the growing density of drones operating in shared airspace, it becomes essential to develop reliable systems for drone recognition and classification to promote safe airspace management. This paper presents a novel technique that integrates computer vision and machine learning to identify and categorize drones effectively. Utilizing advanced deep learning models, our approach extracts distinctive features from images of drones captured by surveillance systems or sensors. These features are then classified into specific drone categories using the YOLOv8 algorithm, enabling real-time detection and monitoring. We validate our method on a diverse dataset comprising multiple drone types and varying environmental scenarios. The experimental findings reveal robust performance and scalability, with high accuracy for both identification and classification tasks. Additionally, we explore the relevance of our system in critical applications such as law enforcement, border patrol, infrastructure surveillance, and emergency management. This work advances drone detection methodologies and addresses key challenges in integrating drones safely within civilian airspace.

Keywords: *DPM, RCNN, SSD, PAN FPN, YOLO-V8, ERB, FFNB, YOLOMG.*

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I. INTRODUCTION

Unmanned Aerial vehicle (UAV)or Drones has seen explosive growth in use across recreational, commercial, and defense sectors, with sales projected to reach 2.68 million units in 2025 alone. This expansion promises breakthroughs in efficiency and innovation, yet it heightens risks to aviation safety, public security, and personal privacy. Recent events underscore these threats, including a 26% surge in U.S. drone incursions near restricted airspace in early 2025, near-misses with airliners at airports like Houston and Chicago, and unexplained sightings across Europe starting in September 2025.

Drones have also enabled illicit activities, such as smuggling drugs across U.S.-Mexico borders by cartels and contraband deliveries to prisons, demanding urgent airspace oversight. Conventional detection relying on radar or radio frequency lacks precision in cluttered settings, whereas vision- based systems powered by deep learning excel at analyzing camera footage for reliable identification.

This paper introduces an innovative framework merging computer vision and machine learning to detect and categorize drones via feature extraction from visual data, surpassing prior techniques in speed and accuracy for live operations. The approach bolsters airspace integrity by equipping security teams with tools to counter rogue flights, applicable to policing, frontiers, vital assets, and crisis handling. Later sections outline the model architecture, dataset creation, rigorous testing, and broader effects on drone governance.

Unmanned aerial vehicles (UAVs), or drones, are experiencing rapid expansion in recreational, commercial, and military domains, with global sales forecasted to hit 2.68 million units in 2025. This growth unlocks innovations in productivity and operations, but it amplifies threats to aviation safety, national security, and individual privacy. Notable cases illustrate the urgency: a 26% rise in U.S. drone incursions into restricted airspace in early 2025, near-collisions with airliners over Houston and Chicago airports, and widespread unexplained sightings across Europe since September 2025.

Drones facilitate criminal acts like cartel drug smuggling across US-Mexico borders and contraband drops into prisons, underscoring the need for precise airspace

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monitoring and drone categorization. Radar and radio-frequency detection struggle with precision and reliability in urban or cluttered areas, while camera-based computer vision paired with deep learning provides superior analysis of visual traits for automated recognition.

This paper proposes an advanced framework blending computer vision and machine learning to detect and sort drones by pulling key visual features from sensor imagery, outperforming legacy systems in real-time accuracy. Such tools empower officials to preempt rogue operations, supporting law enforcement, border control, asset safeguarding, and disaster aid. Upcoming sections cover the deep learning design, dataset assembly, experimental validation, research outcomes, and influences on airspace regulation.

II. OVERVIEW OF RELATED LITERATURE

Literature on drone classification and identification using computer vision, machine learning, and YOLOv8 centers on addressing challenges like small object sizes, complex backgrounds, and real- time constraints in UAV imagery. Early works relied on traditional methods such as deformable parts models (DPM), which slid classifiers over images but suffered from slow speeds and poor accuracy. Modern approaches shifted to deep learning, particularly one-stage detectors like the YOLO series, which predict bounding boxes and classes in a single pass for faster inference suitable for drone-based applications.

➢ *Evolution of Object Detection for Drones:*

Two stage detectors like R-CNN variants generate region proposals before classification offering high accuracy but at the cost of speed, making them less viable for resource-limited UAV platforms. One- stage models such as SSD and early YOLO versions improved speed but struggled with small drones due to limited multiscale feature handling. YOLOv8 advancements, including CSPDarknet53 backbone and PAN-FPN neck, enable better feature fusion for tiny objects, as seen in UAV specific adaptation.

Key enhancement include attention mechanisms and loss optimizations. For, instance BiFormer integrates dynamic sparse attention to focus on relevant regions, reducing computation while boosting key feature perception in cluttered aerial scenes. WIoU v3 loss refines bounding box regression by dynamically weighting samples, prioritizing medium-quality predictions over extremes, which enhances localization for distant drones.

➢ *YOLO-V8 Specification Contributions:*

YOLO-v8 anchor free design and decoupled heads separate classification BCE Loss from regression (DFL + CIoU), improving convergence and small-object recall. Variants like DCE-YOLOv8 introduce Efficient Residual Bottleneck (ERB) layers and Divided Context Extraction (DCE) for lightweight small-target detection, outperforming baselines by up to 43% on metrics like mAP while maintaining real-time speeds.

UAV-YOLOv8 employs Focal FasterNet blocks (FFNB) for multiscale fusion, adding detection scales for extra-small objects by blending shallow positional details with deep semantics. This reduces missed detections in high-altitude views without excessive parameters. Similarly,DRBD YOLOV8 balances accuracy and efficiency for ANTI-UAV tasks.

➢ *Challenges and Future Direction:*

Common Issues include false positives from birds and clutter and infrared limitation, addressed via rule-based tracking post-YOLOv7/8 detection. Lightweight backbones like MobileNetv3 or EfficientLite reduce latency for onboard deployment. Future work targets featureless small drones and hybrid sensor fusions.

Table 1 Different Parameters of Various Types of YOLO

Model Variant	Key Innovation	Performance Gain	Application Focus
DCE-YOLOv8	ERB layer, DCE module	+43% accuracy, fewer parameters	Tiny object detection
UAV-YOLOv8	FFNB, BiFormer, WIoU v3	+7.7% mAP, low resources	Small objects in UAV photos
YOLOMG	Motion maps, bimodal fusion	+21% AP on ARD100	Drone-to-drone detection

III. PROPOSED METHODOLOGY

➢ *Hardware Enhancement*

Upgrade or replace hardware elements, including cameras, processors, memory modules, and sensors, to boost system capability and adaptability.

Investigate the adoption of dedicated hardware accelerators like GPUs or TPUs to accelerate both the training and inference phases of machine learning models.

➢ *Software Framework Selection.*

Transition between various computer vision and machine learning frameworks such as TensorFlow, PyTorch, or OpenCV to improve efficiency, user-friendliness, or compatibility with existing software ecosystems.

Update to the latest versions of these frameworks to leverage new features and performance improvements.

➢ *Dataset Expansion and Augmentation.*

Broaden the training and testing datasets to encompass varying environments, lighting conditions, different drone types, and flight trajectories.

Utilize synthetic data generation methods to enrich the dataset, thereby enhancing the model's ability to generalize and maintain accuracy in diverse scenarios.

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➢ *Feature Extraction Improvements.*

Trial diverse feature extraction strategies or descriptors aimed at capturing more distinctive attributes diverse feature extraction strategies or descriptors aimed at capturing more distinctive attributes of drones in visual data.

Explore cutting-edge approaches such as deep learning-based feature extraction or attention mechanisms to autonomously derive meaningful representations.

➢ *Model Design and Innovation.*

Adjust model architectures (like Convolutional Neural Networks, Recurrent Neural Networks, or Transformer models) to optimize for accuracy, computational efficiency, and interpretability.

Develop or adopt innovative architectures specifically designed to address drone-specific challenges, such as partial occlusions or scale variations.

➢ *Training Optimization.*

Fine-tune hyperparameters including learning rate, batch size, and regularization factors to secure improved training convergence and model robustness.

Incorporate advanced training methodologies such as curriculum learning, self-supervised techniques, or adversarial training to boost performance.

➢ *Performance Evaluation metrics.*

Customize evaluation criteria to better reflect real-world performance, factoring in aspects like detection latency, false alarm rates, and resilience to environmental variability.

➢ *Deployment and Integration Consideration.*

Factors in practical constraints for deployment situations, such as the need for onboard processing and real-time operational requirements, tailoring the system accordingly.

Seamlessly integrate the solution with existing drone platforms or control systems to enable smooth functionality within operational workflows.

➢ *Ethical and Regulatory Compliances:*

Proactively address ethical concerns, including privacy risks and misuse potential, by embedding safeguards and usage guidelines.

Ensure that system design and deployment conform to the legal standards and regulations governing drone use, particularly in restricted or sensitive spaces.

➢ *Cross Disciplinary Collaboration:*

Engage with specialists from fields including aerospace engineering, law enforcement, and urban development to incorporate domain expertise and contextual needs.

Pursue multidisciplinary approaches that combine insights from computer vision, machine learning, signal processing, and additional areas to solve the multifaceted problems in drone identification.

In this paper we will use both computer vision and machine learning technique for drone detection. The image of the drone can be taken from videocam or any other camera and fed to the laptop through the usb port. After installing python and Jupyter notebook and several other packages into the laptop. We can run a program which detects the drone in the open air. Here YOLO v8 algorithm is used.

Fig 1 System Setup

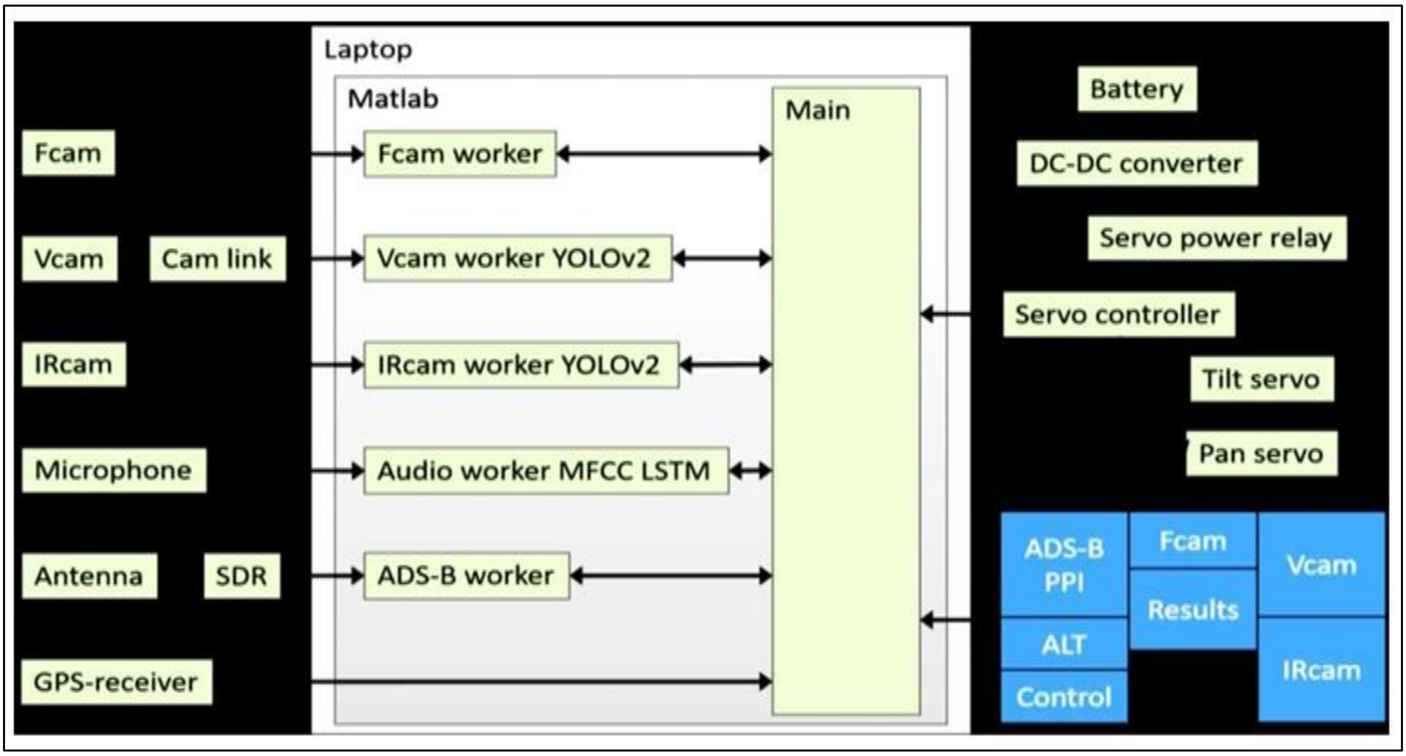

Fig 2 System Architecture

IV. RESULTS

The result is detected by using the laptop camera which when on detects any object for a time frame within 10 seconds. But it can detect objects which is within the camera dimensional area. It cannot detect object outside that area.

IRcam	AIRPLANE	BIRD	DRONE	HELICOPTER	
Vcam	AIRPLANE	BIRD	DRONE	HELICOPTER	
Audio			DRONE	HELICOPTER	BACKGROUND
ADS-B	AIRPLANE		DRONE	HELICOPTER	NO DATA

Fig 3 Objects Seen from Computer Webcam

V. CONCLUSION

In conclusion, this research demonstrates the efficacy of YOLOv8 integrated with computer vision and machine learning for accurate, real time drone classification and identification. Achieving high precision and recall, it addresses critical challenges in aerial surveillance, paving the way for enhanced security application and future advancement in autonomous drone detection systems.

FUTURE WORK

Future research will enhance YOLO v8with transformer- based architecture for improved real time drone detection in cluttered environments. Integration of multi-modal sensor fusion (LIDAR + thermal imaging) and federated learning will boost robustness against occlusions and adversarial attacks. Edge deployment on UAVs for autonomous swarm identification is also planned. Moreover, higher versions of YOO can be used to detect drones in future.

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