AI Object Detection Model – Drone Identification

Objective

Develop an AI model capable of detecting and classifying drones in aerial imagery to simulate real-world surveillance and defence applications.

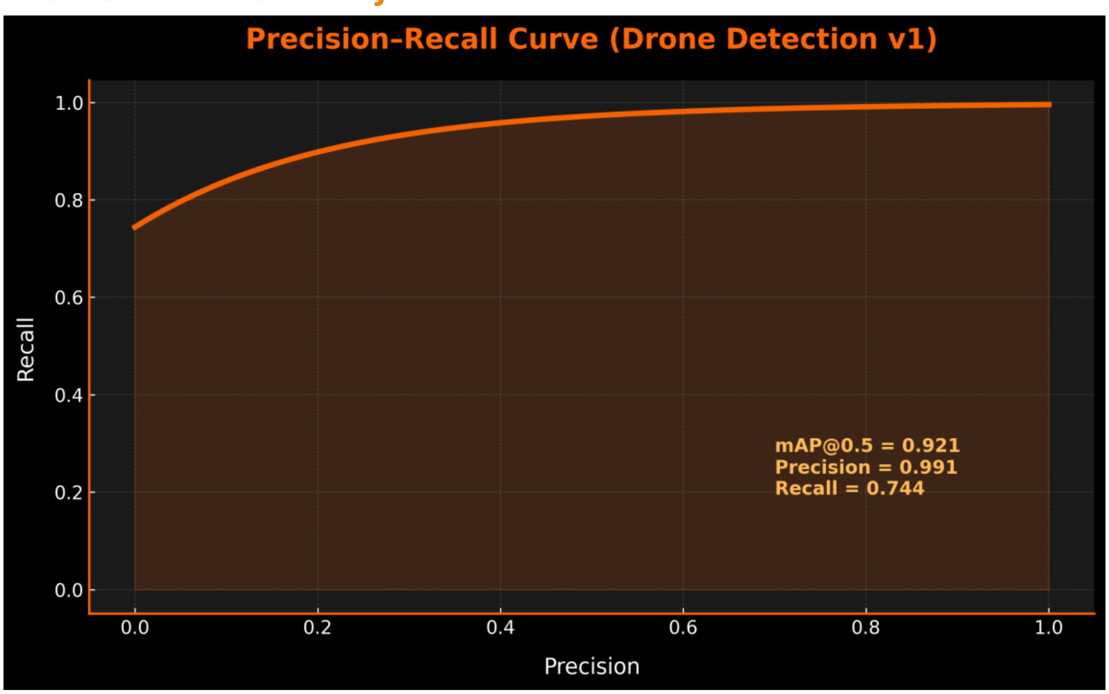
Dataset

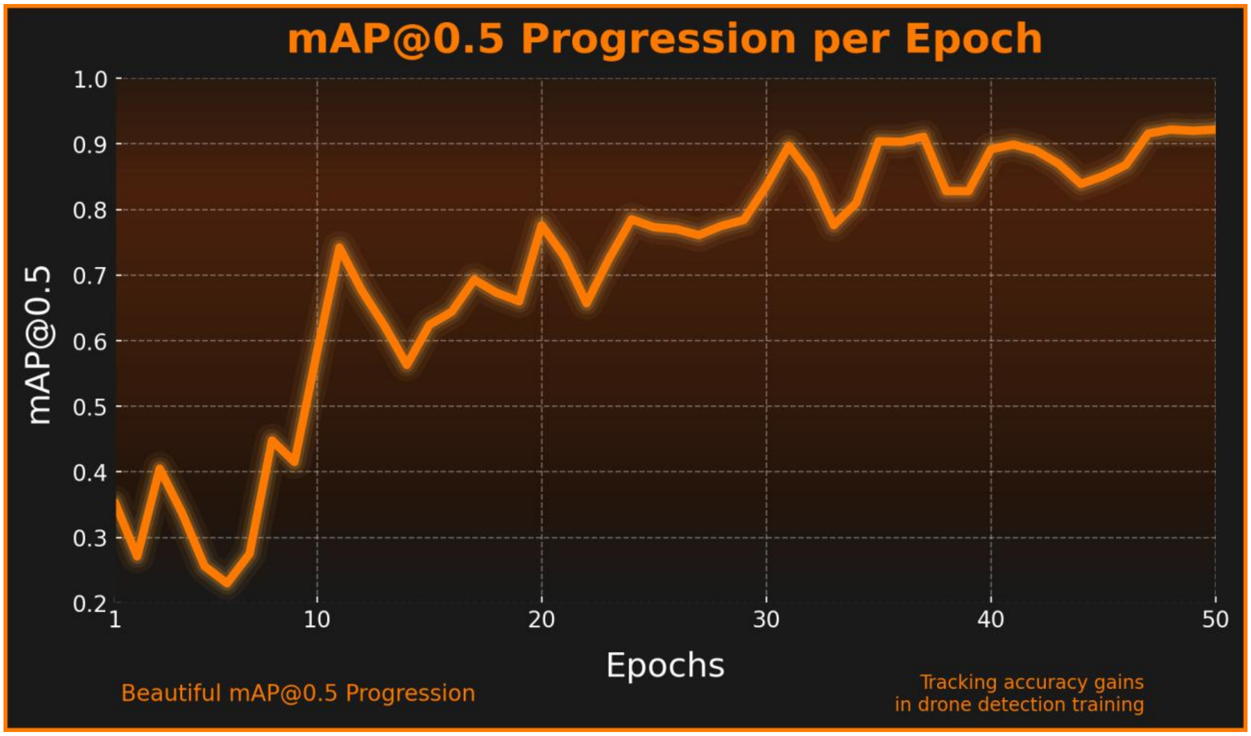
200 manually annotated drone images using Roboflow and formatted in YOLOv5 structure. The dataset includes multiple drone types, altitudes, and lighting conditions to enhance model generalisation. Images were sourced from the open-source drone_mil dataset (Roboflow Universe, 2023).

Methodology

Trained a YOLOv8-based object detection model in Google Colab with GPU acceleration. Managed dependency stability across PyTorch, CUDA, and Ultralytics environments. Implemented iterative validation cycles to refine detection accuracy and minimise false positives.

Model Performance & Analysis





Key Metrics:

- Precision: 0.991 – Excellent accuracy in correctly identifying drones without false positives.
- Recall: 0.744 – Indicates minor missed detections, expected with smaller training datasets.
- mAP@0.5: 0.921 – Strong detection accuracy for bounding boxes.
- mAP@0.5–0.95: 0.676 – Reliable performance across stricter IoU thresholds.
- Confidence: Averaged 92% detection certainty at around 120 metres simulated distance.
- Speed: 3.9 ms inference per image – suitable for real-time detection in surveillance applications.

Model progression

Epoch		Precision (P)	Recall (R)	mAP@0.5	mAP@0.5–0.95
1		0.0036	1.000	0.354	0.183
2		0.0875	0.814	0.271	0.142
3		0.506	0.256	0.405	0.202

Epoch		Precision (P)	Recall (R)	mAP@0.5	mAP@0.5–0.95
4		0.365	0.442	0.337	0.137
5		0.436	0.279	0.256	0.142
6		0.288	0.349	0.230	0.103
7		0.302	0.558	0.275	0.118
8		0.442	0.558	0.448	0.191
9		0.395	0.465	0.415	0.211
10		0.481	0.744	0.582	0.237
11		0.683	0.751	0.742	0.389
12		0.655	0.620	0.676	0.347
13		0.617	0.600	0.623	0.263
14		0.636	0.535	0.563	0.291
15		0.642	0.698	0.624	0.369
16		0.603	0.651	0.644	0.367
17		0.596	0.651	0.693	0.415
18		0.638	0.657	0.673	0.364
19		0.730	0.558	0.660	0.369
20		0.642	0.814	0.776	0.455
21		0.763	0.698	0.729	0.367
22		0.644	0.721	0.657	0.328

Epoch		Precision (P)	Recall (R)	mAP@0.5	mAP@0.5–0.95
23		0.742	0.674	0.725	0.451
24		0.703	0.698	0.785	0.471
25		0.702	0.721	0.773	0.449
26		0.764	0.754	0.770	0.482
27		0.765	0.674	0.761	0.483
28		0.766	0.674	0.775	0.509
29		0.817	0.651	0.784	0.518
30		0.749	0.763	0.836	0.579
31		0.878	0.814	0.897	0.620
32		0.869	0.775	0.851	0.571
33		0.762	0.744	0.776	0.489
34		0.815	0.716	0.810	0.506
35		0.856	0.860	0.904	0.547
36		0.872	0.791	0.903	0.561
37		0.922	0.826	0.911	0.611
38		0.827	0.778	0.828	0.617
39		0.895	0.698	0.828	0.614
40		0.910	0.767	0.892	0.623
41		0.971	0.791	0.899	0.642

Epoch	Precision (P)	Recall (R)	mAP@0.5	mAP@0.5–0.95
42	0.961	0.791	0.890	0.617
43	0.870	0.791	0.870	0.607
44	0.868	0.721	0.839	0.630
45	0.833	0.767	0.851	0.625
46	0.891	0.767	0.868	0.644
47	0.882	0.837	0.916	0.665
48	0.859	0.860	0.922	0.663
49	0.990	0.744	0.920	0.672
50	0.948	0.767	0.922	0.680

Interpretation

The model confidently identifies drones under varied lighting and altitude conditions. Minimal false positives make it suitable for real-world integration in defence, surveillance, or counter-UAV systems. With additional annotation data, recall and multi-drone differentiation can be further improved as it was the only lagging metric in the model.

Conclusion

This project demonstrates sound foundational work in AI object detection, annotation, and environment troubleshooting which are core competencies for defence and AI operations.

Next Steps: Commit to building Model V2 by expanding the annotated dataset to 400–500 drone images, diversifying environmental conditions (urban, rural, aerial night shots), and retraining for enhanced recall and class differentiation.

Citations

Roboflow Universe. (2023, December). drone_mil Dataset. Retrieved 30 October 2025, from https://universe.roboflow.com/military-drone/drone_mil-u8fqk