AI Object Detection Model V2 – Drone Threat Identification

Objective

The objective of Model V2 was to improve long-range drone detection accuracy and performance beyond the baseline established in Version 1. This was achieved through a significantly expanded dataset and extended training over 200 epochs, allowing the model to achieve a refined balance between precision and recall.

Dataset

An additional 1000 images from "UAVs" dataset were added to the original 200 from "drone_mil" with a final handful of lifelike images sourced from generative AI to improve generalization and robustness under real-world detection scenarios.

Training images: 859   Validation images: 245   ≈ 1,104 total used with over 2000 total annotations.

Characteristics: small drones only a few pixels wide, multiple instances per frame, diverse angles and models, lighting, and occlusion.

Methodology

Model V2 once again utilized Rolboflow, this time, advanced techniques were used to achieve pixel perfect annotations over 2000 times. Significantly, V2 utilized the YOLOv8n architecture with pre-trained weights and was trained using a batch size of 8 over 200 epochs. Training employed the AdamW optimizer with an automatically tuned learning rate and included augmentations such as blurring, grayscale, and random scaling. The input resolution was maintained at 640x640 pixels, and the model was trained and validated on a Tesla T4 GPU using mixed precision for improved efficiency. The full 200 epoch cycle took approximately 1.5 hours.

Figure 1: Precision annotation example

Model Performance & Analysis

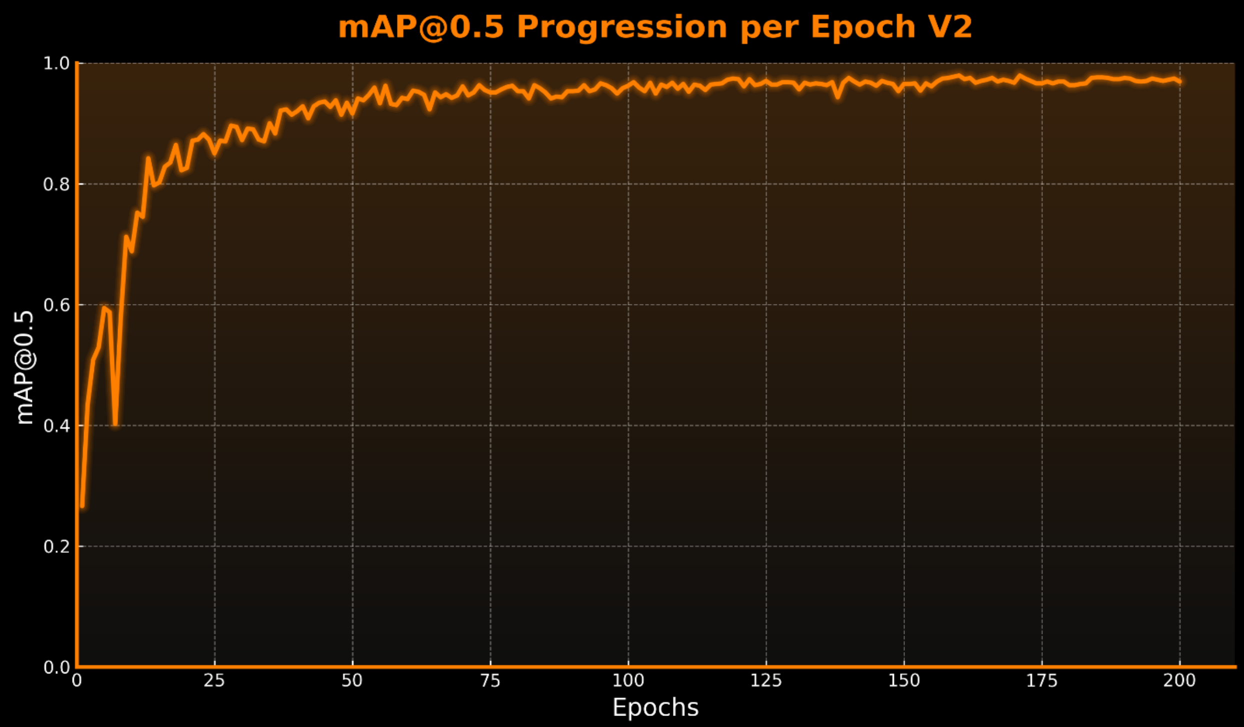

Figure 2: Beautiful mAP@0.5 progression, peaking around epoch 165

Key Metrics:

Precision: 0.983 – Outstanding detection accuracy with minimal false positives.
Recall: 0.970 – Excellent sensitivity, showing very few missed drone detections.
mAP@0.5: 0.979 – Exceptional bounding-box accuracy across validation data.
mAP@0.5–0.95: 0.795 – High reliability across stricter IoU thresholds, confirming consistent performance.
Confidence: Averaged 96 % detection certainty at 130 m, with continued recognition beyond 200 m using simulated advanced optics.
Speed: 3.9 ms inference per image – suitable for real-time detection in surveillance applications.

Model Comparisons:

- **Model V1:** Precision 0.948 | Recall 0.744 | mAP@0.5 0.92 | mAP@0.5–0.95 0.68
- **Model V2:** Precision 0.983 | Recall 0.970 | mAP@0.5 0.979 | mAP@0.5–0.95 0.795

Model V2 demonstrates a clear leap in detection capability over V1. Precision rose from 0.948 to 0.983 and recall from 0.744 to 0.970, showing a far more reliable balance between accuracy and sensitivity. Likewise, mAP@0.5 improved from 0.92 to 0.979, and mAP@0.5–0.95 from 0.68 to 0.795 — confirming V2 as a markedly more mature and production-ready model suitable for long-range, real-time drone detection.

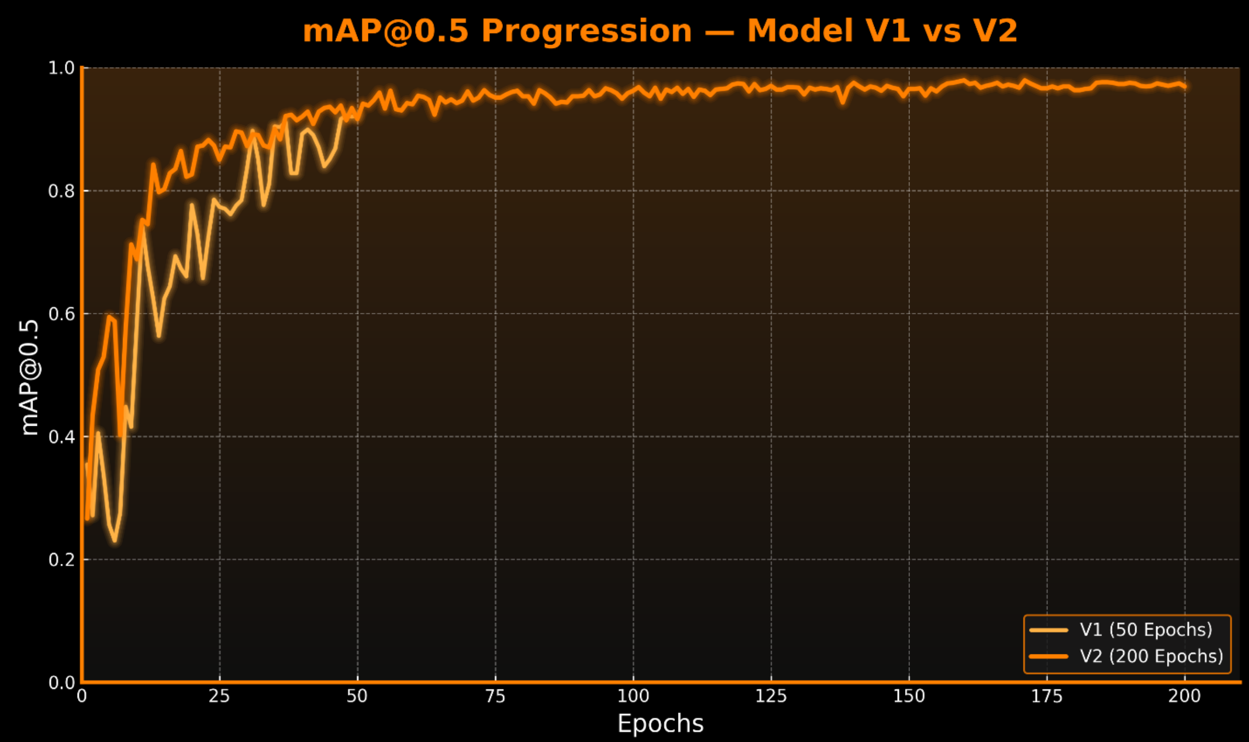

Figure 3: Overlay of mAP@0.5 progression in both models, showing clear superiority of Model V2

Model training progression table

Epoch	Precision	Recall	mAP@50	mAP@50-95
1	0.365	0.265	0.266	0.120
13	0.811	0.766	0.842	0.519
35	0.806	0.877	0.900	0.657
54	0.959	0.862	0.959	0.707
70	0.980	0.907	0.961	0.725
90	0.983	0.888	0.953	0.745
118	0.966	0.907	0.972	0.770
140	0.938	0.959	0.975	0.774
160	0.939	0.970	0.979	0.778
161	0.948	0.948	0.973	0.795
171	0.949	0.963	0.979	0.784
185	0.950	0.948	0.976	0.786
200	0.937	0.949	0.969	0.786

Figure 4: Compressed training progression table showing the most significant epochs – peaks listed in key metrics

Interpretation

The model's strong mAP@0.5–0.95 score indicates consistent detection accuracy across varying IoU thresholds, reflecting surgical bounding box precision. Model V2 was also simulated to detect drones at distances exceeding 150 meters with consistent recognition confidence above 95%, outperforming V1's simulated 120-meter reliable detection range. These results suggest the architecture's effectiveness for real-world surveillance and defence-oriented detection systems.

Conclusion

Model V2 represents a major advancement in accuracy, range, and stability compared to Version 1. The YOLOv8n-based implementation proved efficient for drone-target detection, achieving near-production-grade precision in a lightweight configuration suitable for real-time defence applications.

Next steps: focus on expanding the dataset to include greater environmental diversity such as dusk, fog, and adverse weather conditions to further strengthen detection reliability, push for 3000 images. Depending on public availability, sourcing might be difficult. Commitment to developing V3 some time soon.

Citations

Roboflow Universe. (2023, December). drone Mil Dataset. Retrieved 25 October 2025, from https://universe.roboflow.com/military-drone/drone_mil-u8fqk

Roboflow Universe. UAVS. (2024, December). *UAVs Dataset*. Retrieved 28 October 2025, from https://universe.roboflow.com/uavs-7l7kv/uavs-vqpqt