Adham

Class of 2026

INTRODUCTION

Securing Low-Altitude Airspace

The rapid proliferation of drones presents significant challenges to airspace security, necessitating robust detection and classification systems. A critical hurdle lies in accurately distinguishing between drones and natural aerial phenomena, particularly birds, in low-altitude surveillance scenarios.

Traditional radar systems often struggle with the small size and diverse flight patterns of both drones and birds, leading to false positives or missed detections. Our project addresses this growing concern by developing an intelligent system capable of precise identification.

OBJECTIVES

Real-time Aerial Threat Assessment

1

High-Accuracy Classification

Develop a deep learning model capable of distinguishing between drones and birds with high precision.

2

Real-time Localization

Implement object localization to pinpoint the exact position of detected aerial entities within surveillance feeds.

3

Efficient Performance

Utilize the YOLOv8/v11 framework to ensure the model operates effectively in real-time surveillance environments.

TECHNOLOGY STACK

Foundations of Aerial Guard

Python

Primary language for development, model training, and data manipulation.

Ultralytics YOLO

State-of-the-art framework for object detection, specifically YOLOv8/v11.

OpenCV

Used for image pre-processing, post-processing, and video stream handling.

Streamlit

Chosen for rapid deployment of the interactive web application interface.

Google Colab

Cloud-based platform leveraged for GPU-accelerated model training.

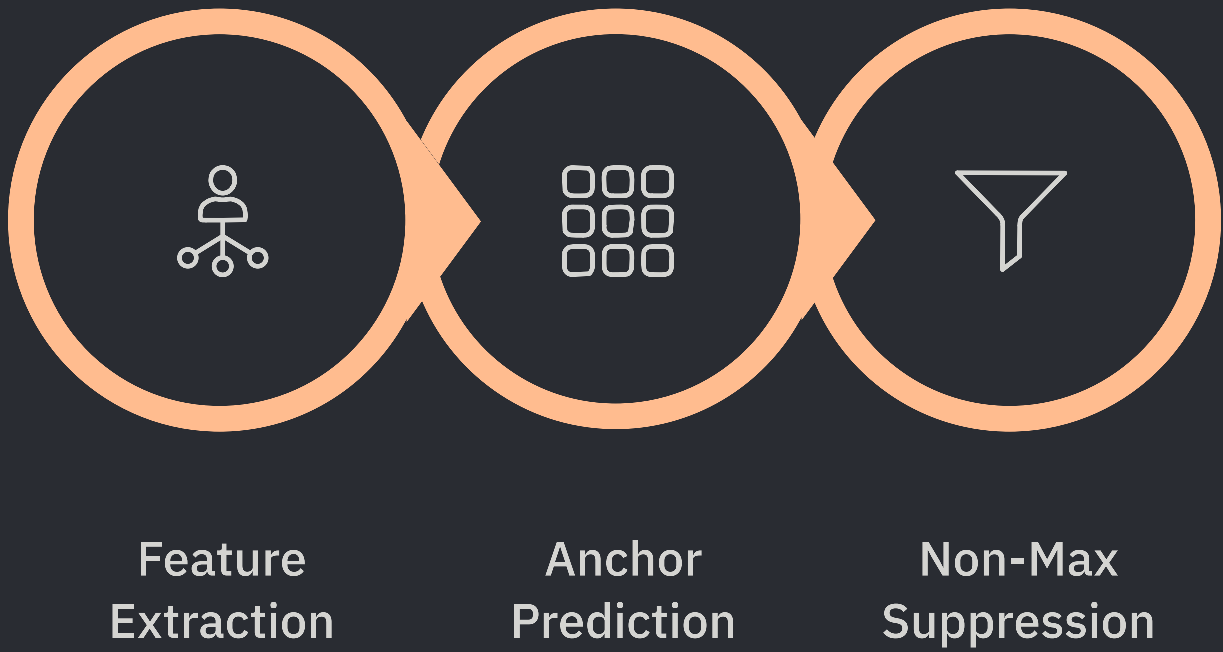
DATA ENGINEERING

Building a Robust Dataset

- **Dataset Size:** Over 1,500 meticulously curated images, featuring a variety of drones and birds in diverse environmental conditions.
- **Data Augmentation:** Employed Albumentations library for advanced augmentation techniques, including rotations, flips, scaling, brightness adjustments, and noise injection, significantly increasing dataset diversity and model robustness.
- **Precise Labeling:** Each image was accurately annotated with bounding boxes, identifying and classifying "drone" or "bird" to ensure high-quality training data for the YOLO model.

MODEL ARCHITECTURE

YOLO: Optimized for Speed & Accuracy



YOLO (You Only Look Once) was selected for its exceptional balance of speed and accuracy in object detection, crucial for real-time aerial surveillance. Its single-pass approach allows for rapid inference by predicting bounding boxes and class probabilities directly from full images.

The model comprises a backbone for feature extraction, a neck for feature aggregation, and a head for prediction. This architecture minimizes computational overhead while maintaining high detection performance.

TRAINING & OPTIMIZATION

Fine-Tuning for Peak Performance

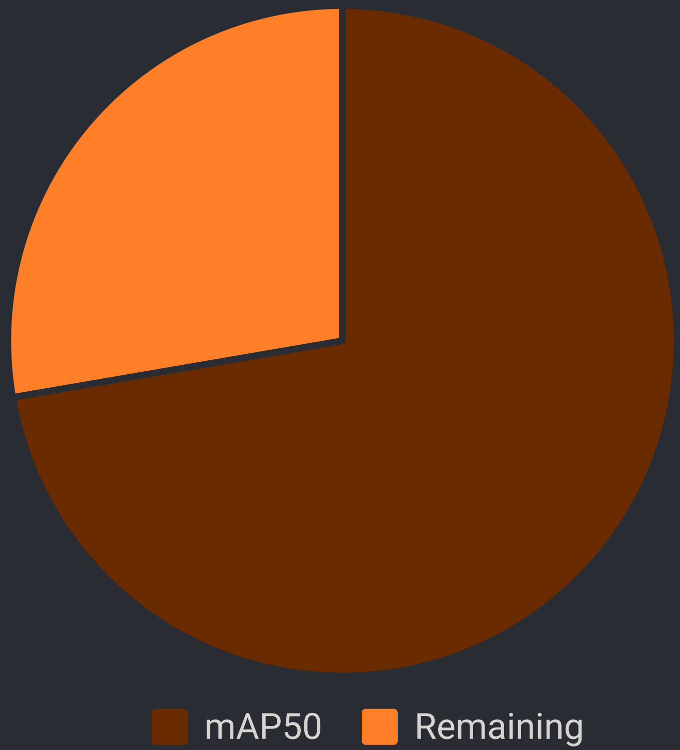
50 Epochs Training: The model underwent 50 full passes over the augmented dataset, allowing for comprehensive learning of drone and bird features.

AdamW Optimizer: The AdamW optimizer was utilized to efficiently adjust learning rates and prevent overfitting, ensuring a stable and effective training process.

Automatic Mixed Precision (AMP): AMP was employed to significantly accelerate training by using a mix of 16-bit and 32-bit floating-point types, reducing memory usage and computational time without sacrificing model accuracy.

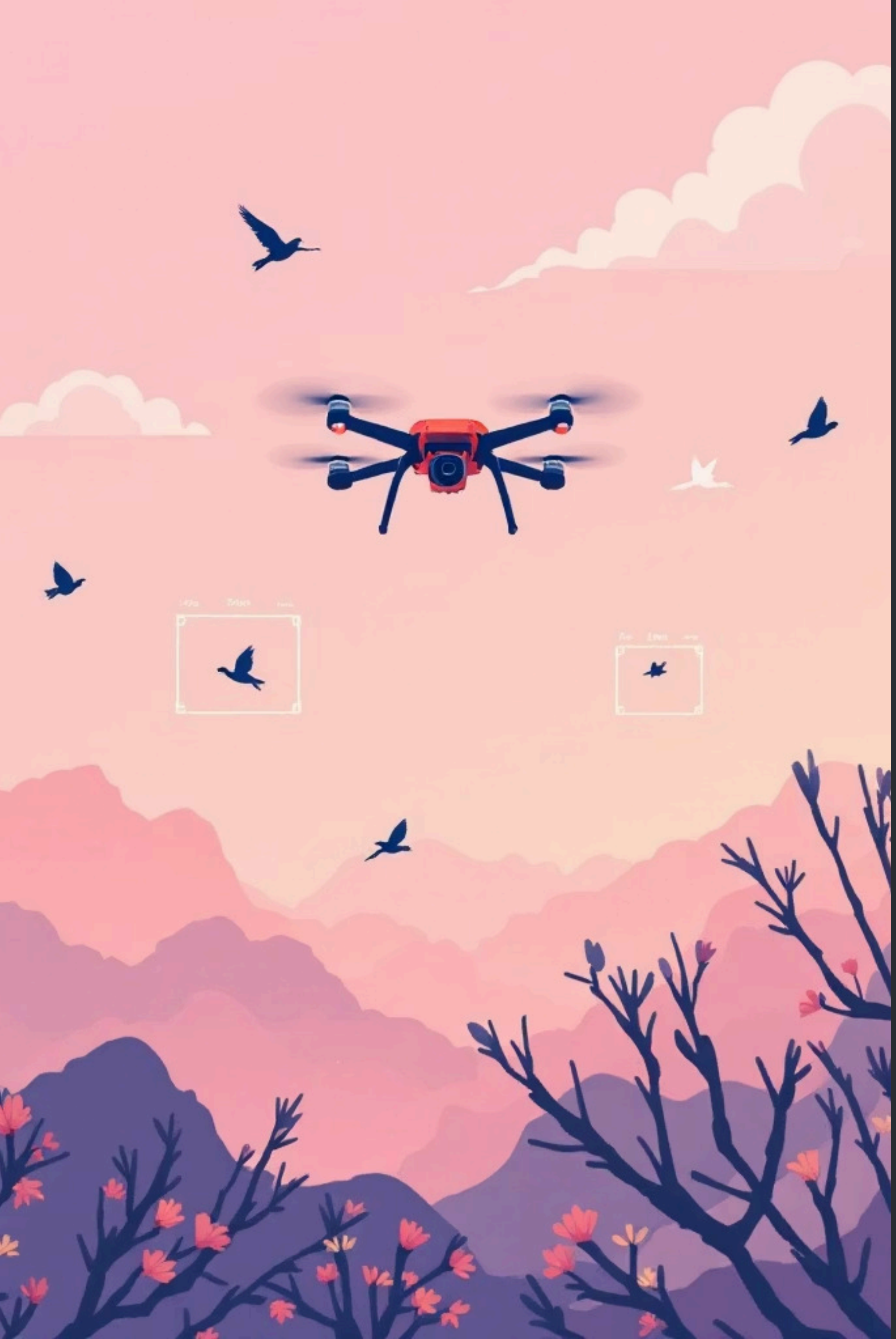
EXPERIMENTAL RESULTS

Achieving High Detection Confidence



Our model achieved a Mean Average Precision (mAP) at an Intersection over Union (IoU) threshold of 0.5 (mAP50) of 0.723.

- **Detection Confidence:** The model demonstrates high confidence in distinguishing between drones and birds, minimizing false positives.
- **Precision:** Bounding box predictions show strong alignment with ground truth, indicating accurate localization of objects.
- **Robustness:** Performance remained consistent across various environmental conditions and object sizes within the test set.



DEPLOYMENT INTERFACE

Intuitive Web Dashboard

The Streamlit web dashboard provides an accessible and user-friendly interface for interacting with the detection system. Users can upload images or video streams, and the dashboard will display real-time detections with bounding boxes and classification labels (drone/bird) along with confidence scores.

CONCLUSION & FUTURE WORK

Advancing Aerial Surveillance

Project Achievements

Successfully developed and deployed a robust deep learning model for real-time drone and bird detection.

Multi-Drone Tracking

Future enhancements include integrating multi-object tracking algorithms for persistent surveillance of multiple drones.

Night-Vision Capabilities

Further research will focus on adapting the model for effective detection in low-light and night-time conditions.