Classifying Drones and Birds from Images using Deep Neural Networks

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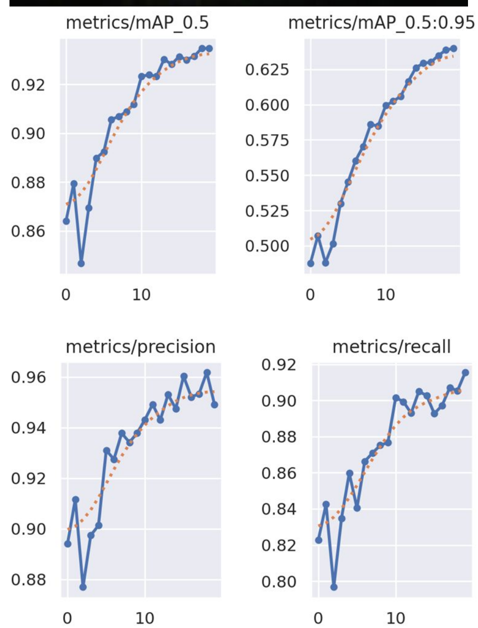
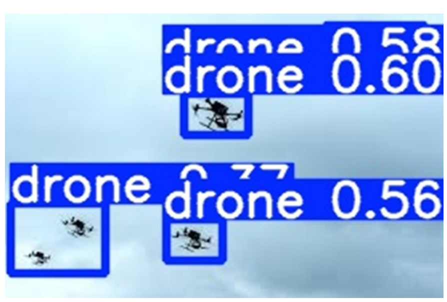
Introduction

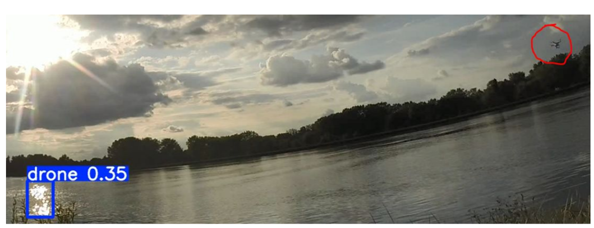
In this study, I investigated if the future integration of camera systems with image recognition and machine learning can help us recognize drones from birds in real time. With drones becoming more common in urban and rural settings, successfully identifying and differentiating them from birds is crucial for security, wildlife management and airspace use. If misidentified, it can lead to losses in efficiency, safety threats, and unprepared actions for enforcement. This system is designed to assist industries such as law enforcement, aviation safety and environmental conservation, making aerial object classification more accurate with advanced detection methods.

Background

Developing systems for distinguishing between drones and birds has become more crucial with the increasing deployment of drones in urban and rural environments. Though drones and birds often occupy similar airspace, their differing shapes, flight patterns and sound signatures can make identification tricky. Accurate differentiation is essential for security, wildlife monitoring, and airspace management to avoid safety risks. While the behavior of birds has been studied extensively, drone technology has been developing much faster, which has created new problems. This project started the summer of 2024 with my internship at JHUAPL where I found myself interested in object detection. Tackling this challenge appealed to me due to my background in object detection in robotics from work I did for my FTC team.







Methodology

To differentiate between a drone and bird, I trained the YOLO object detection model on data from reputable platforms like Kaggle and Roboflow Universe. YOLO was chosen for its speed and accuracy, faster and more accurate than alternatives such as CNN and Faster R-CNN, and real time application. The model learned to associate images with key identifiers as identified by an annotator for the respective birds and drones, using annotated images of both types.

Results

The YOLO model achieved 88% accuracy with a dataset of around 3000 images, staying robust at 80% in tough conditions. It handled overlaps well but struggled with similar speeds and occasional false positives, showing strong potential with room for improvement.

Future Work

Improving the model requires expanding the dataset to include more bird and drone species across varied conditions. Greater diversity will enhance adaptability, making the system more reliable for applications like security, where accurate drone detection is crucial.

Acknowledgments

Special thanks to Janet Zhang as my advisor and the JHUAPL internship program for providing me this opportunity, and last but not least to my parents for their support through everything.