Team Name: SkyWatch
Project Title: Real-Time Flying Object Detection for Airspace Monitoring and Threat Identification.

Project summary:
This project will be using a dataset to detect a flying object in real time. The dataset contains 40 classes containing birds,commercial airliners, drones, bombers,and fighter jets.

Airspace Monitoring → Can identify specific types of aircraft near airports to ensure proper air traffic/runway/taxi flow and security. For example, a response to a flock of birds over the runway will most likely cause a pilot to go around on approach, whereas a swarm of drones will cause a security team to issue a quick and appropriate response.

Threat Identification and Strategic Response → The dataset mostly holds classes related to military aircraft. A reconnaissance/fighter aircraft can use this algorithm to relay information about the type of aircraft(threat) detected and its defense/weapons capabilities.

Environmental considerations -> If possible, it may be advantageous to use our tool to monitor bird population within a given area. Use cases include analyzing the seasonal migratory patterns and population levels for environmental considerations.

What you will do
The plan is to implement single stage object detection algorithms (yolov7 yolov8) instead of two stage due to better inference speed. This is because aircraft are usually moving at high rates of speed and we will want the same for our bounding box prediction. Different architecture code will come from github/ultralytics. Multiple single state architectures will be evaluated as well transfer learning with pre-trained models. The end goal is to pick the model with best trade-off between inference speed and (insert accuracy/precision metric here) while extrapolating potential reasons for this result.

Evaluation Criteria

There are several analysis techniques that could be used to evaluate the performance of our object detection algorithm. It should be noted that all the metrics listed will also be evaluated against inference speed. Some commonly used ones include:

Precision and Recall -> Precision for measuring the accuracy of detected objects while recall for measuring the completeness of positive predictions
Precision = True Positive / Actual Results , Recall = True Positive / Predicted Results

Intersection of Union (IOU) -> Measures the overlap between the predicted bounding box and the ground truth bounding box

IOU = Area of overlap / Area of Union

F1 Score -> Measure of the balance between precision and recall. Also good for unbalanced datasets

F1 Score = 2 * Precision * Recall / (Precision + Recall)

False Positive and False Negative Rate -> FPR measure the proportion of incorrectly labeled examples while FNR measures the proportion of missed objects.

We may also want to include some visualizations for our project to highlight areas of interest during object detection. Some of these methods include:

Saliency Maps -> Visual representation of an image that highlights areas of interest.

Class Model Visualization -> Helps visualize the features the networked learned during object detection.

Resources / Related Work & Papers:

- "Deep Learning for UAV-based Object Detection and Tracking: A Survey" Wu et. al (2021) https://arxiv.org/pdf/2110.12638.pdf
    - This paper covers the progress of research in DL-based UAV object detection and tracking. They include statistics of previously used methods and solutions for three divisions of research - object detection from an image, detection from a video, and object tracking, where the first two focuses are more relevant to our project. In summary, it is an overview of what has been done and the advancements in DL-based UAV detection.
- "Small-Object Detection for UAV-Based Images Using a Distance Metric Method" by Zhou et al. (2022) https://www.mdpi.com/2504-446X/6/10/308
    - They presented a modification of YOLOv4 they made in order to resolve issues that naturally come with our problem: UAVs are recorded at high altitudes, therefore having small pixel sizes and high uncertainty in results.
- "Unmanned Aerial Vehicle Visual Detection and Tracking using Deep Neural Networks: A Performance Benchmark" Isaac-Medina et. al (2021) https://arxiv.org/pdf/2103.13933.pdf
    - Prior to this paper, there has not been any official benchmark formed for deep neural networks regarding UAV image detection. This provides a benchmark to follow. It may not be completely relevant to the goals of our project, but we may use it as a benchmark reference if possible, or as an inspiration for our own analysis. In addition, they also have results in a drone-vs-bird detection challenge. They utilized YOLOv3, so we may be able to compare their results to our YOLOv7 and YOLOv8 results.
- The YOLOv7 architecture repository. https://github.com/WongKinYiu/yolov7 We will refer to this for standards, use cases, examples, etc.

Datasets https://universe.roboflow.com/new-workspace-0k81p/flying_object_dataset

List your Group members: Dillon Reis, Ahmad Daoudi, Jordan Kupec, Jacqueline Hong