EVALUATION OF DRONE DETECTION TECHNOLOGIES

Introduction

In the year 2050, machines have taken over the world and the Mega Lethal (ML) robots are looking to destroy humanity. They primarily use drones for surveillance, target acquisition and bomb deployment. We have been given a drone detection model and are tasked to evaluate its effectiveness such thatit can protect humankind.

Research Question

How does a computer vision model perform in detecting drones under different situations and how can we improve its performance?

1. Methodology

1. Data Collection

a. Drone data

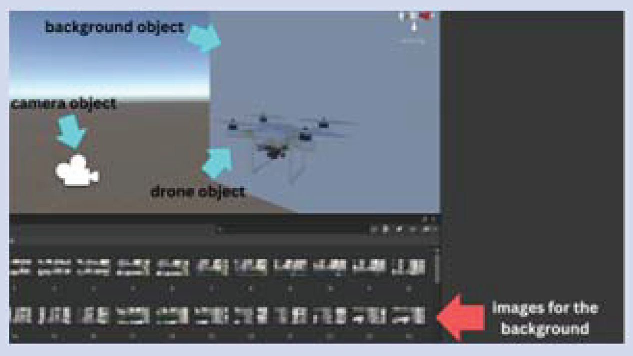
- Testing for true positives and false negatives
- 9 bins, sorted by distance and background

Sky background			Field background			Urban background		
d <= 5	5 < d <= 15	d > 15	d <= 5	5 < d <= 15	d > 15	d <= 5	5 < d <= 15	d > 15

b. Distractors data

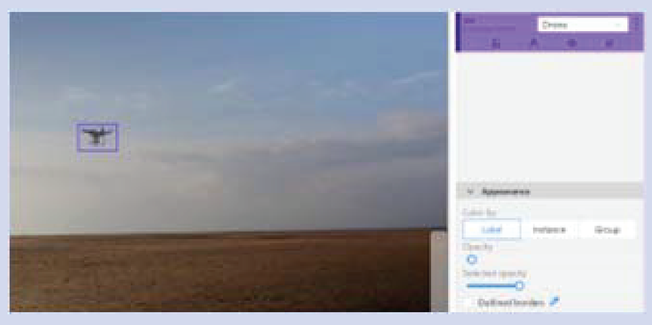
- Testing for false positives
- Distractors: helicopters, planes, birds, cars, buildings, people

💥💥OH NO! Evil machines have deleted some of our data. To overcome data shortage, we used Unity to generate synthetic data. A drone object was positioned against desired backgrounds and images were captured at random angles and distances to generate data as desired.



2. Data Labelling

To score the model accurately, we needed to acquire data regarding the size and position of drones within the images. Data labelling involved the drawing ofbounding boxes around drones, generating coordinates known as groundtruths. This process was executed using the Computer Vision Annotation Tool (CVAT).



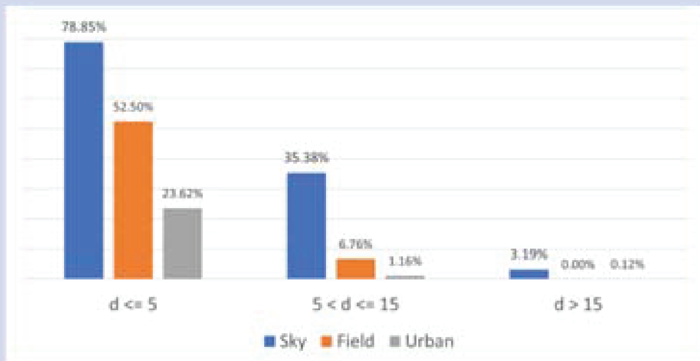
3. Testing and Scoring

Using command [i] below, we tested the model with drone data collected in Step 1. Next, we compared the model's results with groundtruths generated in Step 2. Using command [ii], an object detection metrics tool was used to generate Average Precision (AP) scores. The AP score ranges from 0% to 100%, with a higher score indicating higher accuracy.

```
[i] python detect.py --weights drone_detect.pt --conf-thres 0.5 --img-size 640 --save-txt --save-conf --source <images folder path> --project <output folder path>
[ii] python pascalvoc.py -gt <groundtruth folder path> -det <detection folder path> -sp <output folder path>
```

2. Results

a. AP score across the 9 bins



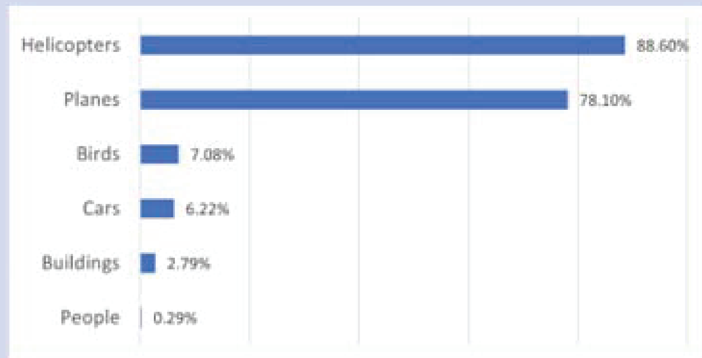
As distance increases, the model's performance drops.

➢ The model likely struggled with feature extraction of objects at further distances due to insufficient details.

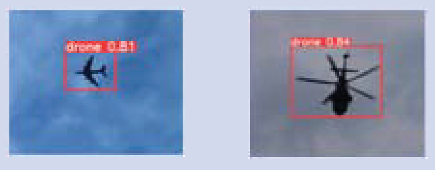
A sky background yields the best performance, followed by field then urban.

➢ Sky background is the least noisy with lesser distractors present. In an Urban environment, objects such as buildings and roads could have reduced the clarity ofthe outline ofthe drone.

b. False Positive Rate of Distractors

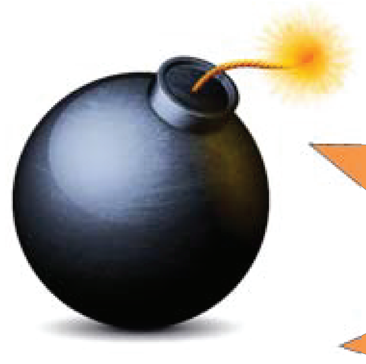


Helicopters and planes had a significantly higher probability of being wrongly detected. This could be because their shapes and propeller features resembled that of drones.



c. Overall Benchmark Results

AP Score: 11.5%
False Negative Rate: 85.6%
False Positive Rate: 31.0%



Unfortunately, it seems like our model is not performing well! This could be because the training data set contains images oflarger drones, but a large proportion oftest data comprises images of smaller drones. Could humankind potentially be in danger?

3. Retraining

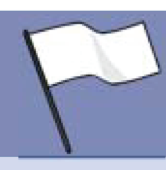
To improve the model, we decided to retrain it with larger models. As larger models have more layers and parameters, we hypothesised higher accuracies for these models. The original model was trained on the YOLOv5 nano model. We trained the small and large versions with the same dataset and observed changes in the benchmarks.

```
python train.py --img 640 --batch 4 --epochs 50 --data drone_training_data.yaml --weights yolov5s.pt (small model)
python train.py --img 640 --batch 4 --epochs 50 --data drone_training_data.yaml --weights yolov5l.pt (large model)
```

Results

✅ Overall AP score increases
✅ False negative rate decreases
❌ False positive rate increased slightly

- While larger models detect more drones accurately, more distractors were also wrongly detected, possibly due to data overfitting.



4. Conclusion

Fortunately, the machines have been defeated and the era of ML robots has ended. Our learning points regarding the machine learning (ML) process and possible future works are summarised below.

Learning Points	1. Establishing a consistentframework is key when comparing across different categories. 2. Synthetic data can overcome limitations in data collection.
Future Works	Itis paramountthattraining data size is relative to model size. In order to better improve the performance oflarger models, a larger training dataset should be used. Rather than reusing the same training dataset, a possible extension would be to curate new datasets relative to the different model sizes.

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YDSP Young Defence Scientists Programme
DSTA Defence Science & Technology Agency
DSO National Laboratories