

DEEP LEARNING TAKES FLIGHT: DETECTING JACKRABBITS WITH THERMAL DRONE IMAGERY

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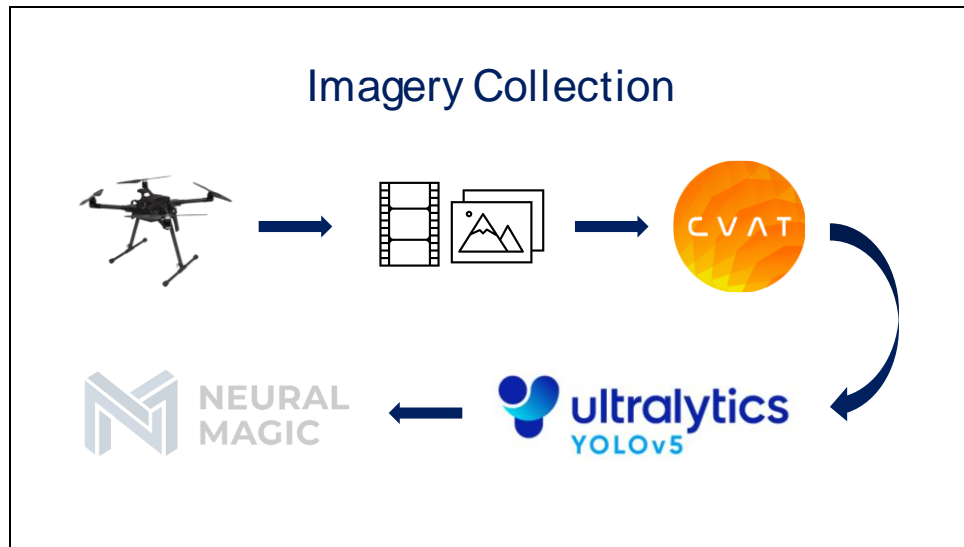
Background and Purpose

- Black-tailed jackrabbits (BTJR) are an important prey species – abundance has not been surveyed at the NCA since 1997



Background and Purpose

- Develop protocols to detect jackrabbits using drones with thermal cameras
- Test deep learning models to automate video processing



UAS Sensor and Platform

FLIR DUO PRO R Thermal

Imaging Sensor:

- 640 x 512 resolution
- 25 mm lens
- 25° x 20° FOV
- 30 frames per second
- 7.5 - 13.5 μm spectral band



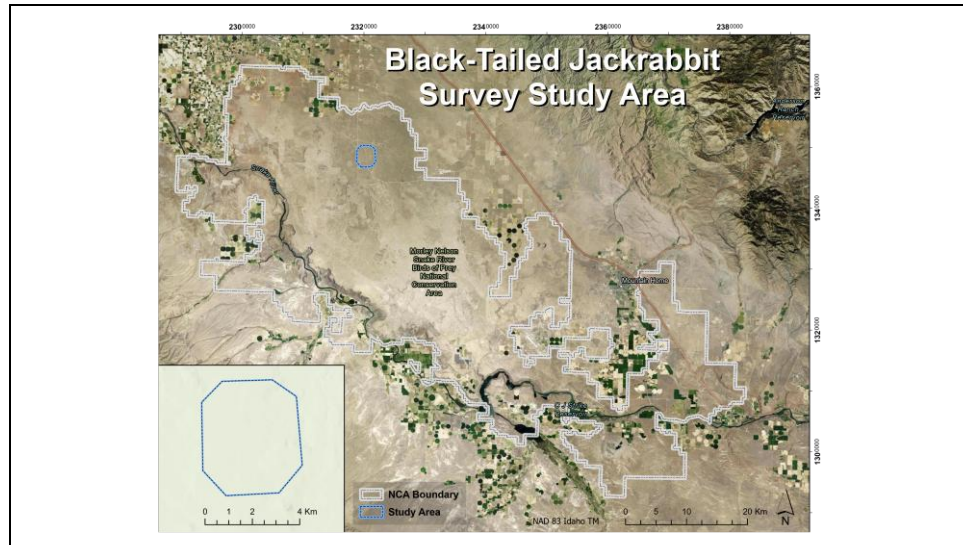
Inspired Flight IF 750

- NDAA/Blue List Compliant Drone
- Wind resistance up to 10 m/s
- Flight time ~20 min

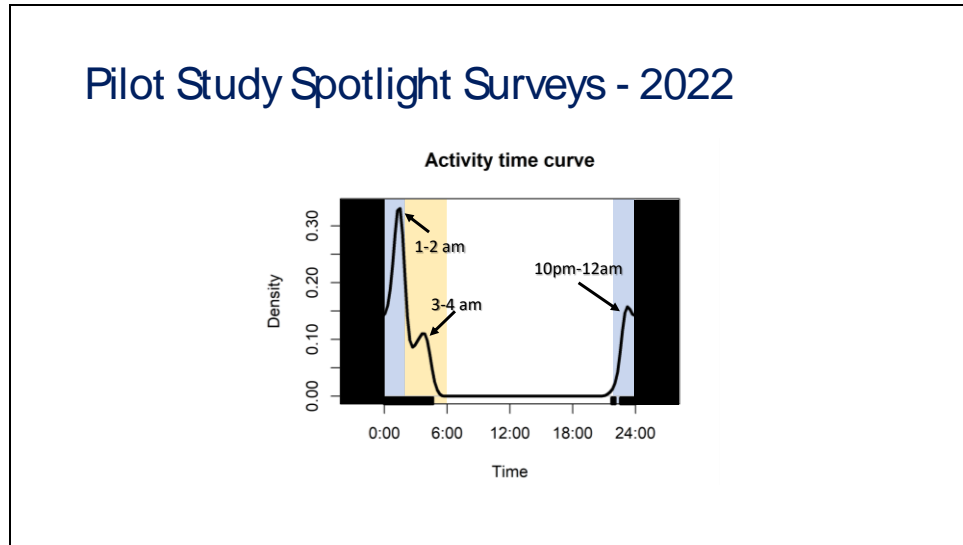


We used a FLIR DUO PRO R thermal imaging camera on an Inspired Flight IF 750 drone.

Slide 6

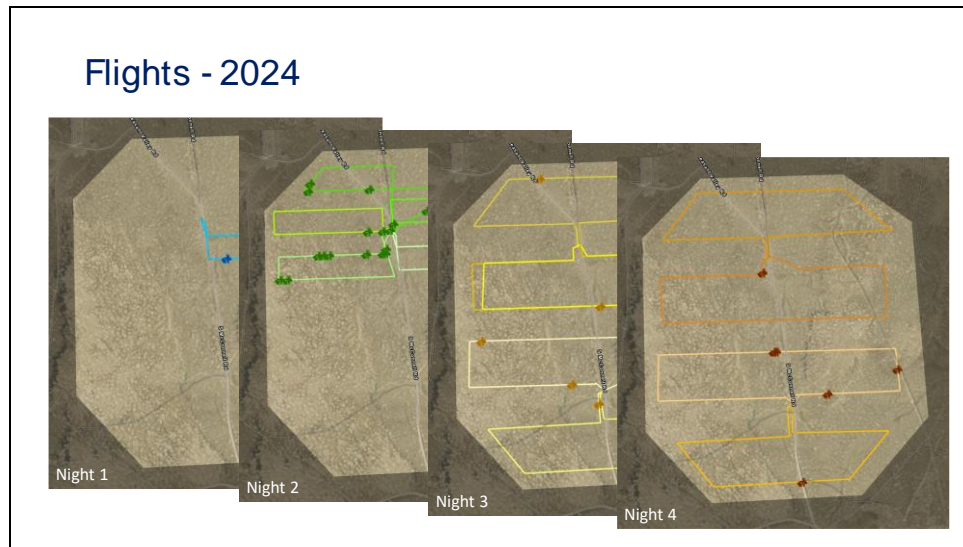


Conduct 3 to 4 transect flights at each study site during the dark, cooler hours to maximize contrast between the body temperature of BTJR and the background environment. Spotlight surveys are also conducted at night, using the spotlights to see the jackrabbit's eyeshine.



The x-axis is the time of day, and y-axis is jackrabbit density, and this shows the optimal detection time is 10pm to 2am. Drone flights were to determine the altitude, speed, and transect distance for optimal detection.

Slide 8

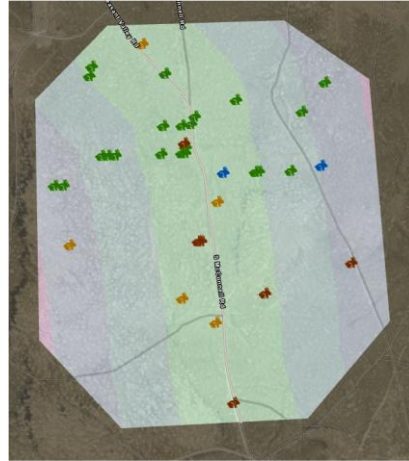


Due to wind, flights were flown at different times on different nights. Additionally, the first two nights were flown at slower speeds and shorter transects than the third and fourth nights. This affected detection, as you can see from the maps, and highlights the importance of multiple night surveys.

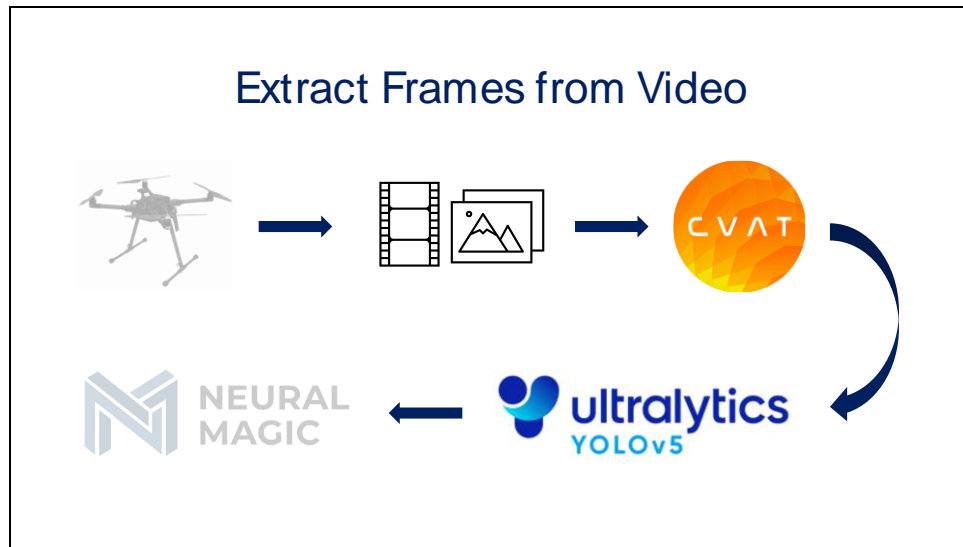
Distance & Counts

Night	# Flights (times)	Jackrabbits
1	3* (11:30p - 2:30a)	2
2	5 (8:15p - 11:15p)	30
3	5 (3:45a - 7:15a)	6
4	6 (12a - 2:45a)	7

* BTR detected during 1st flight only



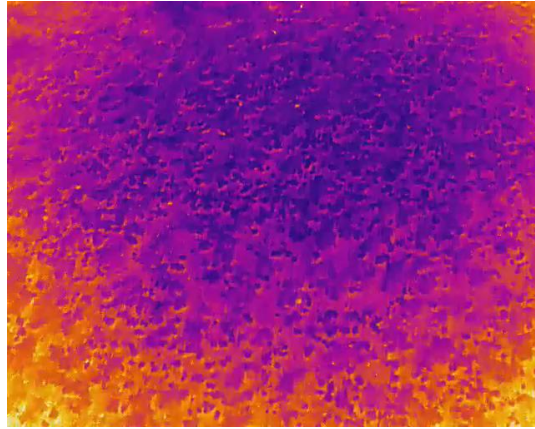
Highest detections were the second night, and the second flight had the most detections, which was flown at 9:30pm, close to the optimal detection time. Spotlight surveys were performed the week before, detecting jackrabbits within 5 meters of the road to try to determine if there is any road bias. As you can see from the map, there does not appear to be any road bias. Also, it's fun to note that with the drone we were able to detect jackrabbits over 1500 meters from the road.



Automated jackrabbit detection reduces the amount of personnel-hours.

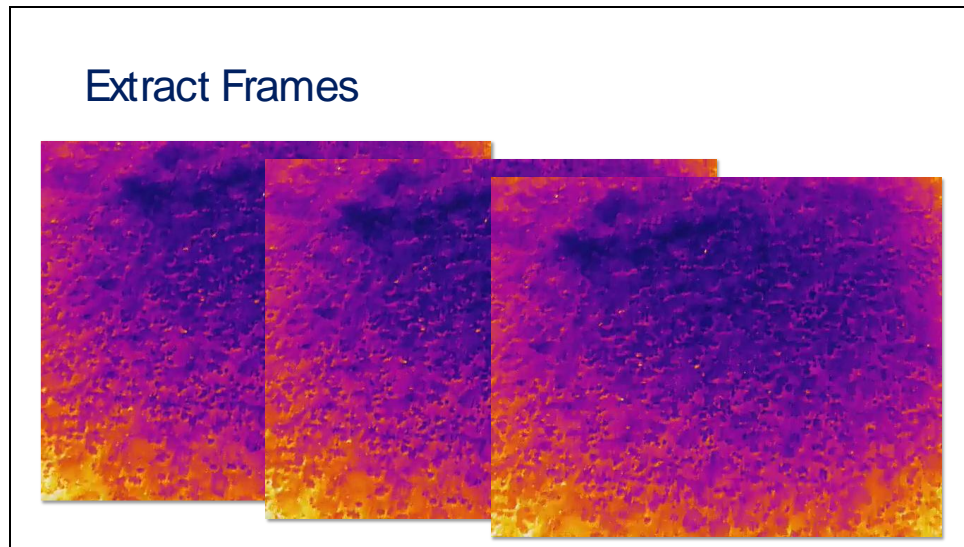
Slide 11

Colorized Video:
Jackrabbits 2022

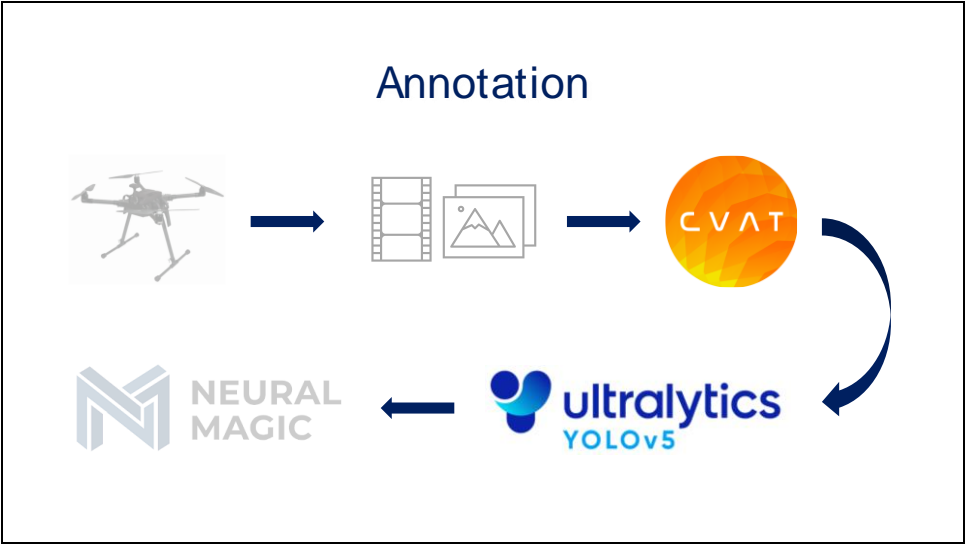


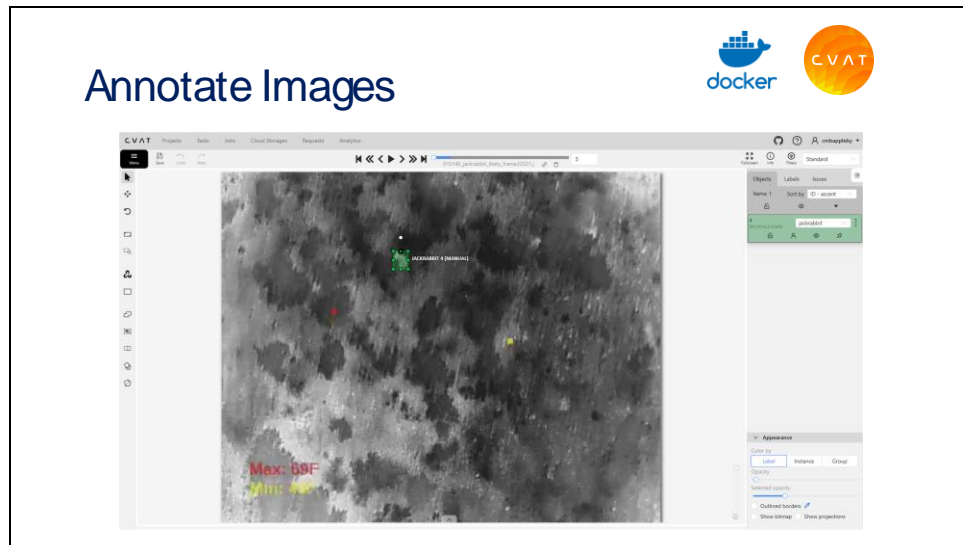
Video from 2022. You can see two jackrabbits at the top middle of the video hopping towards the left side.

Slide 12

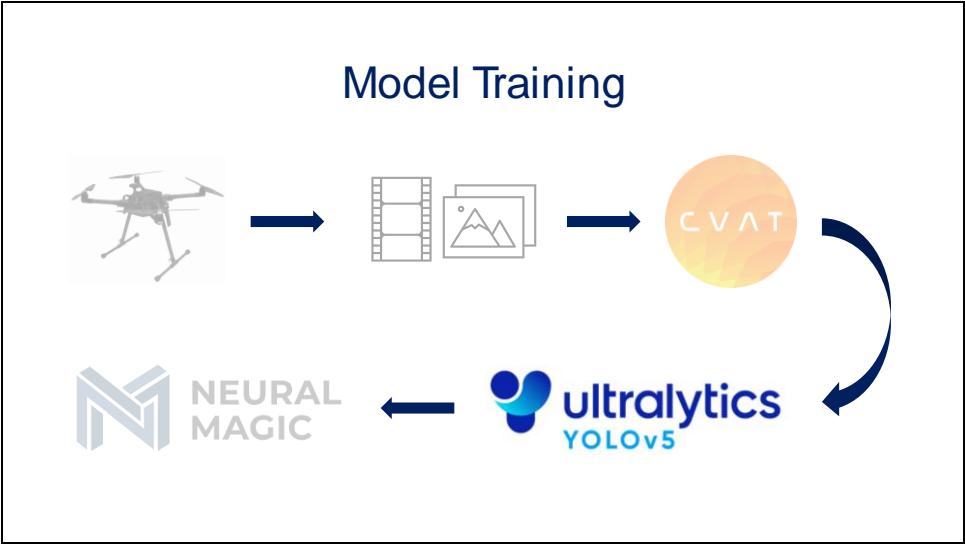


Extracted and used 590 frames with 543 frames labeled with jackrabbits and 47 frames of background. 105 of the frames were from the 2022 video shown in the previous slide



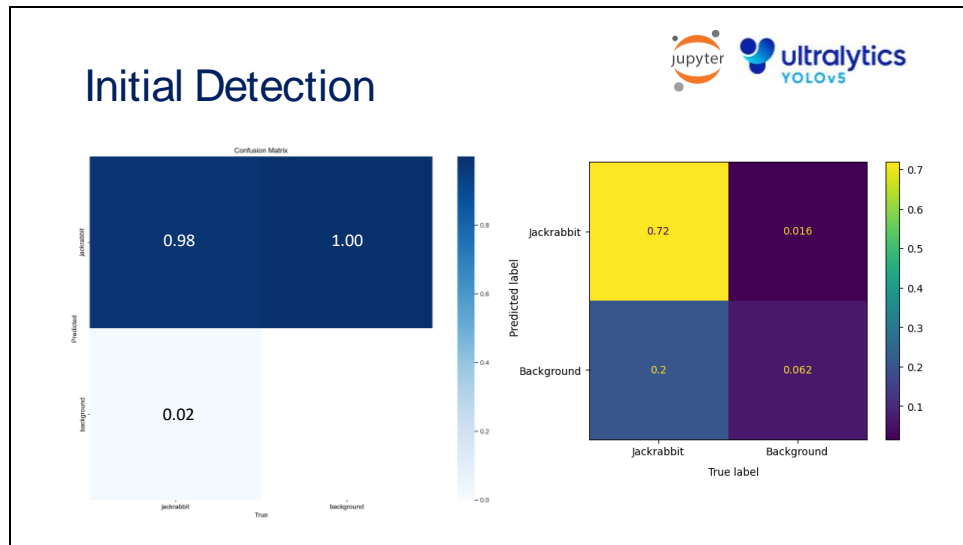


Jackrabbits were manually identified from the video, which took over eight hours for all the videos. These manual detections allowed me to pull only video frames around the times where jackrabbits were present in the video, significantly reducing annotation time. Annotations took about three hours. Annotating is just drawing a box around the object and labeling it.

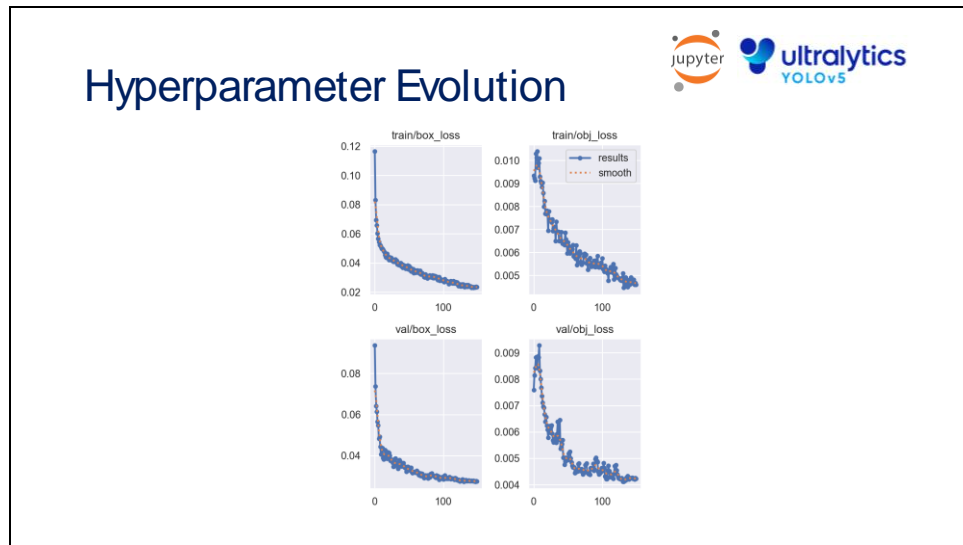




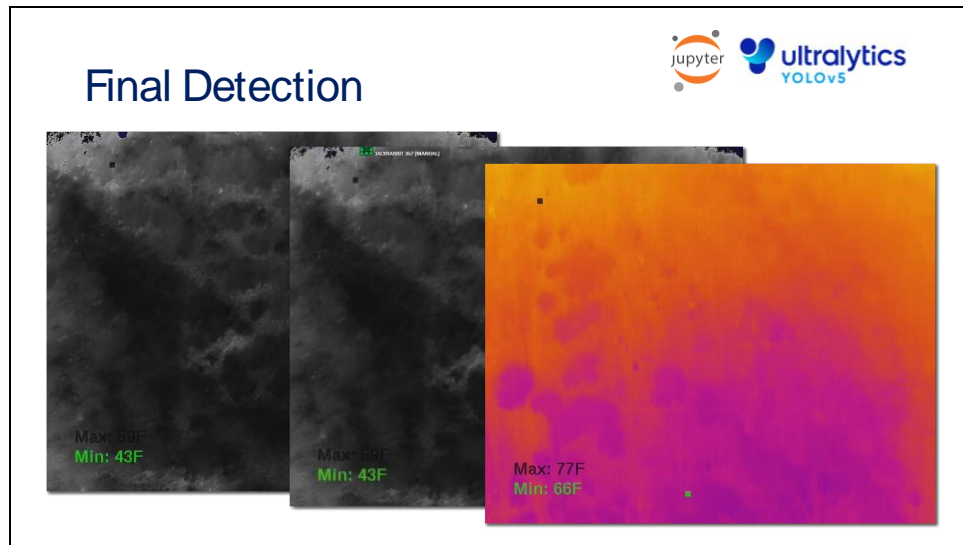
The x-axis is epochs (complete cycle of data processed through the model), and the y-axis is model error. We want both curves to go down over time for a good fit.



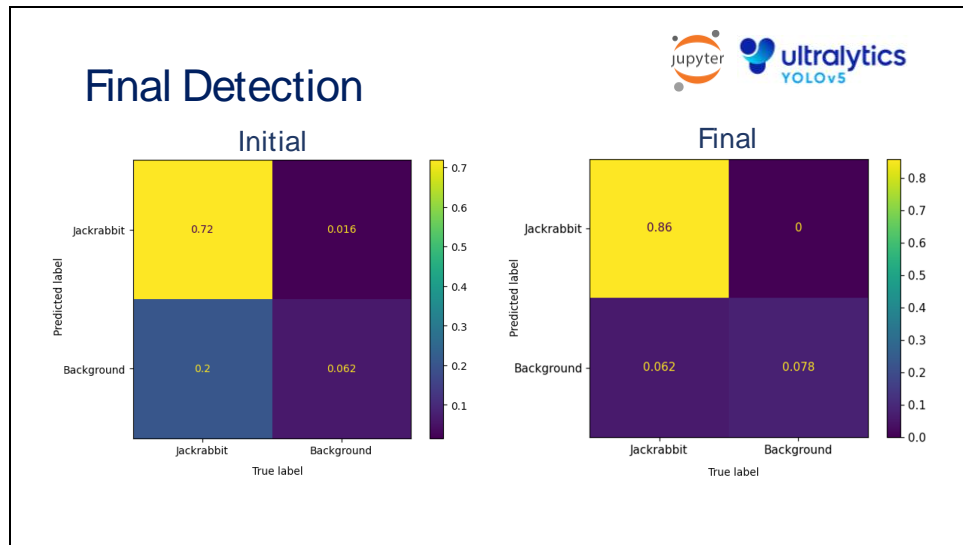
The x-axis is the true image values, and the y-axis is the predicted values. This is a confusion matrix and used to evaluate model accuracy. True and false negatives and positives. The images were split into training, validation, and testing with an 80/10/10 split. The training images are used to train the model, and the validation images are used to check the accuracy of the model. Used the model on the test images and performed a manual evaluation.



Want to optimize the results. Hyperparameters control the model's behavior during training and inference. The initial training uses default hyperparameters. During hyperparameter evolution, different parameters are adjusted and then tested, the hyperparameters from the best generation are then used for final training of 150 epochs.



During initial detection, only one of the jackrabbits in the 2022 frames was detected. During final detection, 75 percent were detected. However, the model still did miss a few jackrabbits, like the one at the very top of the image. Last image is a background image that was positively identified as such.



After manual evaluation of the test images, that confusion matrix shows improved model performance over the initial detection.

Comparison

	300 epochs	450 epochs*
True Positive	46	54
False Positive	1	0
False Negative	13	5
True Negative	4	5
Precision	0.979	1
Recall	0.780	0.915
F1 Score	0.868	0.956

**with hyperparameter evolution*

Tps from initial to final went up from 46 to 54, and false positives went down from 1 to 0. Most models that estimate abundance are designed to account for false negatives, aka, missing individuals. However, they cannot handle false positives. These results demonstrate that the output of this pipeline is suitable for integration with traditional abundance models.

Summary

- Used pilot flights and spotlight surveys to determine optimal parameters for BTJR detection
- Performed flights and spotlight surveys using optimal parameters to detect BTJR
- Trained a YOLOv5 deep learning model to automate BTJR detection

Next steps

- Quantify road bias in detection
- Use drone results with spotlight surveys as an integrated model that leverages the advantages of both methods

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