

AI AND DRONES FOR SEAL MONITORING

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GREY SEAL

(*Halichoerus grypus*)

35% of the world's grey seals breed on UK coasts.

Grey seal WERE in decline:
Only 500 in the UK at the beginning of the 20th century

But today the population has increased to over 162,000 across the UK.

Horsey to Winterton in Norfolk is an important breeding area for grey seals.

Protected species.



GROUND COUNTS

- 10 volunteers
- 8 hrs
- Difficult visibility





1

Identify suitable deep learning architecture to detect pups and adults.



2

Detect and provide counts for seal pups and adults in the drone imagery.



3

Validation
Compare results with ground counts.



4

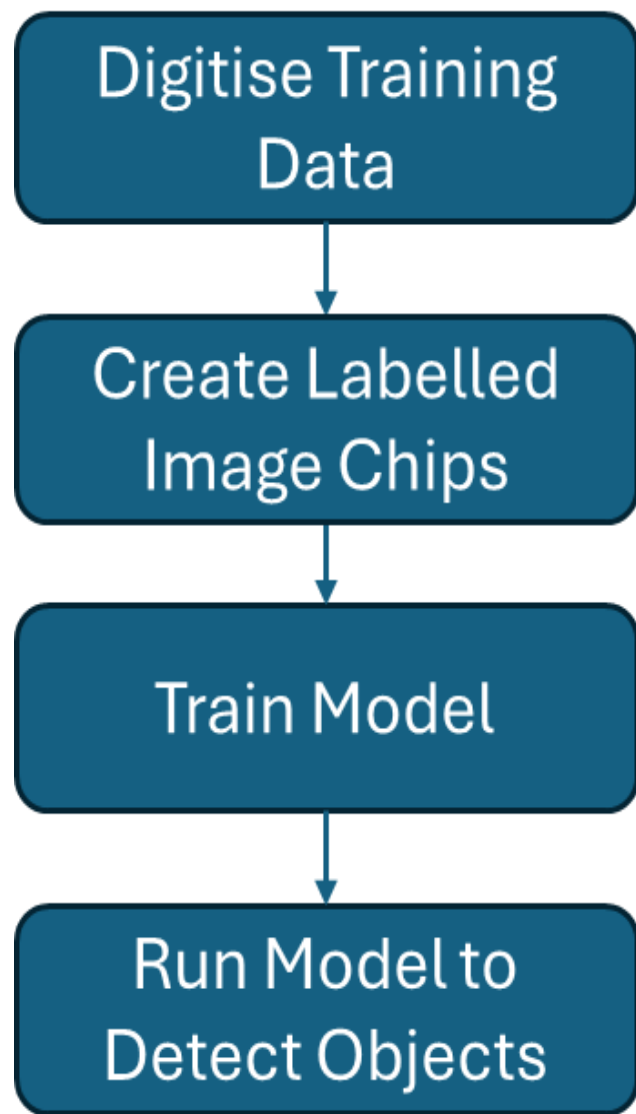
Next Steps - Carry out future drone surveys and apply the model.

DRONE SURVEY

- WINTERTON – HORSEY, 8KM
- DJI MATRICE 300, RGB SENSOR
- 110M ALTITUDE, 12M/S
- 1.38CMS/PIXEL







Overview of the deep learning workflow.

Train Deep Learning Model

Parameters Environments

Input Training Data

Training

Output Folder

Training_DLmodel

Max Epochs

20

Pre-trained Model

Model Type

MaskRCNN (Object detection)

Model Arguments

Name	Value
rpn_pre_nms_top_n_train	2000
rpn_pre_nms_top_n_test	1000
rpn_post_nms_top_n_train	2000
rpn_post_nms_top_n_test	1000
rpn_nms_thresh	0.7
rpn_fg_iou_thresh	0.7
rpn_bg_iou_thresh	0.3
rpn_batch_size_per_image	256
rpn_positive_fraction	0.5
box_score_thresh	0.05
box_nms_thresh	0.5
box_detection_per_image	100

< Previous Run

Geoprocessing

Detect Objects Using Deep Learning

No pending edits.

Parameters Environments

Input Raster

Drone5WaterClip.tif

Output Detected Objects

Drone5WaterCli_DetectObjects

Model Definition

C:\Seals\Models\alltrainingdata_maskRCNN_epochs20_defaug_resnet50_nofre

Objects of Interest

Arguments

Padding	128
Batch Size	8
Confidence Threshold	0.5
Bounding Boxes	False
Test Time Augmentation	False
Merge Policy	mean
Tile Size	512

☐ Non Maximum Suppression

☐ Use pixel space

Run

TRAINING DATA

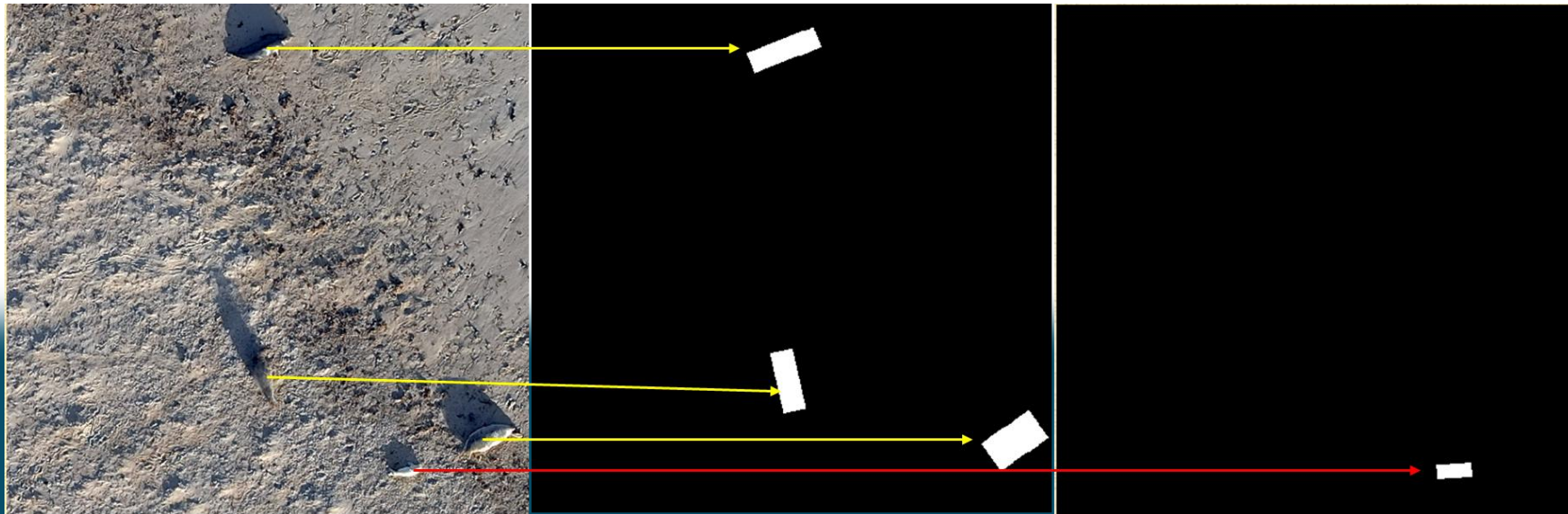
- 2 of 8 images selected
- Bounding boxes
- Labelled adults and pups
- 2400



Image chip

Adult seal labels

Seal pup label

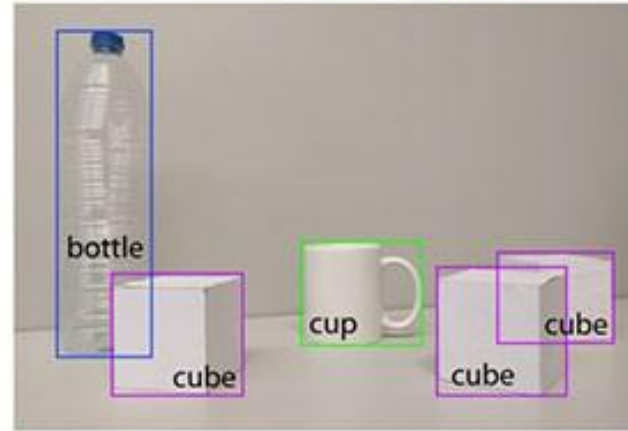


Example of an image chip and labels.

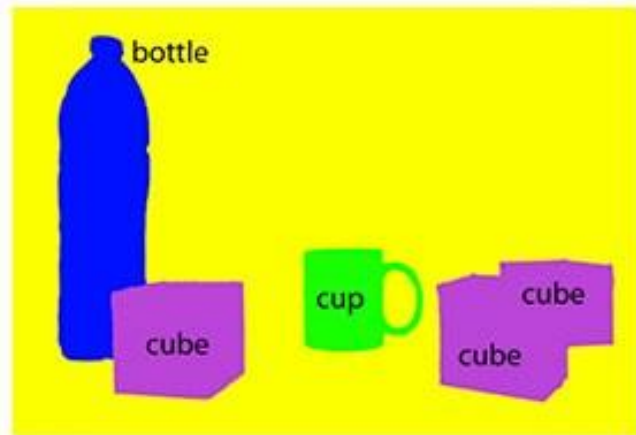
Inferencing techniques



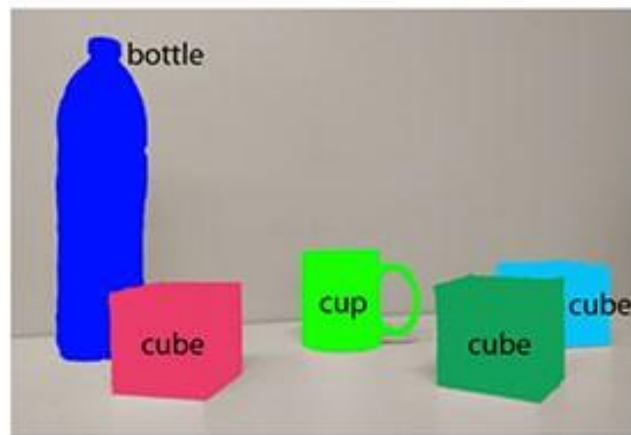
(a) Image classification



(b) Object localization



(c) Semantic segmentation



(d) Instance segmentation

MaskRCNN ResNet-50



RESULTS



RESULTS



VALIDATION (1 of 8 images)

IoU >=0.5	Precision	Recall	F1 Score	AP	True Positive	False Positive	False Negative
All Classes	0.956	0.985	0.970	0.956	1155	53	18
Adults	0.958	0.975	0.966	0.946	574	25	15
Pups	0.954	0.99	0.974	0.966	581	28	3

IoU >=0.75	Precision	Recall	F1 Score	AP	True Positive	False Positive	False Negative
All Classes	0.908	0.935	0.922	0.862	1097	111	76
Adults	0.895	0.910	0.902	0.823	536	63	53
Pups	0.921	0.961	0.941	0.901	561	48	23

INCORRECT DETECTIONS

Wall to wall visual checks of all images (8506
detections)

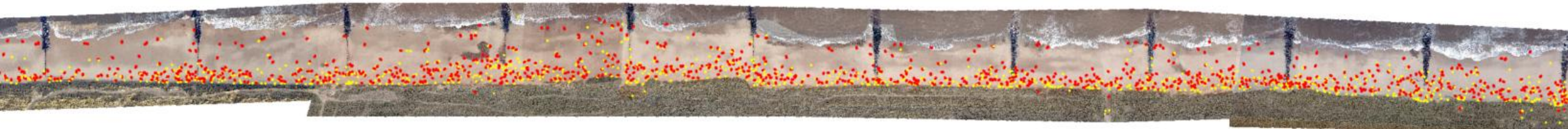
37 false negatives

396 false positives



RESULTS

Method	Adult Seal Count	Seal Pup Count	Total Count
Drone/AI	4377	4129	8506
Ground Count	3426	2782	6208



CONCLUSIONS

Results indicate that drones and AI are an effective tool

- Large training dataset
- Homogenous sandy beach

Method	Advantages	Disadvantages
Ground-based counts	• Increase public ownership • Frequent monitoring • Richer data (etc body condition)	• Limited visibility, difficult to access some areas • Observer bias/counting errors
Drone and AI surveys	• Can access remote/inaccessible areas • Scalable and repeatable across other areas • At this site, better count data	• Weather limitations • More expensive equipment and training needed • Requires special permissions and careful planning



ADDITIONAL APPLICATIONS

