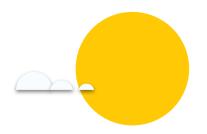
## OTTERS!

Tensorflow object detection



By Desmond Yap

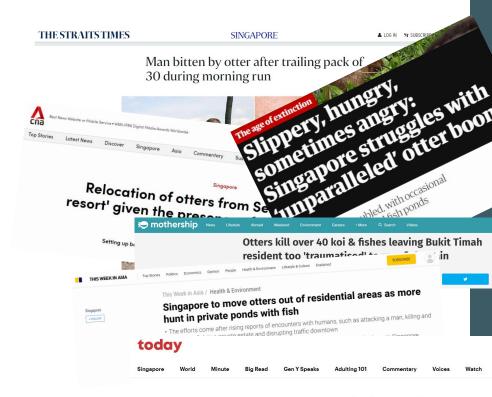


## **BACKGROUND**



#### What is happening in Singapore?

- Otter population has more than doubled since 2019
- 2. Number of citizen reports a year about otters have increased from 208 in 2020 to more than 300 in by August in 2022
- 3. Incidents of otters attacking people Kallang Riverside Park and Botanic Gardens
- Incidents of otters killing residents' koi and fishes
- 5. Sightings were rare up until late 1998 when a pair of otters were spotted at Sungei Buloh Wetlands Reserve
- 6. Talks on culling or co-existing



Otter population up sharply but still manageable, say experts who urge public to learn to co-exist with them



## **CONTENT PAGE**



#### 01

#### INTRODUCTION

- Background
- Problem Statement

#### 04

#### **TENSORFLOW 2**

- Training a pretrained model SSD Mobilenet V2
- Model Evaluation

#### 02

#### **OBJECT DETECTION**

- Types of technique
- Mean Average Precision

#### 05

#### **STREAMLIT**

Deployment

#### 03

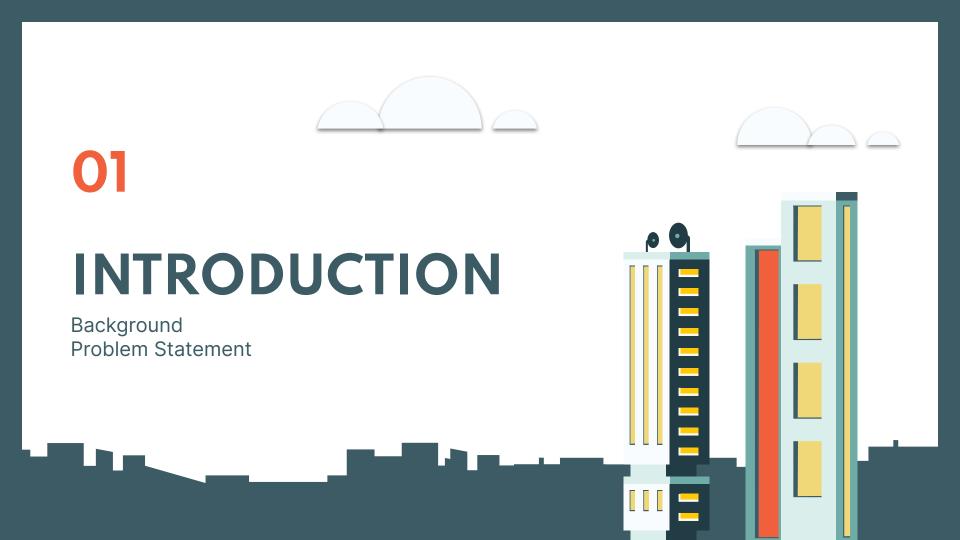
#### **IMAGE DATA**

- Flickr scraper API
- Roboflow

#### 06

#### **SUMMARY**

 Conclusion, limitations and recommendations





## **PROBLEM STATEMENT**



How do we co-exist with the growing otters population

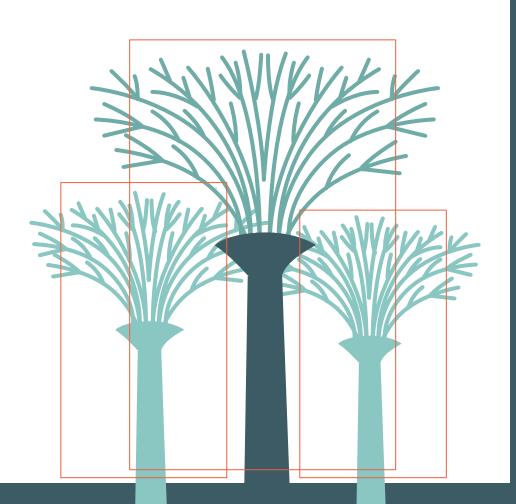
This project aims to detect the number of otters from an image, video or live stream and return the number of counts of otters identified. With that information, it can then be translated into many other uses. For example, security for the home owners and building management - a warning sound could be activate when the number of otters detected is above a threshold number or tracking of the otters by NParks just by counts.



# O2 OBJECT DETECTION

Types of technique Mean Average Precision





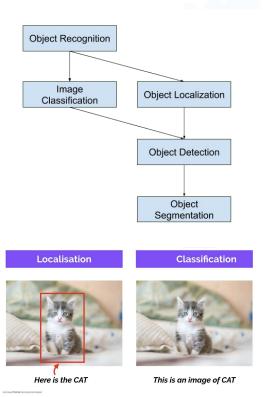
## **OBJECT RECOGNITION WITH DEEP LEARNING**

Object recognition is a general term to describe a collection of related computer vision tasks that involve identifying objects in digital photographs

**Image Classification:** Predict the type or class of an object in an image

**Object Localization:** Locate the presence of objects in an image and indicate their location with a bounding box

**Object Detection:** Locate the presence of objects with a bounding box and types or classes of the located objects in an image



## **OBJECT RECOGNITION WITH DEEP LEARNING**

#### **R-CNN**

Region-Based Convolutional Neural Network R-CNN, Fast R-CNN, Faster R-CNN

#### **YOLO**

'You Only Look Once'

#### **SSD MobileNet**

Single Shot Detectors

Picture

Feature Map

Region Proposal Network
Object:
True/False?
Box regression

Classification

Region Proposal Network
Object:
True/False?
Box regression

Classifier
Classification

Box Refinement

Two-stage (R-CNN)

One-stage (YOLO, SSD)

The major difference between the two is that in the two-stage object detection models, the region of interest is first determined and the detection is then performed only on the region of interest

This implies that the two-stage object detection models are generally more accurate than the one-stage ones but require more computational resources and are slower

Designed to be used in mobile applications and is Tensorflow's first mobile computer vision model

Lightweight deep neural networks

## TF 2 OBJECT DETECTION MODEL ZOO

Model name	Speed (ms)	COCO mAP	Outputs
SSD MobileNet v2 320x320	19	20.2	Boxes
SSD MobileNet V1 FPN 640x640	48	29.1	Boxes
SSD MobileNet V2 FPNLite 320x320	22	22.2	Boxes
SSD MobileNet V2 FPNLite 640x640	39	28.2	Boxes
Faster R-CNN ResNet50 V1 640x640	53	29.3	Boxes
Faster R-CNN ResNet50 V1 1024x1024	65	31.0	Boxes
Faster R-CNN ResNet50 V1 800x1333	65	31.6	Boxes
Faster R-CNN ResNet101 V1 640x640	55	31.8	Boxes
Faster R-CNN ResNet101 V1 1024x1024	72	37.1	Boxes
Faster R-CNN ResNet101 V1 800x1333	77	36.6	Boxes
Faster R-CNN ResNet152 V1 640x640	64	32.4	Boxes
Faster R-CNN ResNet152 V1 1024x1024	85	37.6	Boxes
Faster R-CNN ResNet152 V1 800x1333	101	37.4	Boxes
Faster R-CNN Inception ResNet V2 640x640	206	37.7	Boxes
Faster R-CNN Inception ResNet V2 1024x1024	236	38.7	Boxes
Mask R-CNN Inception ResNet V2 1024x1024	301	39.0/34.6	Boxes/Masks

#### What is COCO?









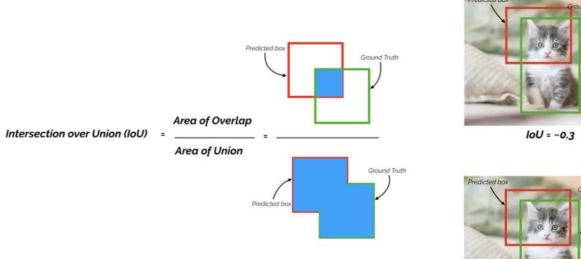


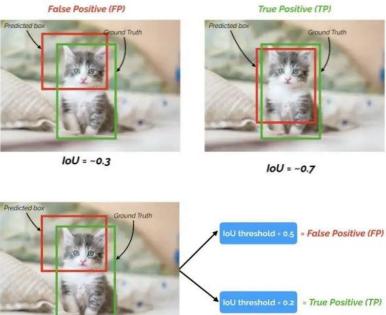
COCO is a large-scale object detection, segmentation, and captioning dataset. COCO has several features:

- Object segmentation
- Recognition in context
- Superpixel stuff segmentation
- 330K images (>200K labeled)
- 1.5 million object instances
- ◆ 80 object categories
- 91 stuff categories
- ◆ 5 captions per image
- 250,000 people with keypoints

## Mean Average Precision (mAP)

If IoU threshold = 0.5





IoU for the prediction = ~0.3

## Mean Average Precision (mAP)

TP = 1, FN = 1, FP =0



 Rank (confidence)
 Correct?
 Precision(TP/ TP+FP)
 Recall(TP/(TP+FN))

 1
 True
 1/(1+0) = 1
 1/(1+1) = 0.5

mAP = 0.545

11 Point Interpolated Precision-Recall Curve

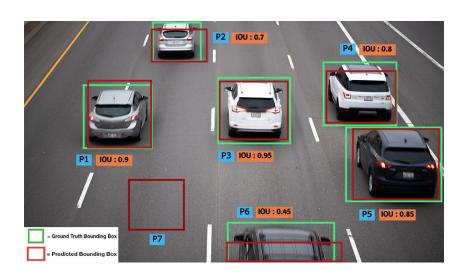
Object detection example for Advanced driver-assistance systems (ADAS)

Ground Truth Bounding Box

Predicted Bounding Box

Precision and Recall is calculated for each predicted bounding box in the image at a particular IoU threshold ranked according to decreasing confidence of prediction

## Mean Average Precision (mAP)



Rank (confidence)	Correct?	Precision(TP/ TP+FP)	Recall(TP/(TP+FN))
P1	True	1/(1+0) = 1	1/(1+5) = 0.167
P2	True	2/(2+0) = 1	2/(2+4) = 0.33
P3	True	3/(3+0) = 1	3/(3+3) = 0.5
P4	True	4/(4+0) = 1	4/(4+2) = 0.67
P5	True	5/(5+0) = 1	5/(5+1) = 0.83
P6	True	6/(6+0) = 1	6/(6+0) = 1
P7	False	6/(6+1) = 0.857	6/(6+0) = 1

Precision and Recall is calculated for each predicted bounding box in the image at a particular IoU threshold ranked according to decreasing confidence of prediction



03

## **IMAGE DATA**

Flickr Scraper API Roboflow







## **IMAGE DATA PREPARATION**



 $\longrightarrow$ 

roboflow

Flickr Scraper API

700 images

500 training 50 validation

## **IMAGE DATA PREPARATION**

#### Labels

Al assist labelling

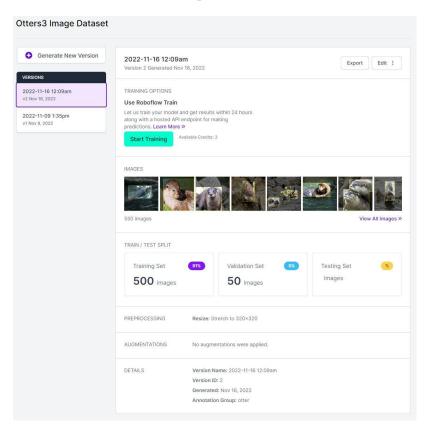
#### **TF Record**

For Tensorflow 2

#### **Preprocessing**

Resize

**Augmentation** 



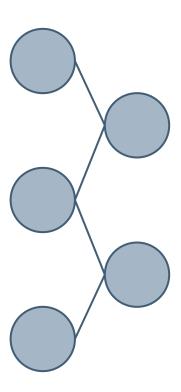


04

## **TENSORFLOW 2**

Training a pretrained model Model evaluation







## TENSORBOARD MODEL EVALUATION

ssd\_mobilenet\_v2\_fpnlite\_640×640\_coco17\_tpu-8 with 2000 training steps, 500 training images, 50 validation images

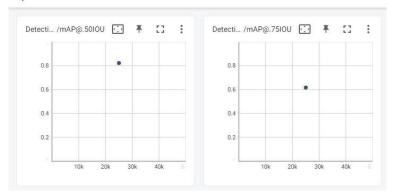
Average Precision (AP) @[ IoU=0.50	area= all	maxDets=100] = 0.661
Average Precision (AP) @[ IoU=0.75	area= all	maxDets=100] = 0.252
Average Recall (AR) @[ IoU=0.50:0.95	area= all	maxDets=100] = 0.576

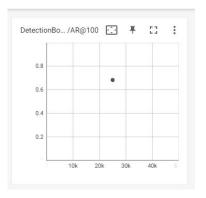
ssd\_mobilenet\_v2\_fpnlite\_320×320\_coco17\_tpu-8 with 25000 training steps, 500 training images, 50 validation images

Average Precision (AP) @[ IoU=0.50	area=	all	maxDets=100] = 0.822
Average Precision (AP) @[ IoU=0.75	area=	all	maxDets=100] = 0.617
Average Recall (AR) @[ IoU=0.50:0.95	area=	all	maxDets=100 ] = 0.683

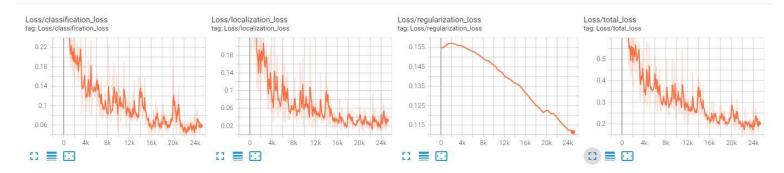
## TENSORBOARD MODEL EVALUATION

Pinned 4 cards

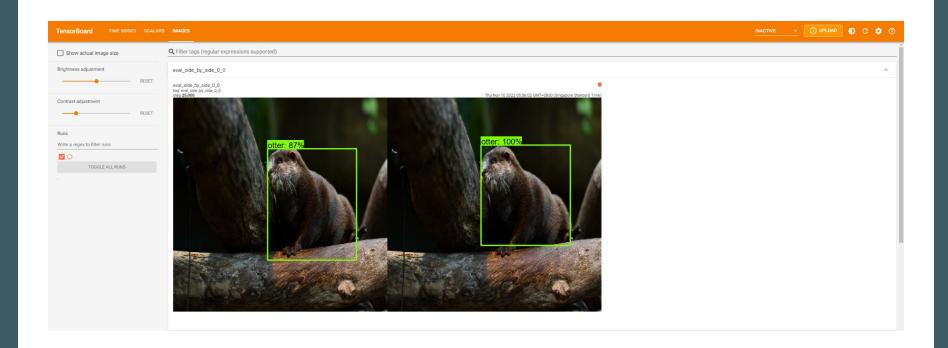




Loss

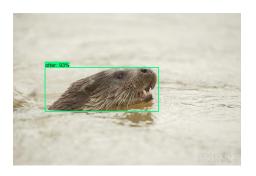


## TENSORBOARD MODEL EVALUATION

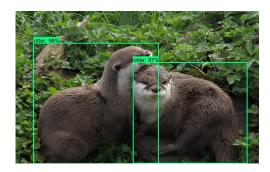


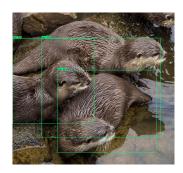


## MODEL PREDICTION WITH IMAGES

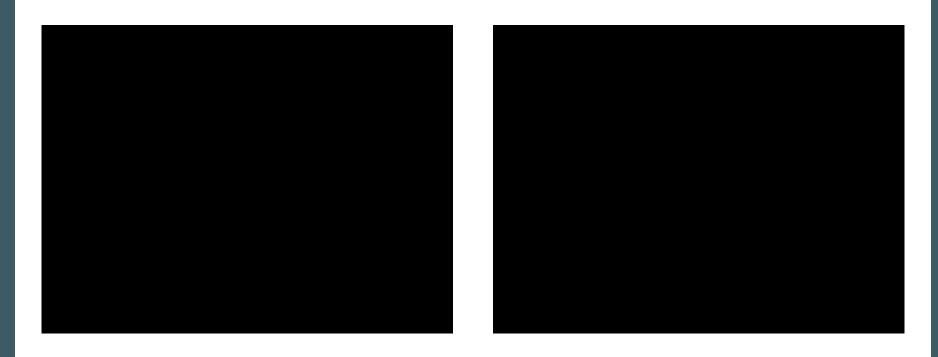






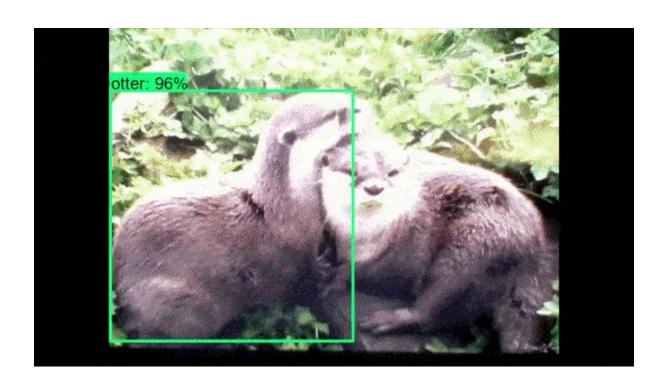


## MODEL PREDICTION WITH VIDEO



## MODEL PREDICTION WITH LIVE WEBCAM



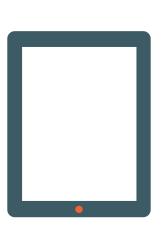




05



Deployment







### STREAMLIT DEPLOYMENT

Simulation of surveillance camera

**USER INPUT** 

Upload or take photos

**PROCESS** 

Utilizes TF Lite model for processing

**OUTPUT** 

Returns bounding boxes with confidence Number of otters detected Warning sound if 3 or more otters are detected

**LIMITATIONS** 

Live streaming possible but excluded in this exercise TF Lite model is less capable after exporting but lighter

# 06 SUMMARY

Conclusion, limitations and recommendations



## **SUMMARY**

#### Conclusion

As the otters' population grows, it would be necessary to find methods to co-exist with them. There are two main concerns to be addressed, from residents and building managements' point of view - a deterrence, and from local authority's point of view - a way to track and identify the otters

SSD Mobilenet V2 returned decent scores

```
Average Precision (AP) @[ loU=0.50 ] area = all maxDets=100 ] = 0.822
Average Precision (AP) @[ loU=0.75 ] area = all maxDets=100 ] = 0.617
Average Recall (AR) @[ loU=0.50:0.95 ] area = all maxDets=100 ] = 0.683
```

Computer vision/ object recognition can be very adaptable - the usage should be compounded with other current measures in place to deter otters (deployment of inanimate objects that can be on guard 24/7 is better than risking being attacked by otters if they turn aggressive)

#### Limitations

Time required for model training, GPU, number of image dataset, preprocessing and augmentation

## **SUMMARY**

#### Recommendation

The number of models and improvements are constantly being pushed out

Increase the number of images collected, quality of photo, different views and distant in the images play a part in model training and prediction

Does not have to stop at just otters - it is very possible to include any other kind of wildlife, object detection is capable to handle more than one class

It is also possible to retrieve counts from a live stream video - more akin to a real surveillance camera



## **THANK YOU**



Streamlit - Try it!



https://www.linkedin.com/in/desmond-jjyap/



https://github.com/DesmondYapJJ



desmondyap\_jj@hotmail.com



