

IE 406: Machine Learning

Final Project Presentation

Group 29



Animal detection and classification



Introduction

Problem Statement in brief:

- The aim of this project was to detect the presence of an animal in any image and provide with the name of the animal present if any.
- Input: Typically an image
- Output(expected): Detect the presence of an animal, if present show the name.



Motivation:

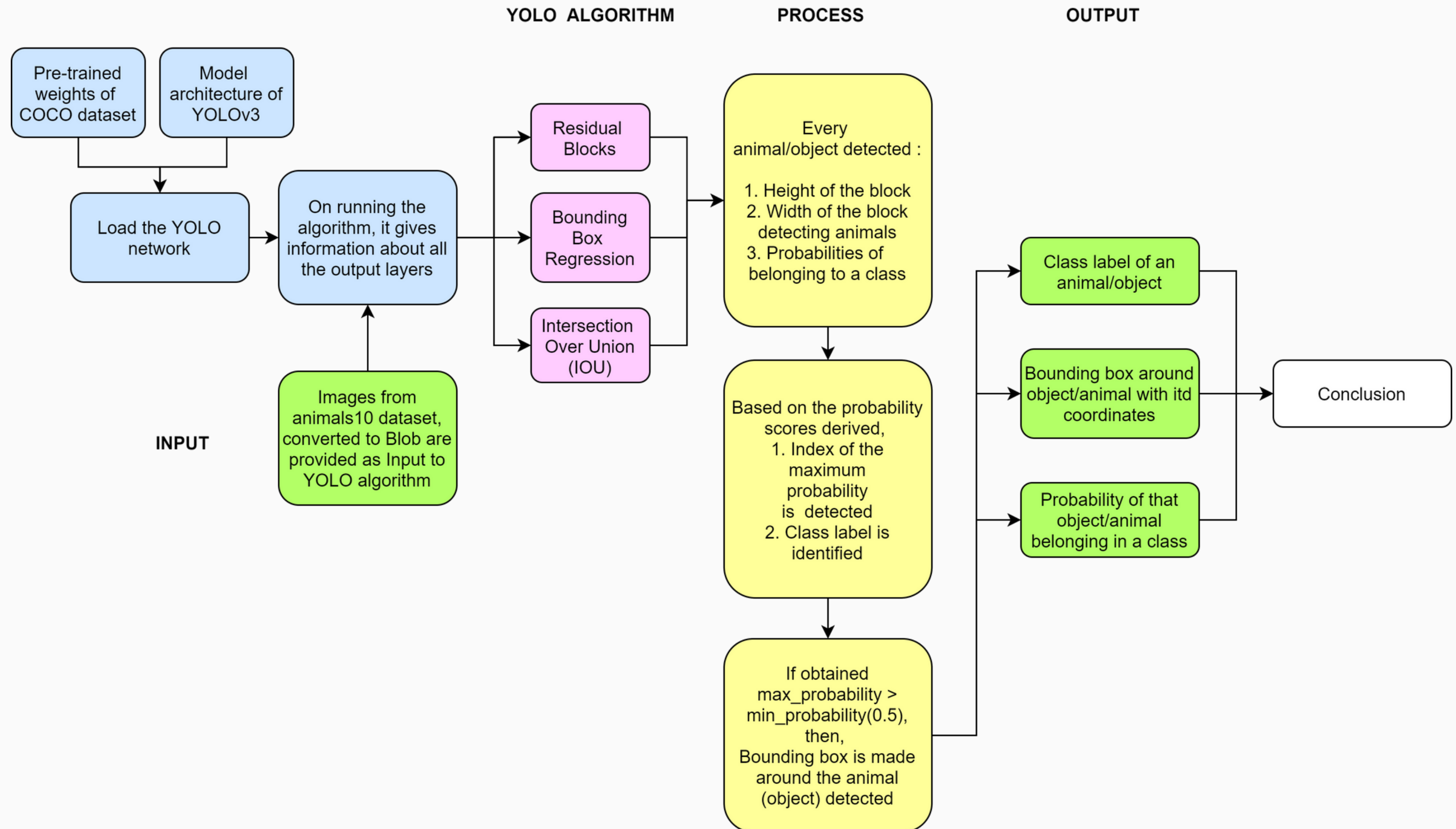
- Nowadays, surveillance of animals, keeping a count of the number of animals belonging to a particular species, keeping an eye on the illegal poaching and killing of animals, maintaining logs of tourists activities to restrict them to a permissible level, etc. are crucial activities that will require digital monitoring of animals via cams, drones, etc. In such a case, manually keeping counts, or even real-time identification of animals is very difficult and inefficient.
- Hence, in such cases, a real-time algorithm to detect presence of animals in a given frame, can make the process smooth and efficient. Essentially an algorithm that detects the presence of animals in a given shot, and detect the animal presence can help.
- Such algorithms can also be used to prevent negative human-animal interventions.

Dataset details:

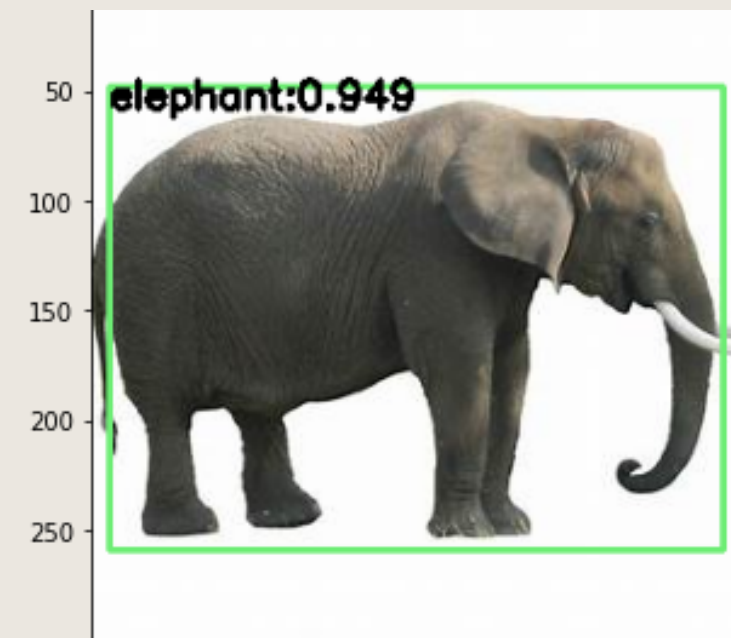
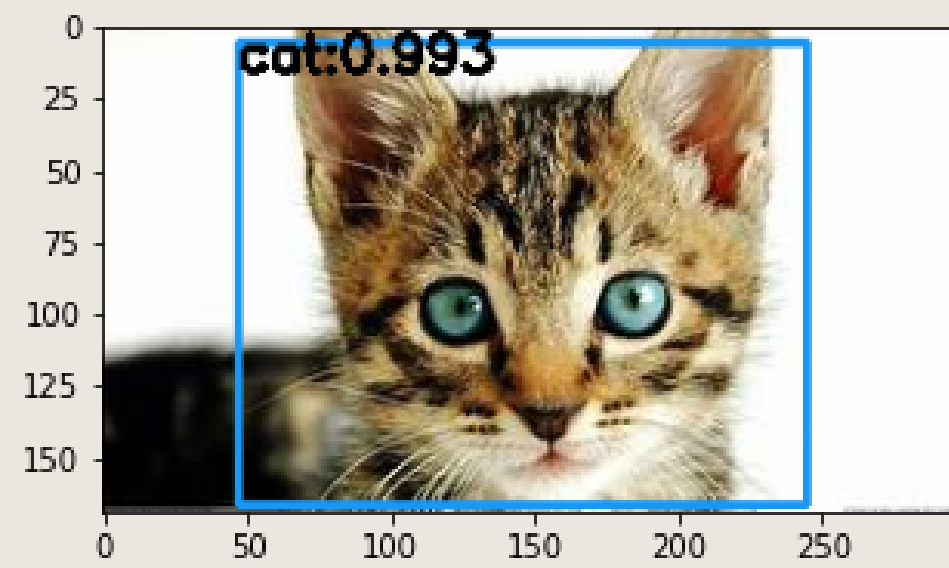
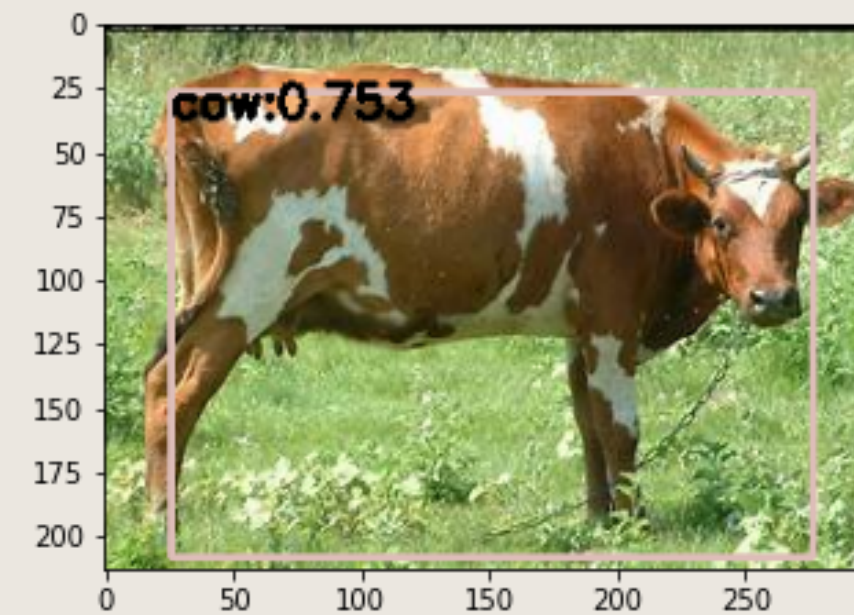
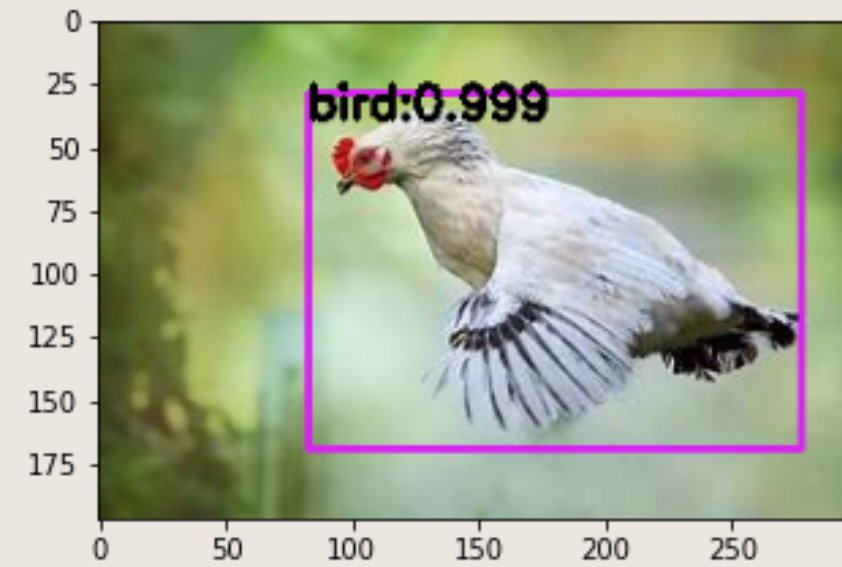
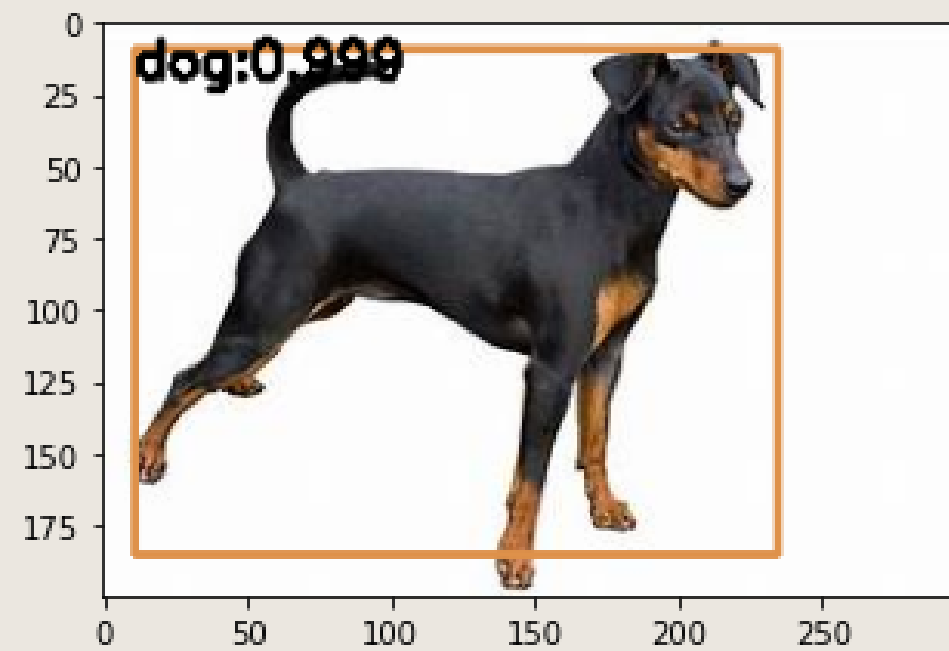


- We have employed the YOLO-v3 algorithm in order to detect the presence of animals in an image. We have essentially used the weights that are obtained by training on the COCO data set.
- The COCO(Common Objects in Context) data set by MS, is a widely used data set used for deep learning problems in the field of object detection.
- It has around 80 classes or labels each of which corresponds to a common object in context and has high-resolution images pertaining to it. It has among these nearly 8 classes of animals, namely 'bird', 'cat', 'dog', 'horse', 'sheep', 'cow', 'elephant', 'bear', 'zebra', 'giraffe'.
- In order to test the results, we use several different images of animals from the animals10 data set.

Flow chart/Block Schematic:



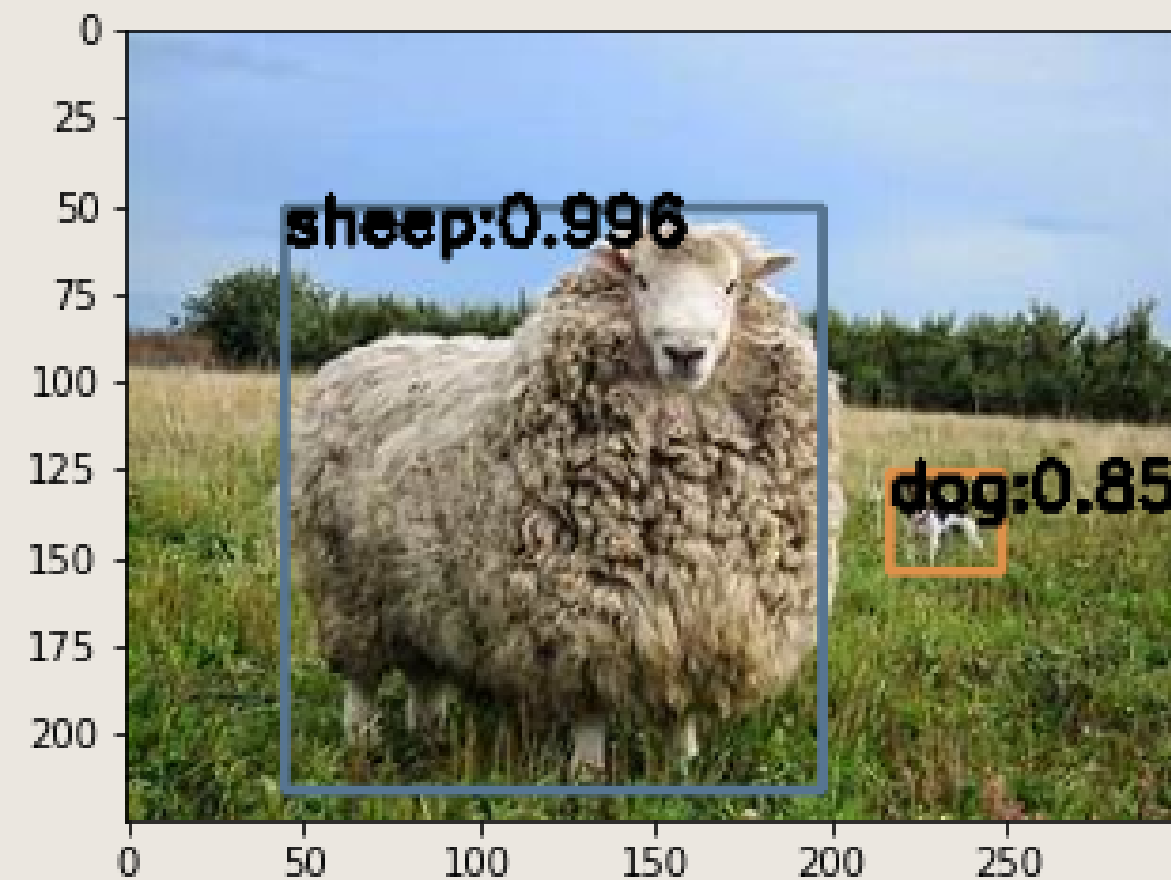
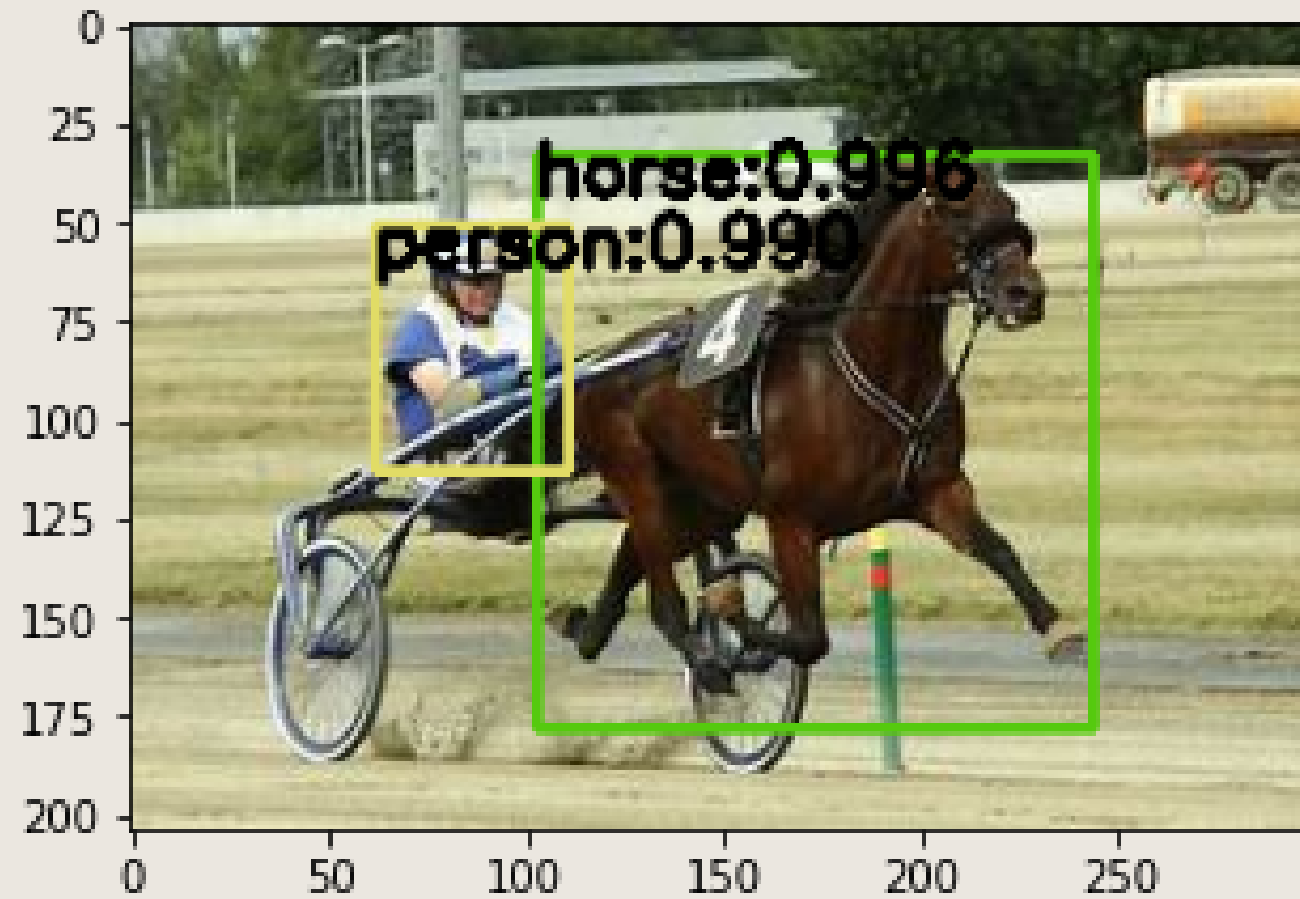
Results and Discussion (I):



Results and Discussion (2):

- As we can observe in the figures obtained in the previous slide, animals are detected in the image.
- There is a single bounding box that surrounds the animal to locate its position in the image. It also displays a probability. It is the probability of the animal present there belonging to that particular class.
- For instance, in the previous slide, a bounding box surrounds the cat, which locates the cat in the whole image, with a probability of 0.993 that the animal present belongs to the cat class.

Results and Discussion (3):



Results and Discussion (4):

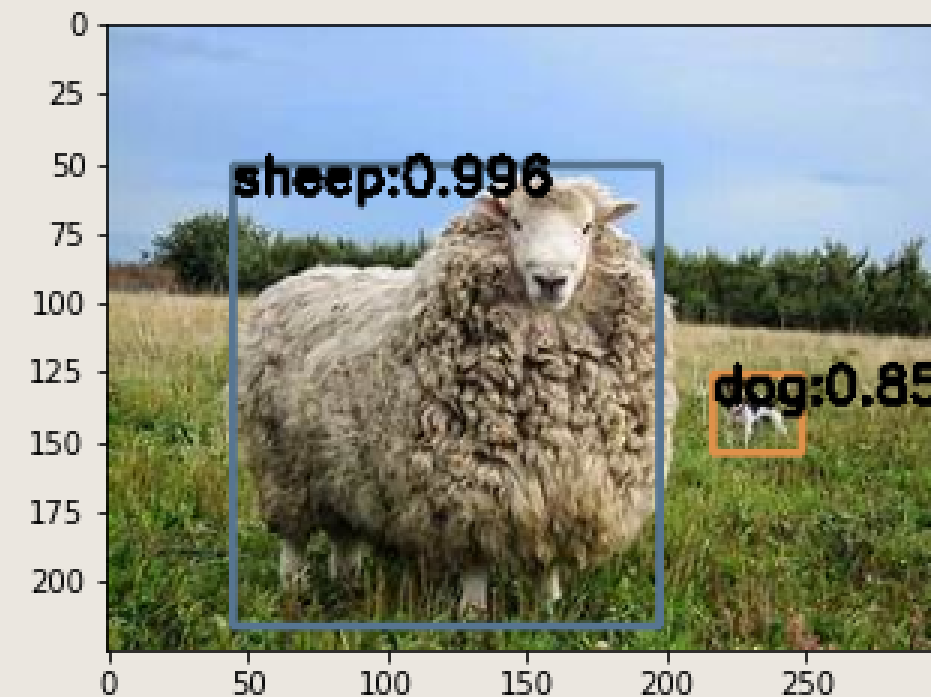
- As we can observe in the previous slide, two different animals are also detected in the image.
- Each comes with its own bounding box and probability.
- An object: a person is also detected alongside the horse; this is because we have used weights of the model trained on the COCO dataset and hence, it detects 'person' that was one of the 80 classes present in the COCO dataset.

Results and Discussion (5):

- Along with the pointing out in the image, we also extracted the coordinates of the bounding box. Each animal can hence be detected with a set of 2-dimensional coordinates.
- For an image with 2 animals, as shown:
'Sheep':
 - Bounding Box Coordinate 1 : (45 , 51)
 - Bounding Box Coordinate 2 : (198 , 51)
 - Bounding Box Coordinate 3 : (45 , 216)
 - Bounding Box Coordinate 4 : (198 , 216)

'Dog':

- Bounding Box Coordinate 1 : (217 , 126)
- Bounding Box Coordinate 2 : (249 , 126)
- Bounding Box Coordinate 3 : (217 , 154)
- Bounding Box Coordinate 4 : (249 , 154)





Conclusion:

Usability and further scope:

- The bounding boxes and its co-ordinates obtained can essentially be very helpful in a certain number of ways:
 - One can not only spot animals via surveillance, but easy location detection can also be possible.
 - One can inform about the coordinates of an animal lost in its habitat when carrying on a drone search, one can spot animals being poached and also spot the person responsible for doing so using surveillance systems. These are a few of the many uses of this automation.
 - The detection of animals can also be useful to keep a count of the number of animals for a particular species in a habitat.
 - Annual surveys can be carried out automatically without human involvement or only a little assistance. That would make conservation of bio-diversity easier.

References:



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2. Banupriya, N., S. Saranya, Rashmi Jayakumar, Rashmi Swaminathan, Sanchithaa Harikumar, and Sukhita Palanisamy. "Animal Detection Using Deep Learning Algorithms." January 15, 2020. <http://www.jcreview.com/fulltext/JCR070185.pdf>.
3. A. Gomez., A. Salazar, F. Vargas, towards automatic wild animal monitoring: Identification of animal species in camera-trap images using very deep convolutional neural networks, 2016.
4. What Is YOLO Algorithm? | Deep Learning Tutorial 31 (Tensorflow, Keras & Python). Youtube. code basics, 2020. <https://www.youtube.com/watch?v=ag3DLKsl2vk>.
5. Norouzzadeh, Mohammad Sadegh, Anh Nguyen, Margaret Kosmala, Alexandra Swanson, Meredith S. Palmer, Craig Packer, and Jeff Clune. "Automatically Identifying, Counting, and Describing Wild Animals in Camera-trap Images with Deep Learning." PNAS. June 19, 2018. Accessed October 03, 2021. <https://www.pnas.org/content/115/25/E5716>.
6. <https://www.kaggle.com/valentynsichkar/yolo-coco-data>
7. <https://www.kaggle.com/alessiocrrado99/animals10>

thank you

THE END

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