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STATISTICAL MACHINE LEARNING

FINAL PROJECT

OBJECT DETECTION WITH YOLO

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Abstract

Computer vision has long been one of the main foci in the field of computer science. This branch aims to utilize images or videos, and the computational power of machineries to perform tasks like classification, object detection, and recognition. Since the invention of convolutional neural network (CNN), computer vision models have been enhanced tremendously. Different from normal feed-forward networks, CNN utilizes kernels to extract regional features from the image, thus making calculations more accurate. Architectures like You Only Look Once (YOLO) leverages this advantage of preserving dimensionality to perform robust and high precision object detection. In this project, we aim to establish an overall understanding of this series of models, as well as use it to construct our own detection website. We will discuss the technicalities and notable features of YOLO, as well as give an overview of our website and details on our own model.

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1 INTRODUCTION

You Only Look Once or YOLO (Redmon et al. 2016) is a well-known series of object detection models. Throughout the years, more revised versions have been developed and published, with each later model having more modifications thus boosting its accuracy and performance.

In this project, we aim to establish an understanding of YOLO's architecture. We then used our own dataset to retrain the model, and developed a web interface for object detection. In this report, we present our overview on YOLO's features and our website's development. Details on our training process, including data, evaluation metrics, and results are also discussed.

2 OVERVIEW ON OBJECT DETECTION MODELS

2.1 Architecture

Object detection models have a number of components that help extract features, perform detection, and some additional supporting modules. In this section, we give an overview of the architecture of such models.

Backbone. As the name suggests, this part of the model is very important to the whole architecture as it is tasked with extracting the features from input images. Instead of encoding the features into a vector (like in convolutional networks) for classification, the backbone network saves the features into a stacked feature maps. This approach is crucial for preserving spacial information of the pixels, which allows for accurate detection of objects throughout the entire image. Some widely used networks for this task include: CSPDarknet53 (Wang et al. 2020) used by Bochkovskiy et al. 2020 in YOLOv4, and EfficientNet (Tan 2019) used in YOLOv8.

Neck. This section is an optional part of the model and lies between the feature extraction stage (backbone) and detection stage (head). The purpose of this part is to construct multiple scales of the feature maps obtained from backbone. By expanding the dimension of the feature maps, the head can detect objects at different sizes. Some widely used methods for this part are: Spatial Pyramid Pooling (He et al. 2015) and Path Aggregation Network (Liu et al. 2018) in YOLOv4,

Head. One last main component of the object detection is responsible for performing the actual detection on the feature maps. For architectures that make use of the neck stage for enriching the scales, detection is performed at each scale independently from each other. Small scale maps are used for the detection of large objects, and larger scale maps are used for smaller objects'. It is in this stage that the bounding box for each object are defined, a classification probability is also calculated.

2.2 Additional features

In addition to the base architecture, some techniques for boosting the model's performance can also be incorporated during various stages. Bochkovskiy et al. 2020 call these adjustments *Bag of Freebies* and *Bag of Specials*. In this section, we give a simple explanation and example for each of those terms.

- Bag of Freebies: a set of techniques or methods that can alter the training strategy to improve the prediction accuracy, namely: Data Augmentation - used to alter the input images which can help create diversity in training data, Semantic Distribution Bias, and Objective Function of Bounding Box Regression.

- Bag of Specials: a set of modules and post-processing methods that can further improve the model's accuracy exchanging for the model's inference time. These methods can range from enhancing features to introducing advanced mechanisms.

3 REQUIREMENT 1: Web interface for pre-built object detection model

In this section, we present the design of our web interface, along with the integration of a pre-trained YOLO model to perform object detection. We used Ultralytics' version 10 medium model for the detection task. The model is loaded into global variables at the website's booting stage. If the pre-trained `.pt` file is not found on the local machine, it will be automatically downloaded. We present screenshots of the interface in Figure 1 and 2.

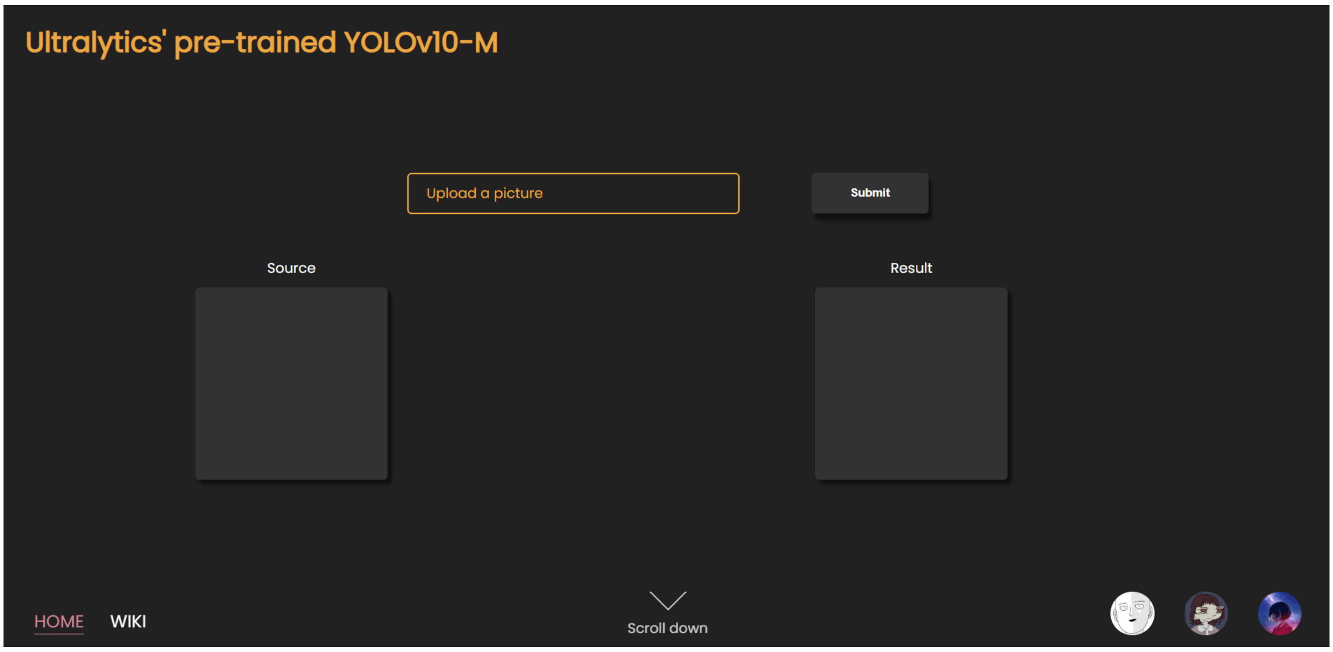


Figure 1. Default user interface for object detection task using Ultralytics's pre-trained model.

4 REQUIREMENT 2: Custom model training and application building

4.1 Data Preparation

In this part we will discuss about the data source and its distribution information. We will not delve deeply into the coding aspect as it is messy and also unnecessary for this report.

4.1.1 Data source

Although there are many image detection datasets available online (mainly on Kaggle), most of them do not meet our requirements which are the ability to filter by class (animal in our case) and having labels written in YOLO format. Therefore, we must come up with a solution to acquire the datasets that are as tailored to our needs as possible. This will be done with the help of Google Open Images Dataset V7 and the `fiftyone` library.

YOLOv4: Implemented with Pytorch, it performs detection with box format as `[id, x1, y1, x2, y2]` (this is different from both Google Open Images Dataset V7 and the YOLO format). Fortunately, there exist Kaggle datasets with this format, and as we don't have high demands for

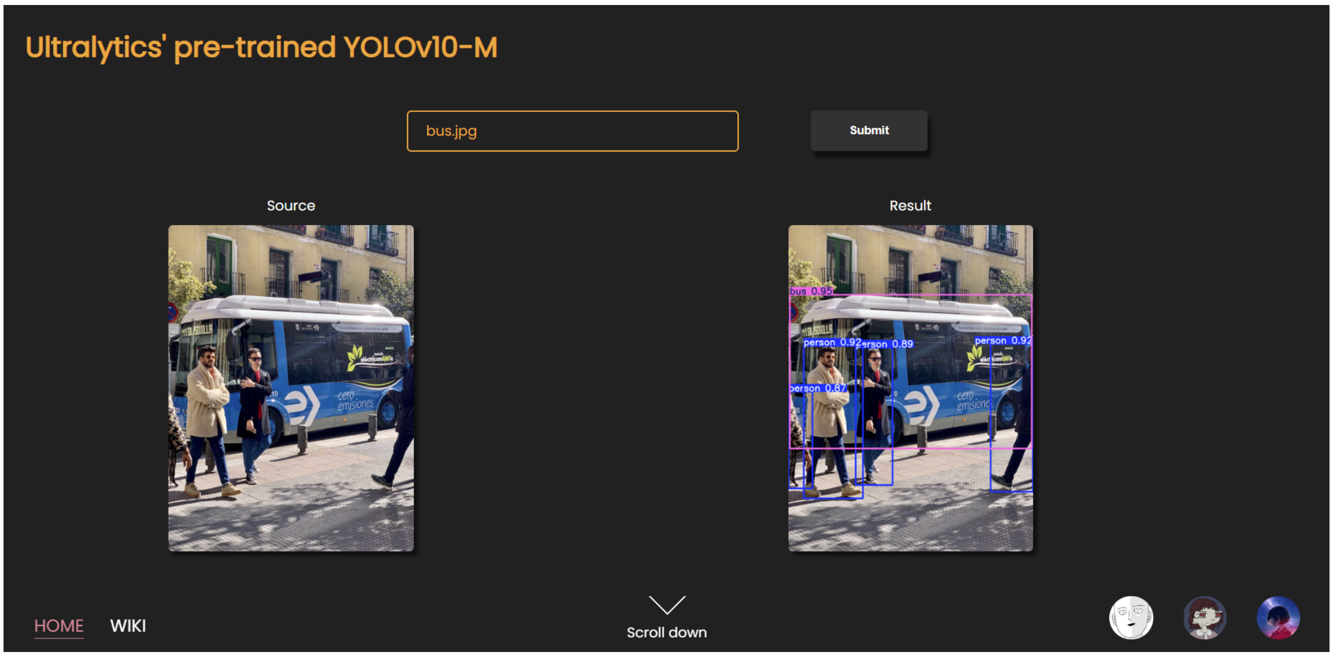
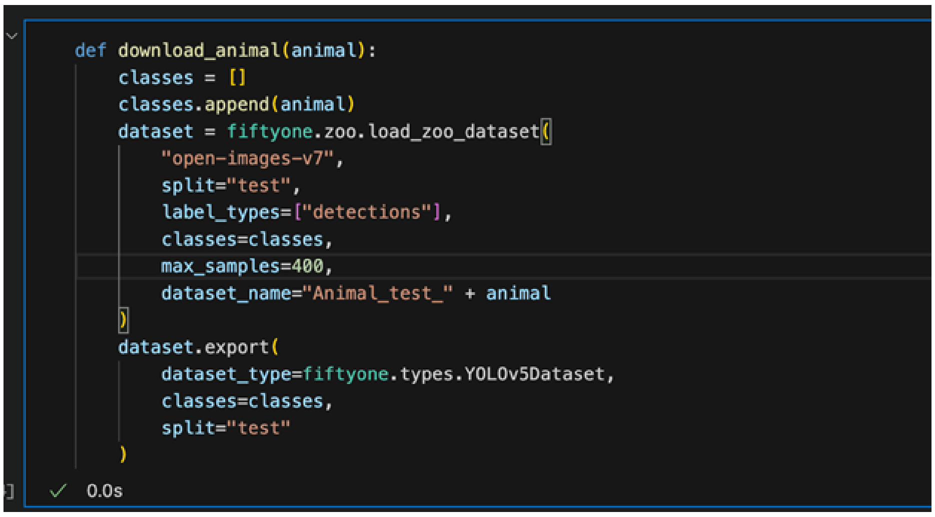


Figure 2. Interface for Ultralytics' model after being prompted with an input image.

this model, it is convenient to leverage resources that are already available. Hence, we will use a subset of the Animals Detection Images Dataset to work with this model.

YOLOv8: As mentioned above, our image database will be Google Open Images Dataset V7, and the required data will be crawled and transformed into YOLO format with the `fiftyone` library. This way, data can be extracted freely, with all required classes, and is only limited by what the database can provide. There is also another advantage of crawling our own data, which will be explained in the next part.



```
def download_animal(animal):
    classes = []
    classes.append(animal)
    dataset = fiftyone.zoo.load_zoo_dataset(
        "open-images-v7",
        split="test",
        label_types=["detections"],
        classes=classes,
        max_samples=400,
        dataset_name="Animal_test_" + animal
    )
    dataset.export(
        dataset_type=fiftyone.types.YOLOv5Dataset,
        classes=classes,
        split="test"
    )
```
```
✓ 0.0s
```

Figure 3. A snippet of code using `fiftyone` to download and convert data to YOLO format.

4.1.2 Data distribution

YOLOv4: A subset of 9 classes is taken from the original dataset, which has highly uneven distribution (Figure 4). This is one of the reasons why data needs to be crawled for YOLOv8. There is a total of 1858 images for training and testing.

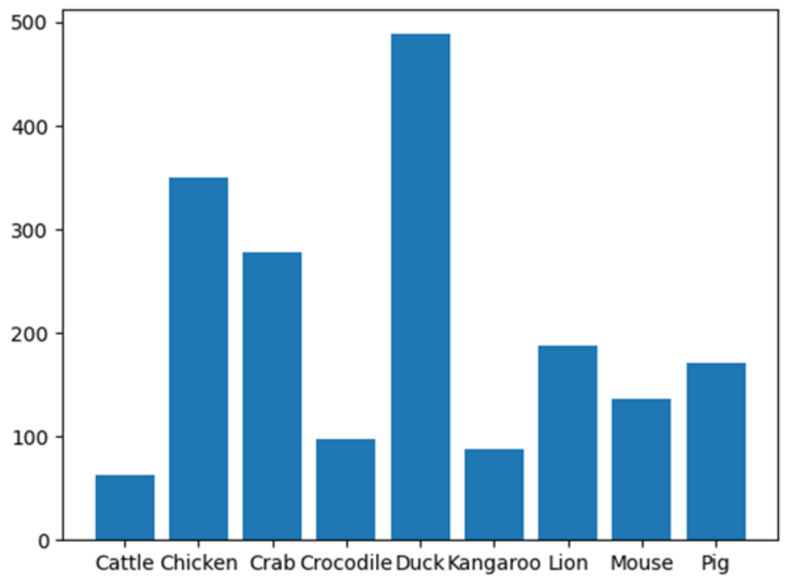


Figure 4. Distribution of the data used to train our YOLO4 model.

YOLOv8: We choose to pick 22 classes from the database and divide it into three complete divisions of train/test/validation, which each have 7094/3691/1692 images respectively. So, the ratio for train/test/validation is nearly 57/30/13.

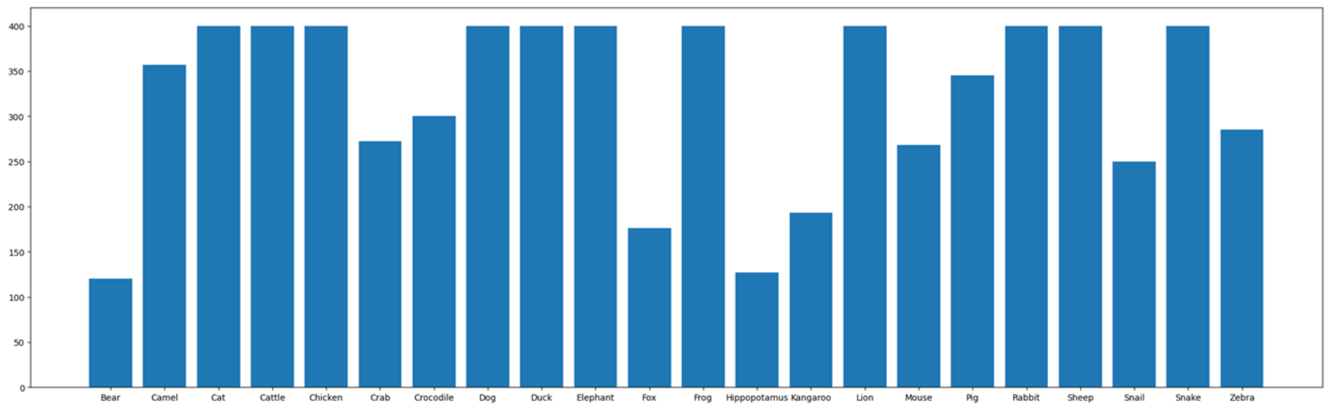


Figure 5. Distribution of the data used to train our YOLO4 model.

Figure 5 is a distribution plot for the training set, which is more evenly distributed thanks to the help of the crawling tool. Although there remain some classes that have a small number of images due to the providing limit of Google Open Image Dataset, they still possess reasonable quantities, which is enough to avoid the bias of providing too many or too little data for a class.

4.2 Training

4.2.1 Basics on training models with YOLOv4

The YOLO architecture comprises of a Backbone network (to extract features from image) and a Detection head (to predict bounding boxes, objectness scores, and class probabilities), we first need to train the backbone network so the extracted information can prove more useful for the detection layer. Then, we apply regression training using a loss function for the Detection head so it can predict bounding boxes and performing classification better at the same time.

A training process goes through these steps:

1. Forward Pass: The input image is passed through the model. The model predicts bounding boxes, objectness scores, and class probabilities for each grid cell.

2. Loss Calculation:

   - Bounding Box Loss: Measures the error between the predicted bounding boxes and the ground truth bounding boxes using mean squared error.
   - Objectness Loss: Evaluates how well the model predicts the presence of an object in a bounding box using binary cross-entropy loss.

3. Class Loss: Measures the error between the predicted probabilities and the true class' using cross-entropy loss.

4. Backpropagation: The total loss is backpropagated through the network to update the weights using an optimization algorithm like Stochastic Gradient Descent (SGD) or Adam.

5. Iteration: This process is repeated for multiple epochs until the model converges to a set of weights that minimizes the loss function.

When talking about training a YOLO model, we often skip the Backbone training part as the Backbone network is highly universal and can be trained once for many different Detection heads. With that, it is recommended to transfer the Backbone network's weights from notably well-trained models (e.g., Darknet53) instead of training them from scratch. Now, the training process mainly focuses on training the Detector.

YOLOv4: Because we only use this model for further insights of how a YOLO model training process works, it is only trained for 100 epochs. The training code is implemented based roughly on the process mentioned above, so it is not yet polished and many flaws may still remain. However, this should be acceptable considering the research nature and self-taught purpose of this model. The code used for this stage is referenced from Tianxiaomo 2021.

4.2.2 Training YOLOv8 models with Ultralytics and Kaggle

From this point onward, we will employ the Ultralytics framework, and because of the demanding training process, everything is going to be done and hosted on Kaggle. A training process with Ultralytics has following steps:

1. Prepare datasets in YOLO format (which is discussed in Section 4.1).

2. Prepare a configuration file to guide Ultralytics for the new classes and train/val datasets.

3. Host these datasets and configuration file on Kaggle, where the training process will be carried out.

4. Tell Ultralytics to carry the Backbone network's weights from its base YOLOv8 model, and use our new configuration to train for the animal detection problem. While training, we need to specify the number of epochs and the input image size of the training dataset, which in our case are 200 epochs and 640.

5. When the training process is completed on Kaggle, the notebook returns outputs containing the trained model and several insight reports of the training process.

4.3 Result and Evaluation

For the sake of simplicity, we are going to evaluate only the YOLOv8 model trained with Ultralytics, as this is the model with the highest potential for a satisfactory evaluation score. Since we are working with an object detection model, the most suitable metric for grading would be mAP. Mean Average Precision (mAP) score is a popular evaluation metric, used in object detection models to measure their accuracy. It is particularly useful because both the precision and recall of the model's predictions are considered. Following is a breakdown of what the mAP score is and how it is calculated:

- The precision-recall curve (Figure 6) shows the trade-off between precision and recall for different threshold values. As you increase the threshold for considering a detection as positive, precision generally increases, but recall decreases, and vice versa.
- AP is the area under the precision-recall curve for a particular class. It is calculated by taking the average of precision values across all recall levels from 0 to 1. In some cases, interpolation is used to ensure that precision is monotonically decreasing. For each object class, the AP is calculated separately.
- mAP is the mean of the Average Precision (AP) values across all object classes. It provides a single score that summarizes the model's overall performance across all classes.
- Ultralytics definition of mAP is a little bit different, they define class' mAP as a mean between all "easy detections" of one class. There is also a model's mAP, which is the mean of all classes' mAP values. Ultralytics provides mAP score calcuted under many IoU (intersection over union) thresholds, and we will choose mAP-50 as the common metric in this report.

4.3.1 Evaluation of the training process

Ultralytics provides mAP-50 score evaluated per epoch using the validation set. Since we are training the model on 200 epochs, it is redundant to show mAP score for every epoch in this report. Instead, we note down a mAP-50 score every 20 epochs in Table 1 (mAP-50 score for every epoch can still be accessed through the notebook output, or the "`result_per_epoch.csv`" file in the "`modelEvaluating`" folder).

Table 1. mAP-50s of the model while training. Measurements are taken every 20 epochs.

Epoch num	mAP-50
20	0.50381
40	0.65829
60	0.71419
80	0.736
100	0.74504
120	0.75555
140	0.76199
160	0.76561
180	0.76819
200	0.76527

As can be observed from Figure 6 and 7, all the metrics of our model (including mAP-50) saw significant changes while training less than 100 epochs. After 150 epochs, while there are

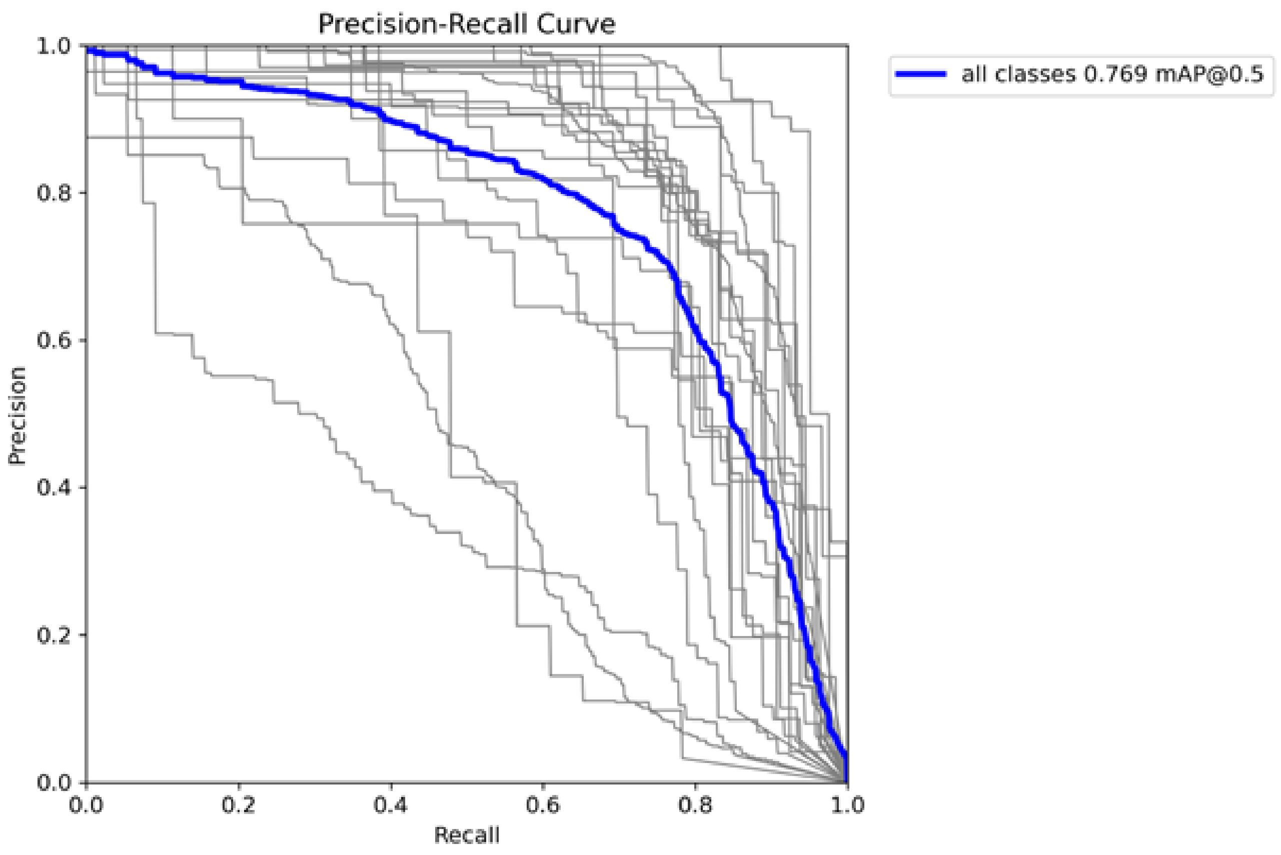


Figure 6. Precision-recall curve.

still notable changes, we can almost say that the value hits its plateau. Maybe with the current dataset and configuration, we just need to train our model for 150 epochs.

In summary, our trained model achieves the mAP-50 score of 0.769, which is a fairly good point (a model with mAP-50 score above 0.5 can be deemed usable). Almost all classes have their own mAP-50 scores above 0.5, except for some special cases like Bear, Cattle or Sheep. This is possibly due to the low number of training samples and the vast number of animals that have similar features. For instance, for camels that have thick fur coats, the model can mistake them for sheep, and the same goes for other animals that have similarities like horns, skin colour, shape, etc. Therefore, the training data also plays an important role in determining the performance of the model. The resolution of the input image can also greatly affect the accuracy as unclear pictures can confuse the model by making it unable to confidently detect and identify the subject.

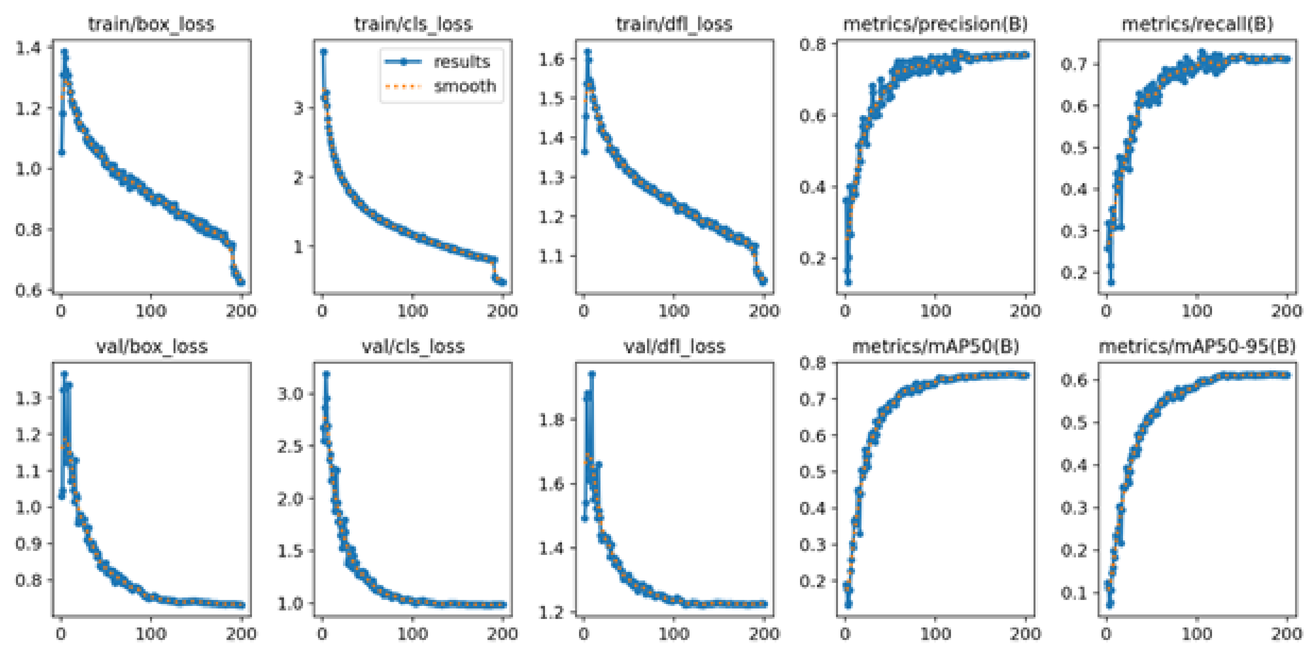
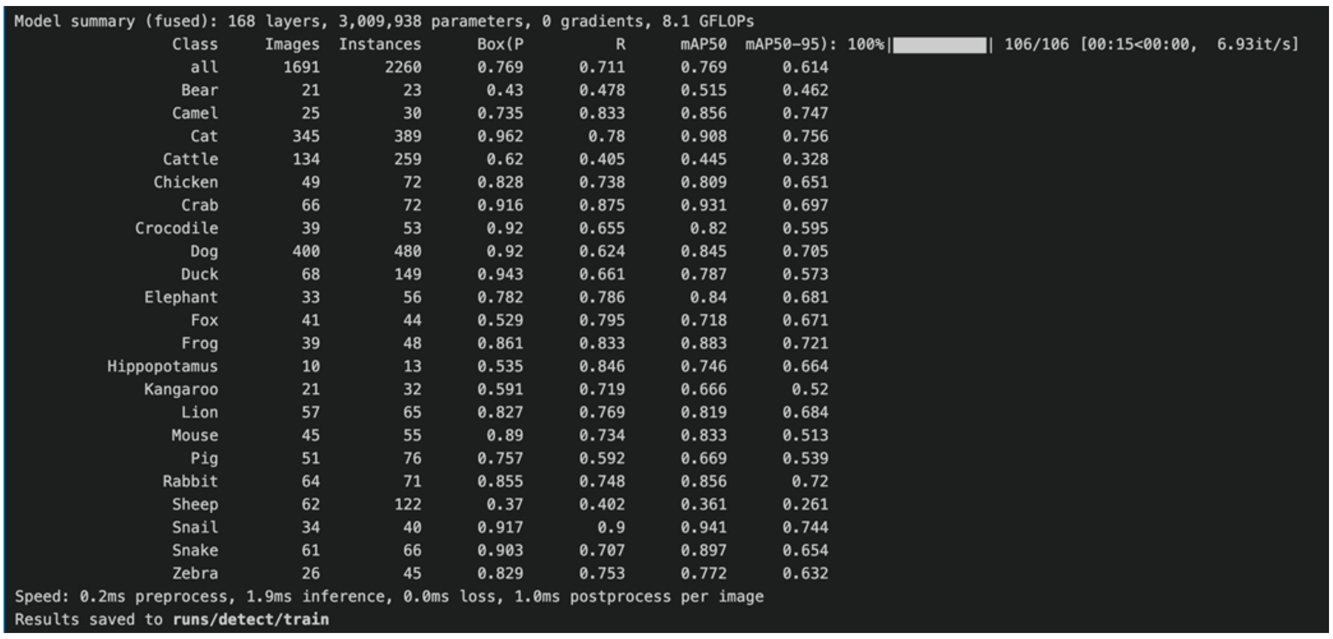


Figure 7. Metric report of the model while training.

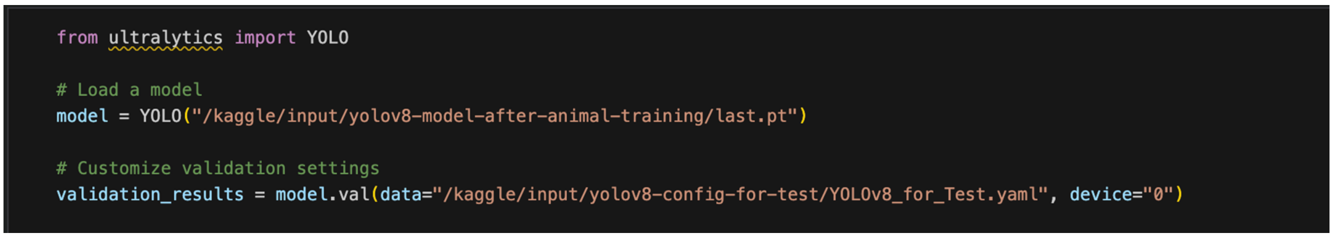


```
Model summary (fused): 168 layers, 3,009,938 parameters, 0 gradients, 8.1 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 106/106 [00:15<00:00,  6.93it/s]
                   all       1691       2260      0.769      0.711      0.769      0.614
                  Bear         21         23       0.43      0.478      0.515      0.462
                 Camel         25         30      0.735      0.833      0.856      0.747
                   Cat        345        389      0.962       0.78      0.908      0.756
                Cattle        134        259       0.62      0.405      0.445      0.328
               Chicken         49         72      0.828      0.738      0.809      0.651
                  Crab         66         72      0.916      0.875      0.931      0.697
             Crocodile         39         53       0.92      0.655       0.82      0.595
                   Dog        400        480       0.92      0.624      0.845      0.705
                  Duck         68        149      0.943      0.661      0.787      0.573
              Elephant         33         56      0.782      0.786       0.84      0.681
                   Fox         41         44      0.529      0.795      0.718      0.671
                  Frog         39         48      0.861      0.833      0.883      0.721
          Hippopotamus         10         13      0.535      0.846      0.746      0.664
              Kangaroo         21         32      0.591      0.719      0.666       0.52
                  Lion         57         65      0.827      0.769      0.819      0.684
                 Mouse         45         55       0.89      0.734      0.833      0.513
                   Pig         51         76      0.757      0.592      0.669      0.539
                Rabbit         64         71      0.855      0.748      0.856       0.72
                 Sheep         62        122       0.37      0.402      0.361      0.261
                 Snail         34         40      0.917        0.9      0.941      0.744
                 Snake         61         66      0.903      0.707      0.897      0.654
                 Zebra         26         45      0.829      0.753      0.772      0.632
Speed: 0.2ms preprocess, 1.9ms inference, 0.0ms loss, 1.0ms postprocess per image
Results saved to runs/detect/train
```

Figure 8. Metric report of the model after running on the validation set.

4.3.2 Evaluation of the testing process

In addition to training evaluation, we utilize a separate testing set to check our model's performance on new and unseen data. Ultralytics provides a `val()` method for valuation after training (Figure 9).

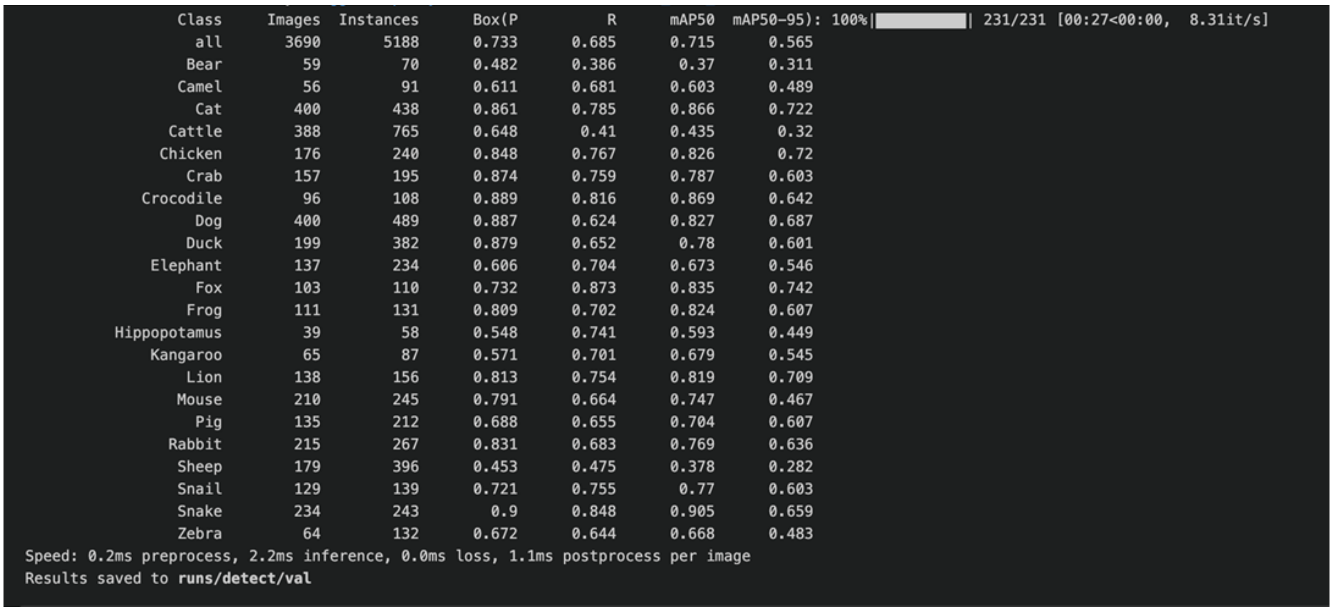


```
from ultralytics import YOLO

# Load a model
model = YOLO("/kaggle/input/yolov8-model-after-animal-training/last.pt")

# Customize validation settings
validation_results = model.val(data="/kaggle/input/yolov8-config-for-test/YOLOv8_for_Test.yaml", device="0")
```

Figure 9. Calling validation method with the trained model and test dataset.



```
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 231/231 [00:27<00:00,  8.31it/s]
                   all       3690       5188      0.733      0.685      0.715      0.565
                  Bear         59         70      0.482      0.386       0.37      0.311
                 Camel         56         91      0.611      0.681      0.603      0.489
                   Cat        400        438      0.861      0.785      0.866      0.722
                Cattle        388        765      0.648       0.41      0.435       0.32
               Chicken        176        240      0.848      0.767      0.826       0.72
                  Crab        157        195      0.874      0.759      0.787      0.603
             Crocodile         96        108      0.889      0.816      0.869      0.642
                   Dog        400        489      0.887      0.624      0.827      0.687
                  Duck        199        382      0.879      0.652       0.78      0.601
              Elephant        137        234      0.606      0.704      0.673      0.546
                   Fox        103        110      0.732      0.873      0.835      0.742
                  Frog        111        131      0.809      0.702      0.824      0.607
           Hippopotamus         39         58      0.548      0.741      0.593      0.449
              Kangaroo         65         87      0.571      0.701      0.679      0.545
                  Lion        138        156      0.813      0.754      0.819      0.709
                 Mouse        210        245      0.791      0.664      0.747      0.467
                   Pig        135        212      0.688      0.655      0.704      0.607
                Rabbit        215        267      0.831      0.683      0.769      0.636
                 Sheep        179        396      0.453      0.475      0.378      0.282
                 Snail        129        139      0.721      0.755       0.77      0.603
                 Snake        234        243        0.9      0.848      0.905      0.659
                 Zebra         64        132      0.672      0.644      0.668      0.483
Speed: 0.2ms preprocess, 2.2ms inference, 0.0ms loss, 1.1ms postprocess per image
Results saved to runs/detect/val
```

Figure 10. Evaluation metrics of our trained model on test dataset.

It is delightful to know that our trained model can achieve a mAP-50 score of 0.715 on the testing set, which is relatively close to the validation's discussed earlier. Considering the large size of the testing set, this result is acceptable. To a certain extent, our trained model is more than capable of accurately detecting animals on larger unseen dataset.

4.4 Application

Here we describe a practical usage of the trained model by incorporating it in building an animal detection website. In terms of technicalities, the model is loaded and used the same way as described in Section 3, with the exception of automatically downloading the trained weights.

We summarize the features of the site as follows:

- Perform wildlife animal detection on input image.
- List facts and related links on detected animals on the Wiki tab.
- Order the facts based on the confidence of each detection or based on the animal names.

To access the wildlife detection model, simply scroll down from the initial Ultralytics' homepage, or click on the *Scroll down* button on the bottom of the screen. To see the facts/links related to the animals, click on the *Wiki* button. Screenshots of the webpage are presented in Figure 11, 12, 13, and 14.

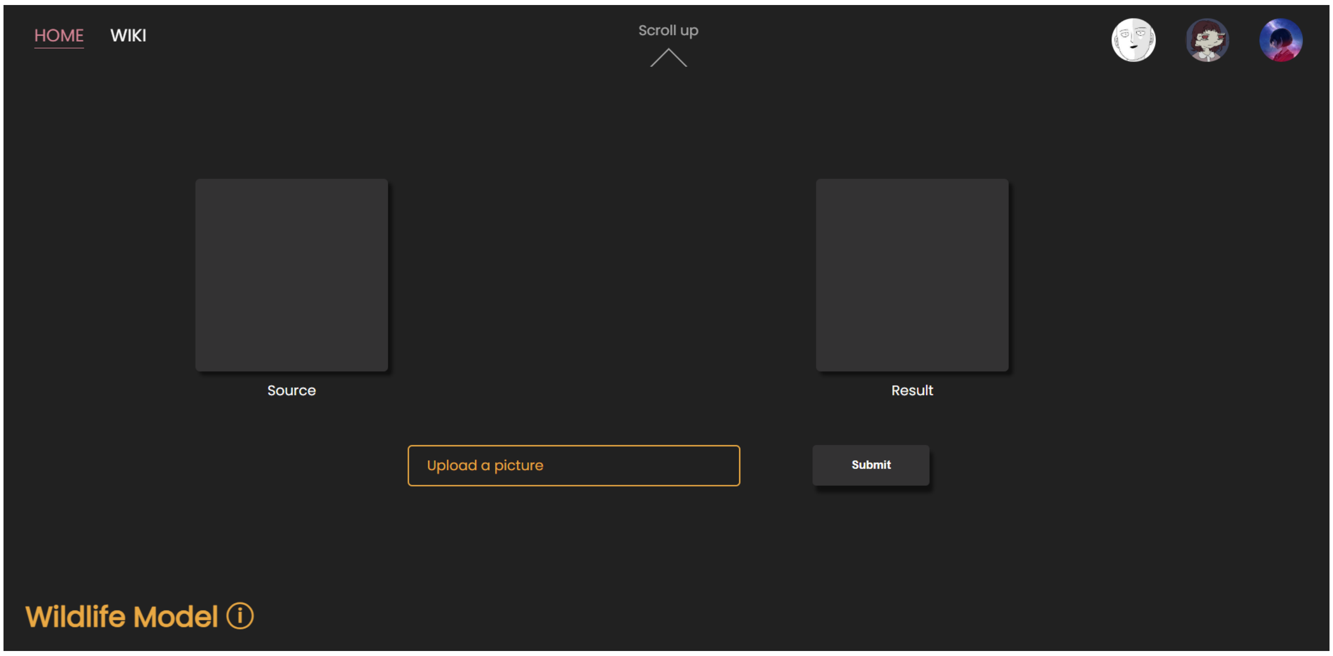


Figure 11. Interface of wildlife detection model's homepage.

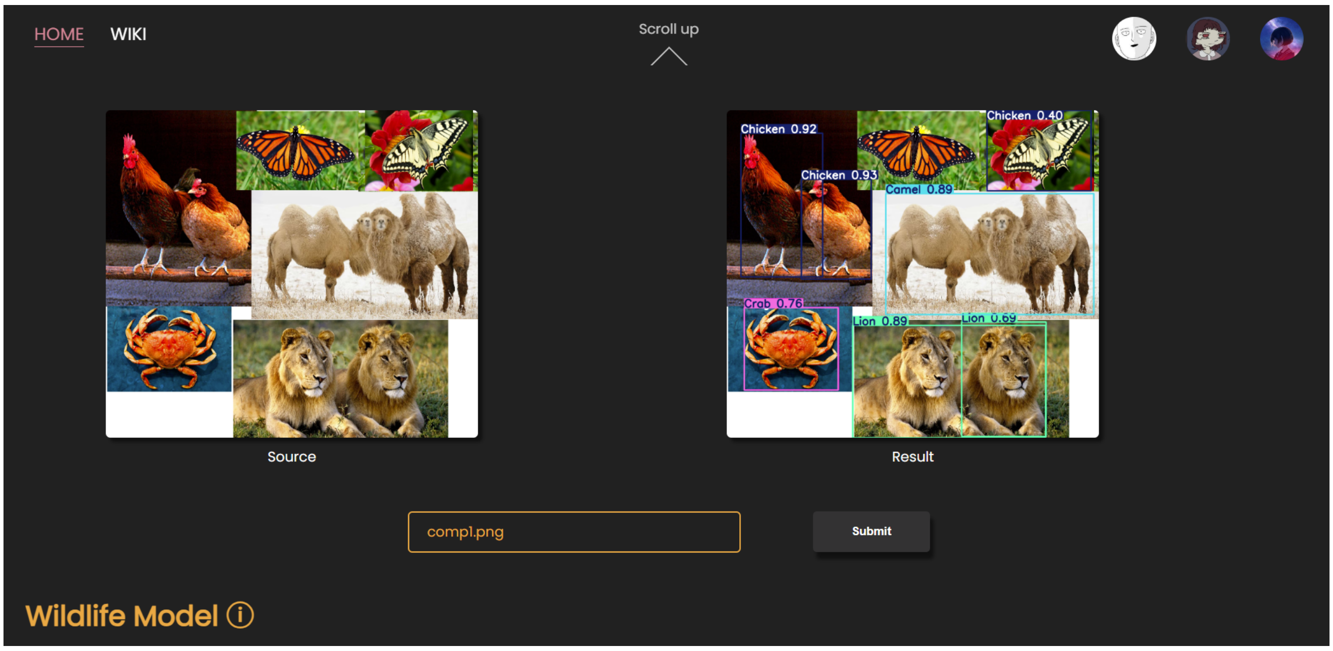
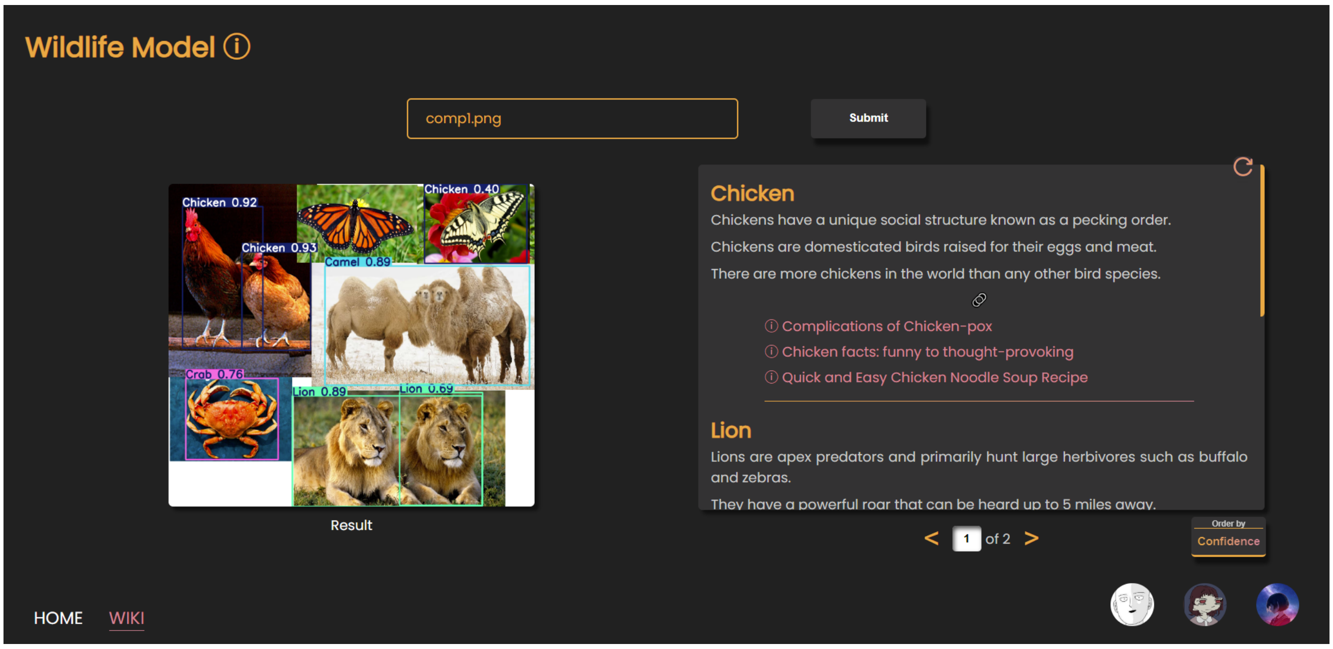


Figure 12. Interface of wildlife detection model after being prompted with an input image.



Chicken

Chickens have a unique social structure known as a pecking order.

Chickens are domesticated birds raised for their eggs and meat.

There are more chickens in the world than any other bird species.

ⓘ Complications of Chicken-pox

ⓘ Chicken facts: funny to thought-provoking

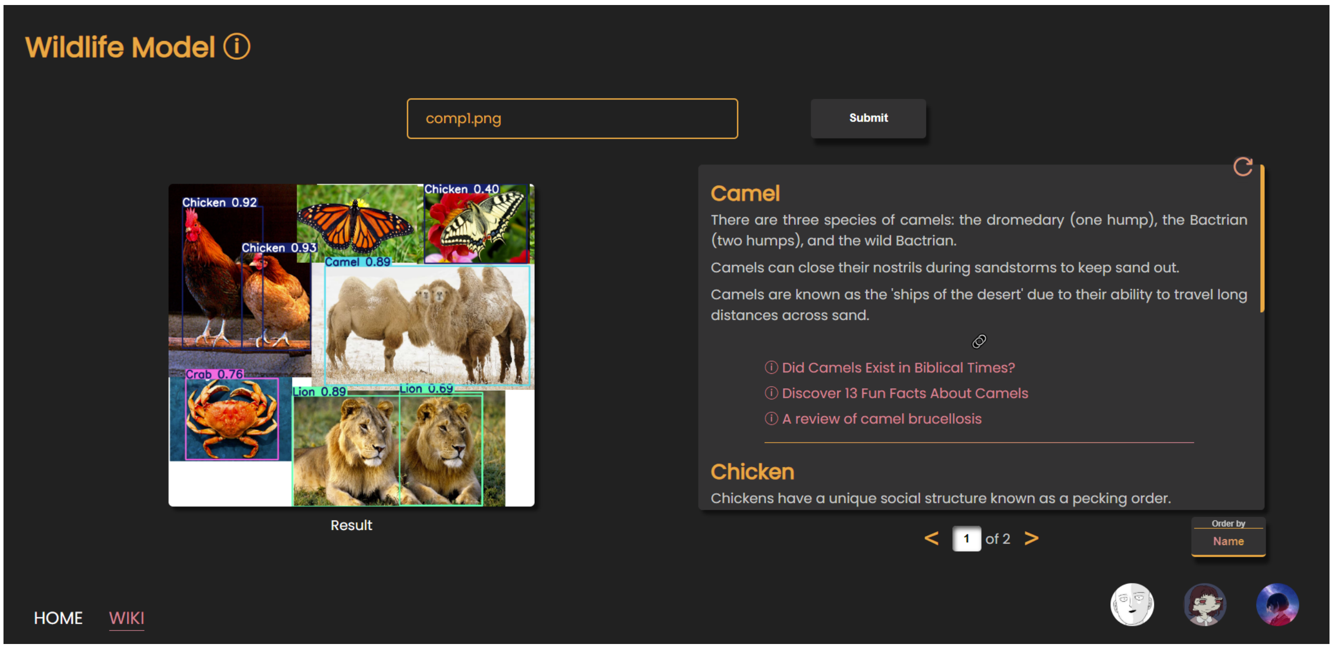
ⓘ Quick and Easy Chicken Noodle Soup Recipe

Lion

Lions are apex predators and primarily hunt large herbivores such as buffalo and zebras.

They have a powerful roar that can be heard up to 5 miles away.

Figure 13. Interface of the Wiki page. The facts are being ordered by the confidence of each detection.



Camel

There are three species of camels: the dromedary (one hump), the Bactrian (two humps), and the wild Bactrian.

Camels can close their nostrils during sandstorms to keep sand out.

Camels are known as the 'ships of the desert' due to their ability to travel long distances across sand.

ⓘ Did Camels Exist in Biblical Times?
ⓘ Discover 13 Fun Facts About Camels
ⓘ A review of camel brucellosis

Chicken

Chickens have a unique social structure known as a pecking order.

Figure 14. Same as Figure 13, but being ordered alphabetically by animal names.

ACKNOWLEDGMENT

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