ANIMAL SPECIES DETECTION USING DEEP LEARNING

[HDSC Spring '23] Capstone Project - Team Opencv

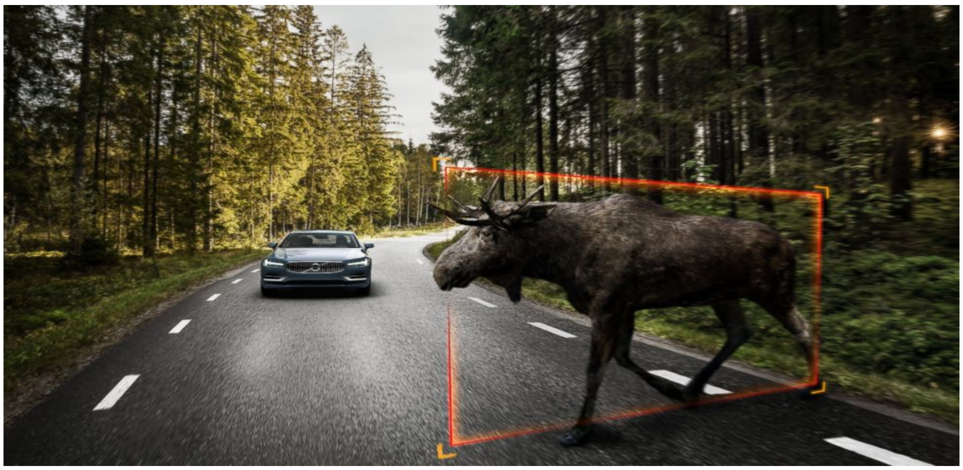

Fig 1 Animal Species Detection

Introduction

Roadkill is one of the highest causes of wildlife mortality and is of global conservation concern. Roadkill[1] is an animal or animals that have been struck and killed by drivers of motor vehicles. In the United States, over 1 million vertebrate animals are killed by vehicle collisions every day. Globally, the number amounts to roughly 5.5 million killed per day, which when extrapolated climbs to over 2 billion annually. In Pilanesberg National Park[3] many zebras and leopards are killed by car accidents each year.

A New Study[2] has identified some animal populations globally that are the most vulnerable to extinction in the next 50 years if observed roadkill levels persist. Mainly these animals include the Leopard (83% increased risk of dying from roadkill), wolf of Brazil (34% increased risk of extinction), cat of Brazil (increased extinction risk ranging from 0 to 75%), hyena of Southern Africa (increased extinction risk ranging from 0 to 75%).

The Wildlife Vehicle Collision (WVC) not only poses a threat to animals' safety but can cause injury to, or death of vehicle occupants and vehicle damage as well. To mitigate the damage caused by these collisions, the Department of Road must take actions like fencing highways, building wildlife crossings, and escape routes, using high beam headlights by vehicles during night, animal sensors in vehicles or alongside highways are some of the safety measures that can be incorporated to ensure the safety of wildlife and humans alike.

Problem Statement

This project seeks to develop an effective computer vision model using a Deep Learning algorithm that can be deployed as part of detection systems to detect wildlife in urban environments, and on highways using real-time visuals to warn humans of potential collision with wildlife.

Data Description

- **Dataset 1:** This is the Dataset of the previous cohort of interns. It was obtained from Kaggle, an open-source data inventory. It contains images of 4 species of animals. The dataset also contains text files containing annotations per image file in **YOLO format.** Dataset 1

- **Dataset 2:** This dataset was provided by Hamoye and directed to the Kaggle website. It contained images of 11 species of animals. However, this dataset had no text files containing annotations and most of the images have low resolution. Dataset 2

- **Dataset 3:** This is the additional dataset, we obtained from Kaggle, containing images of 80 species of animals. The dataset has text files containing annotations in **Pascal format** and high-resolution images. Dataset 3

Data Pre-processing

- **Low to High Resolution:** Many images in dataset 2 have a low image resolution of approx. 250 pixels. Only high-resolution images from Dataset 2 were selected.

- **Annotation:** The high-resolution images selected from dataset 2 were annotated using the Make Sense tool, as the model needs annotated images to be trained on. Also changing the annotation of images of only those classes in dataset 3 that are present in dataset 2, from Pascal format to YOLO format was done.

- **Removing inappropriate data:** Most of the images found in the leopard class contained other classes. Hence leopard class was dropped. Additionally, we added the Tiger class from dataset 3.

Data Exploratory Analysis

The dataset consists of 10 species of animals including zebras, rhinos, pandas, lions, elephants, buffalos, foxes, tigers, cheetahs, and jaguars. It contains a total of 2609 images along with a text file containing annotations per object per image. The dataset is well- balanced with each animal species having a substantial representation

Also, it is worth noting that the majority of images contain only one or two objects, while a few images exhibit a higher number of objects. The aspect ratio of an image plays a crucial role in object detection algorithms. The aspect ratio standard deviation suggests moderate variability as it varies from 0.56 to 3.34.

Number of objects per image

	Number of Objects	Count
0	2	466
1	3	135
2	1	1893
3	25	1
4	4	54
5	11	1
6	5	25
7	6	21
8	8	3
9	7	6
10	10	3
11	9	3
12	14	1

Statistics of Image Dimensions

```
2 df_dimensions.describe()
```

	Height	Width	Aspect Ratio	Pixels
count	2609.000000	2609.000000	2609.000000	2.609000e+03
mean	680.756995	937.675738	1.416894	8.221119e+05
std	380.602572	545.998171	0.316714	1.466427e+06
min	86.000000	99.000000	0.560156	1.109400e+04
25%	435.000000	640.000000	1.333333	2.739200e+05
50%	678.000000	992.000000	1.498829	6.942720e+05
75%	768.000000	1024.000000	1.505882	7.864320e+05
max	3888.000000	5666.000000	3.341067	1.996186e+07

Number of images per class

	Class Label	Image Count
0	zebra	376
1	rhino	376
2	panda	91
3	lion	208
4	elephant	375
5	buffalo	375
6	fox	150
7	tiger	291
8	cheetah	194
9	jaguar	173

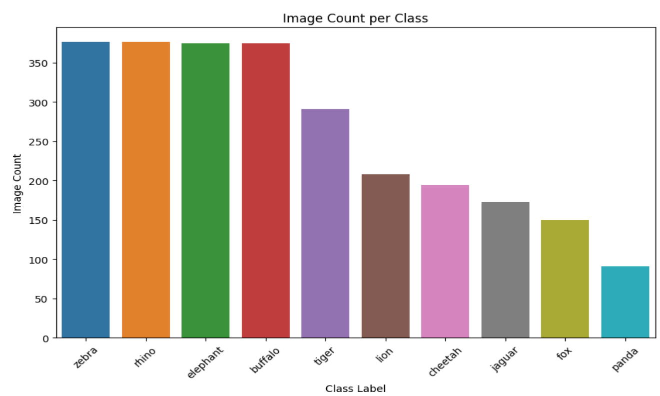

Fig 2 EDA

Modeling

The deep learning algorithm, **You Only Look Once** (YOLO) is used to build an animal detection model. Precisely we have used YOLOv8. The YOLOv8 model is faster and more accurate while providing a unified framework for training models for performing Object Detection, Instance Segmentation, and Image Classification.

The YOLO model directly predicts bounding boxes and class probabilities with a single network in a single evaluation. The simplicity of the YOLO model allows real-time predictions.

The Dataset was split into the train, validation, and test sets in the ratio of 0.7, 0.15, and 0.15 respectively. Yolov8 was implemented using a command-line interface by installing the Ultralytics package. To build a new model, pre-trained weights were used with task argument as detect, mode as train, and model as yolov8n. The model was trained for 50 epochs.

```
!yolo task=detect mode=train model=yolov8n.pt data=custom.yaml epochs=50 imgsz=640
```

Fig 3 YOLO

Evaluation

The performance of the object detection algorithm is evaluated by metrics such as **Mean Average Precision** (mAP), **F1 score**, and **Confusion Matrix**.

Model Performance on the Training Data Set

- The PR Curve below reveals the mean Average precision(AP) of **0.95** across all classes at the **0.5** threshold. Therefore, it suggests that the model is performing well in object detection tasks.

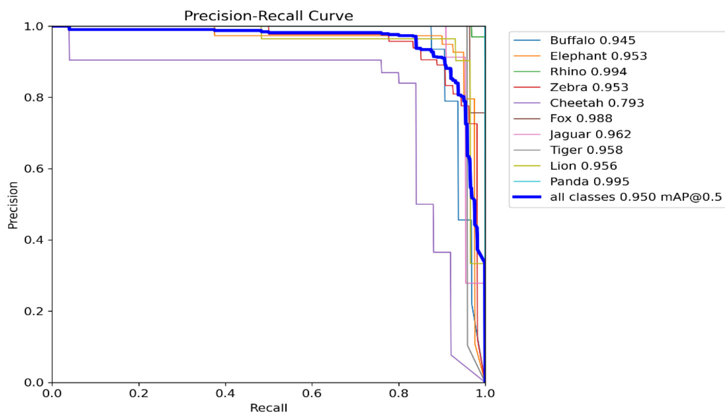

Fig 4 PR curve

- Each training cycle consists of two phases: a training phase and a validation phase.
  The YOLOv8 object detection model achieved good performance with high precision, recall, F1-score, and mAP scores across different thresholds.

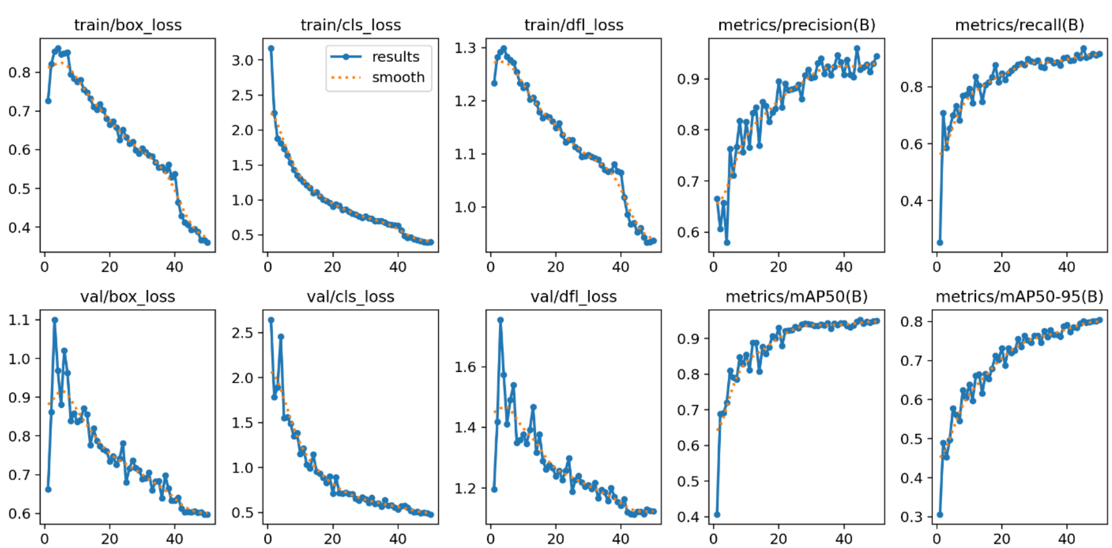

Fig 5 Training

- In the FI-Confidence Curve below, the training F1 score which is a harmonic mean of precision and recall of **0.93** at a confidence threshold of **0.556**, with a **recall of 0.915** and **precision of 0.944**, indicates a balanced performance in accurately identifying and classifying objects in the training dataset.

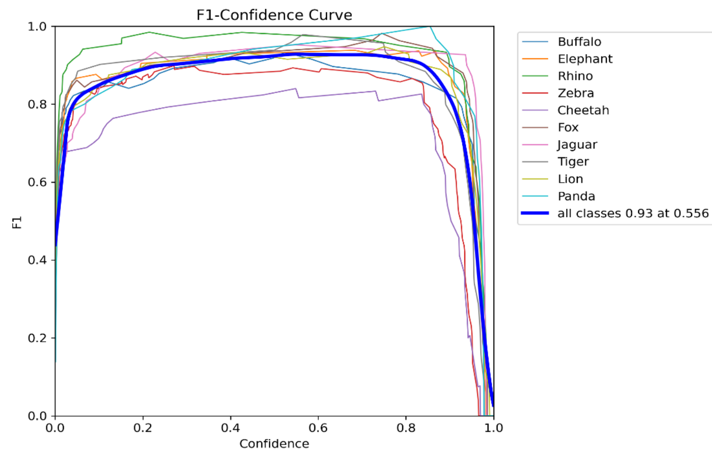

Fig 6 Confidence Curve

CONFUSION MATRIX

- **Training set**

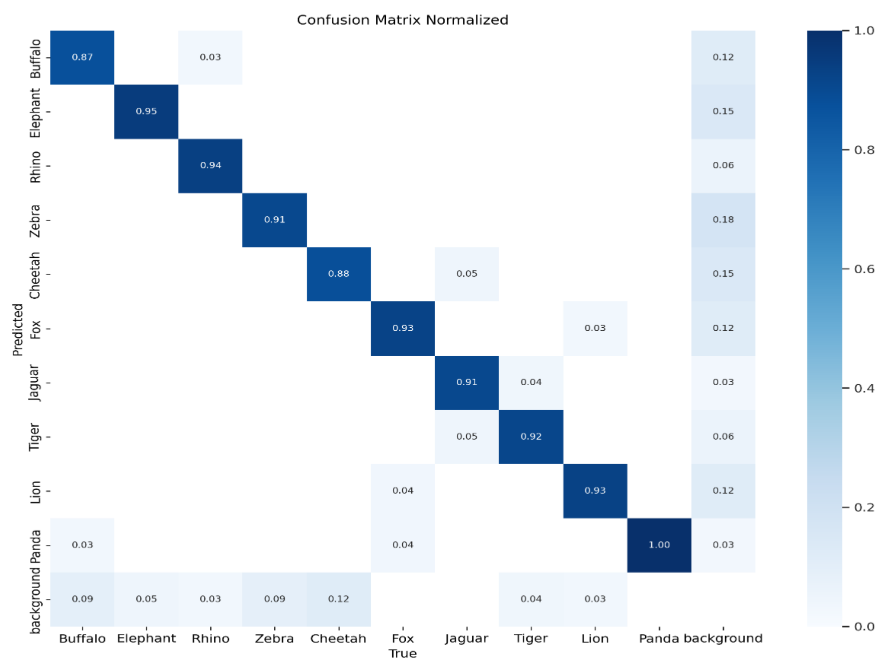

Fig 7 Confusion matrix - Training

- Test set

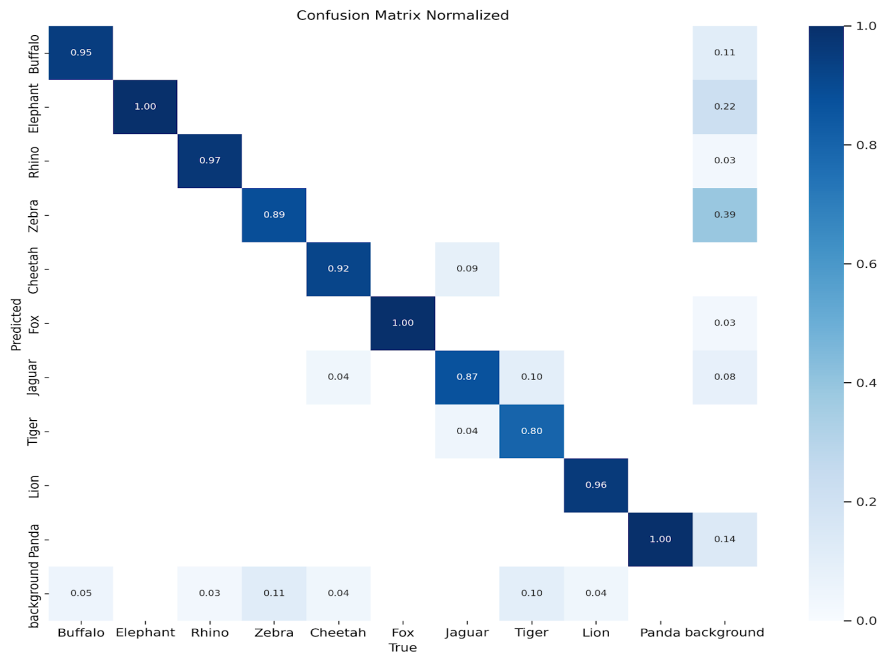

Fig 8 Confusion matrix -Test

Model Deployment

The model was deployed using Streamlit on Hugging Face. Streamlit is an open-source app framework.

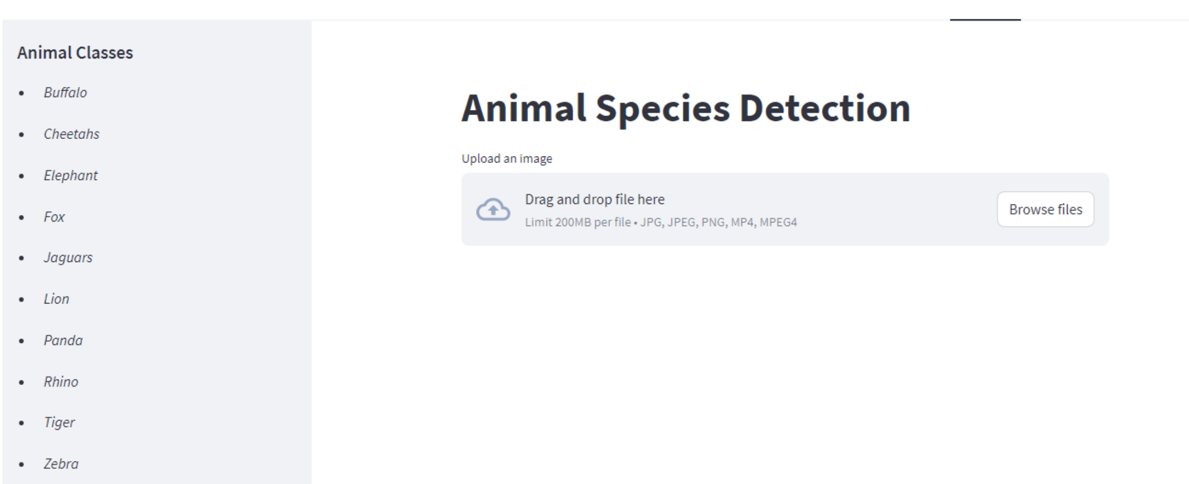

Fig 9 Application Interface

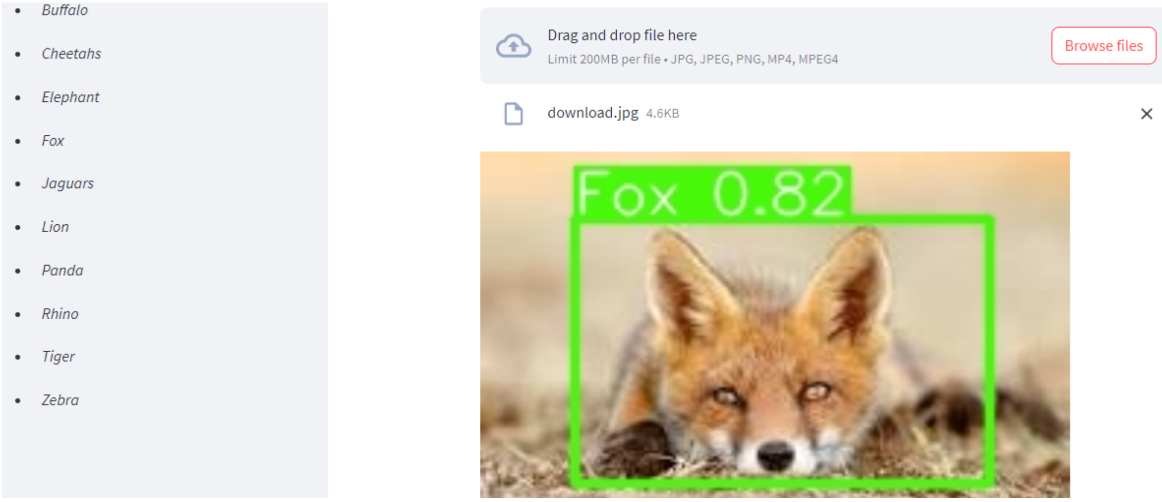

Fig 10 Interaction with the application

Conclusion and Recommendation

Roads are essential infrastructure that connect people and circulate supplies but when they intersect with nature, the impact on species survival can be deadly.

The model can be fed with real-time images of highways to generate a prediction and thereby trigger sensors/alarms on highways or in vehicles to warn drivers of the presence of predicted objects on highways.

This involves expanding the training dataset to encompass a broader range of species, thereby enhancing the model's ability to accurately detect and classify various animals.

The Model can also be used in the fields of Education and Agriculture.

References

[1] https://en.wikipedia.org/wiki/Roadkill

[2] https://www.ucf.edu/news/new-study-shows-impact-of-roadkill-on-worlds-vulnerable-animal-populations

[3] https://www.natucate.com/en/blog/nature/south-africa-roadkills