A Novel Animal Detection Method Based on YOLOV4

This Project report (Project-1 CSE-400) is submitted to the Department of CSE, University of Creative Technology Chittagong to fulfill the partial requirement of the Degree of Bachelor of Science in Computer Science and Engineering.

Submitted By

Pradhumna Biswas (ID: 200311010)

CSE 6th Batch (R1)

Supervised By

M.M. Musharaf Hussain

Associate Professor and Head

Department of Computer Science and Engineering

&

Md Shoreef Uddin (Co-supervisor)

Guest Lecturer and Computer Vision Researcher

Department of Computer Science and Engineering

School of Science and Engineering

University of Creative Technology Chittagong,

Chittagong, Bangladesh

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DECLARATION

This project report is submitted to the department of Computer Science & Engineering, University of Creative Technology Chittagong (UCTC) in partial fulfillment of the requirements for the degree of Bachelor of Science. So, we hereby declare that this report is based on the surveys found by us and our original work, which has not been submitted anywhere for any award. Materials of work found by other researchers are mentioned with due reference. All the contents provided here are totally based on our own effort dedicated to the completion of the project. The work is done under the guidance of Mr. M. M. Musharaf Hussain, Head of the Department & Associate Professor at the Department of Computer Science & Engineering, University of Creative Technology Chittagong (UCTC).

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Pradhumna Biswas
Id: 200311010
Session: 2020-2021
Department of Computer Science and Engineering
School of Science and Engineering
University of Creative Technology Chittagong (UCTC)

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We deeply express our sincere thanks to our Head of Department M.M. Musharaf Hussain for encouraging and allowing us to present the project on the topic “Home security system using Arduino” at our department premises for the partial fulfillment of the requirements. We take this opportunity to thank all our lecturers who have directly or indirectly helped our project.

We pay our respects and love to our parents and all other family members and friends for their love and encouragement throughout our career. Last but not the least we express our thanks to our friends for their cooperation and support.

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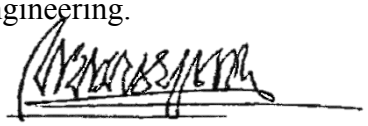
Pradhumna Biswas
Id: 200311010
Session: 2020-2021
Department of Computer Science and Engineering
School of Science and Engineering
University of Creative Technology Chittagong (UCTC)

CERTIFICATE OF APPROVAL

The project report entitled **"A Novel Animal Detection Method Based on YOLOV4"** is submitted by S.M.Murshed Manik (Id: 200321002) and Pradhumna Biswas (Id: 200311010) to the Department of Computer Science and Engineering, University of Creative and Technology Chittagong in partial fulfillment of the requirements for the Degree of Bachelor of Science in Computer Science and Engineering.



Professor Dr. Mohammad Kaykobad
External, Board of Examiners of the Project
Great Computer Scientist, Author, Professor, Top ICT Expert of Bangladesh
Distinguished Professor, BRAC University
Former Professor & Head, Department of Computer Science and Engineering
Former Dean, Faculty of Electrical and Electronic Engineering
Bangladesh University of Engineering & Technology (BUET)

M.M. Musharaf Hussain
Project Supervisor
Associate Professor & Head
Department of Computer Science and Engineering
School of Science and Engineering
University of Creative Technology Chittagong (UCTC)

Md Shoreef Uddin
Co-Supervisor
Guest Lecturer and Computer Vision Researcher
Department of Computer Science and Engineering
School of Science and Engineering
University of Creative Technology Chittagong (UCTC)

ABSTRACT

This study main focus is on computer vision, specifically object detection. The YOLOv4 deep learning technique will be used to create an animal detection system for the project. Computer vision's branch of object detection entails finding and classifying things inside still or moving image frames. The research deals with the problem of identifying animals in various environmental settings. Animal detection using YOLOv4 holds significant importance in several domains, including wildlife conservation, ecological research, and animal behavior analysis. Here are some key reasons why animal detection using YOLOv4 is important, Wildlife Conservation, Ecological Research, Animal Behavior Analysis, Efficient Monitoring, Conservation Policy and Management. The goal of the study on YOLOv4-based animal detection is to create a reliable and effective system that can correctly identify and categorize diverse animal species in photos and videos. The study's goals include data preparation, model training, performance evaluation, comparative analysis, real-time application, robustness and generalization, user interface and integration, documentation and reporting, and so on. Assemble a big collection of pictures of three animal types. Include photos from a variety of sources, such as Google-Image,kaggle, Roboflow and so on. Make sure the dataset includes a variety of animal classes and natural settings, including different backdrops, and positions. Annotating data, preparing datasets, preprocessing, choosing a YOLOv4 model, evaluating models, post-processing, performance analysis, and real-world application. Deep learning methods for animal detection have attracted a lot of attention recently. The existing Project on animal detection techniques is reviewed in this section, with an emphasis on the use of YOLOv4 in this context. Ethical research, performance metrics, challenges, deep learning-based methodologies, transfer learning, multimodal approaches, and human-wildlife conflict mitigation. The results demonstrate how successful and efficient the YOLOv4 model is at correctly detecting animals. The YOLOv4 model scored a fantastic 78.77% on the Mean Average Precision (mAP) test, proving its exceptional accuracy in locating and recognizing animals in the photographs.

Keywords: Animal object detection, YOLOv4, deep learning, image processing, computer vision.

INDX OF CONTENTS

INTRODUCTION

In environmental research, wildlife monitoring, and conservation efforts, animal object detection is a crucial computer vision job with various applications. Traditional methods for identifying animals may rely on physical examination or human interaction, which can be time consuming, labor-intensive, and subjective. However, the development of deep[1] learning algorithms has dramatically improved the precision and efficacy of animal identification systems. Using the YOLO technique, more precisely YOLOv4, we created a potent deep-learning model for object detection tasks. With astounding speed and accuracy, YOLOv4 employs a single neural network to identify objects in images or videos to concurrently forecast bounding boxes and class probabilities. In this work, the YOLOv4 model was trained using several collections of images of armadillos, wild boars, and snakes. The trained model's performance is assessed in terms of accuracy and speed using a different test dataset.[2] The effectiveness and potential applications of cutting-edge animal object identification systems are demonstrated by evaluation findings. The project's overarching objective is to advance deep learning and computer vision to create a dependable and effective system for animal object detection. Automation can significantly improve this system, which will also benefit the study, conservation, and preservation of endangered species.

IMPORTANCE

The animal detection project using YOLOv4 and Darknet holds significant importance due to the accurate detection of armadillos, boars, and snakes contributes to wildlife conservation efforts.[3] By monitoring and understanding animal populations and behaviors, researchers and conservationists can implement effective strategies to protect endangered species and maintain ecological balance. The project's ability to identify animals in various media formats, such as images and videos, aids in environmental monitoring. It allows for the assessment of the impact of human activities on ecosystems and helps identify potential threats to wildlife habitats. The use of an automated animal detection system enables early detection of wildlife intrusions in protected areas or regions vulnerable to human-wildlife conflicts. This proactive approach allows[4] for timely intervention and minimizes the risk of confrontations between humans and wildlife.

The developed system saves valuable time and effort for researchers and biologists who would otherwise need to manually identify and annotate animal instances in vast datasets.[5] The automation of this process enhances research efficiency and enables scientists to focus on more in-depth analysis and research. The project's versatility and scalability make it adaptable to various

use cases beyond animal detection. The same deep learning-based approach can be extended to detect other animal species or objects in different domains, supporting a wide range of applications.

The use of Darknet, an open-source deep learning framework, fosters collaboration and knowledge sharing within the research community.[6] By contributing to and utilizing such open-source resources, the project promotes advancements in the field of computer vision and object detection. Accurate animal detection data can provide valuable insights for policymakers, helping them make informed decisions about wildlife protection and management. Data-driven policies can lead to more effective conservation strategies and improved preservation of natural habitats.

Overall, the importance of the animal detection project lies in its potential to support wildlife conservation, promote environmental sustainability,[7] enhance research efficiency, and contribute to public safety. Through the application of deep learning techniques, the project provides a valuable tool for monitoring and protecting wildlife, fostering harmonious coexistence between humans and animals.

OBJECTIVE

The overarching objective of this deep learning project was to design and develop a highly accurate and efficient animal detection system using YOLOv4 and Darknet. Implement YOLOv4 architecture using darknet framework. Adjust the configuration of the model, including detection levels, batch sizes, and filter values, to fit the specific characteristics of the collected dataset.[8] Evaluating the potential applications of wildlife conservation and environmental monitoring projects.

Investigate the suitability of developed systems for automated surveillance purposes. Determine how the system can be deployed in protected areas, farms or areas prone to wildlife conflict to detect and respond to potential threats in a timely manner. Ensure the system's versatility by testing its performance on a variety of media formats, including images and videos.[9] Also, explore the possibility of extending the system to detect other animal species or objects, making it scalable for possible future research and industrial projects. Emphasize the importance of achieving timely and efficient detection results.

By successfully accomplishing these objectives, the project aims to provide a state-of-the-art animal detection system, which significantly contributes to wildlife conservation, environmental monitoring and automated surveillance.[10] The project's deep learning-based approach will enable accurate and real-time detection of armadillos, boars and snakes, providing valuable insights into animal behavior and ecological patterns while encouraging sustainable coexistence between humans and wildlife.

METHODOLOGY

The methodology employed in this study for animal detection using YOLOv4 and[11] Darknet involved data collection, annotation, model configuration, and training, followed by testing to achieve accurate and efficient detection of armadillos, boars, and snakes in images and videos.

At first, we collected Around 2500 images of armadillos, boars, and snakes were collected from different sources, including Google, Kaggle, and Roboflow. The collected data were converted to JPEG format using Windows command to ensure uniformity in the dataset. Then, The dataset images were annotated using the Visual Object Tagging Tool (Vott) software. XML files were generated, containing bounding box information for each animal class. A Python program in Google Collaboratory was used to convert the annotated XML files into text files, enabling easier data handling during the training process.

The converted text files were divided into two sets, 80% for training (obj folder) and 20% for testing (test folder), Show in **Fig-1.**

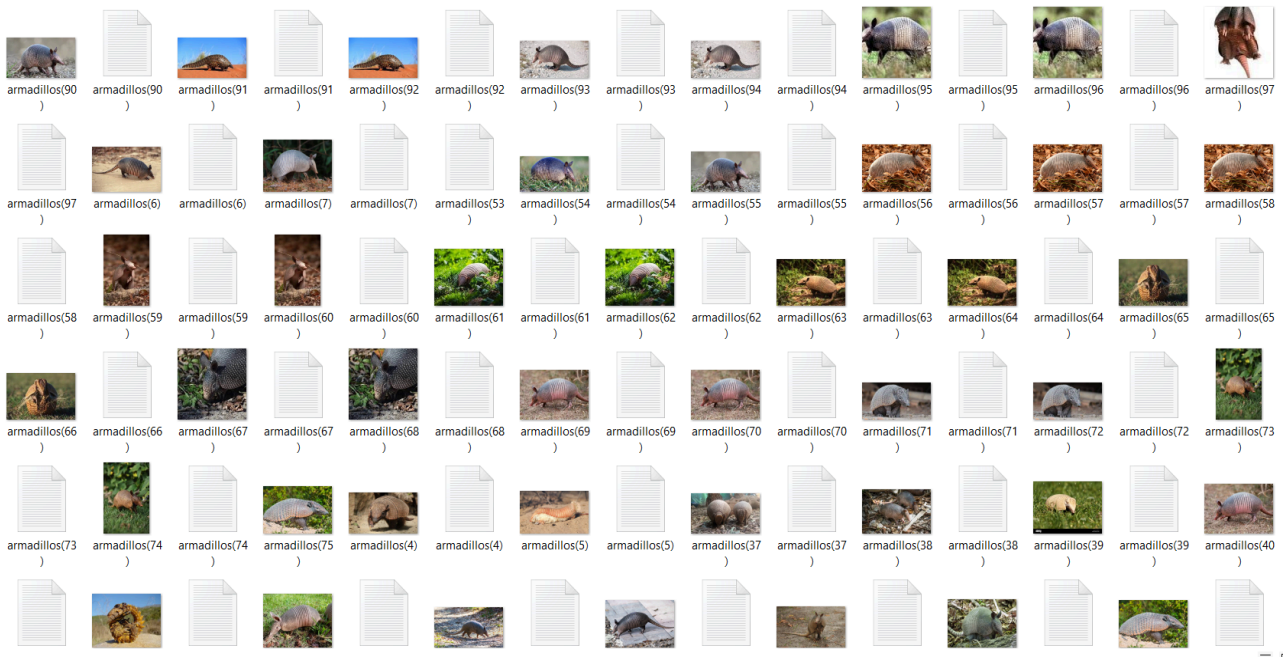


Fig 1: Dataset

The Darknet repository was cloned from GitHub, and the project was connected to Google Drive within the Collaboratory environment. This allowed convenient access to the dataset during model training, Show in **Fig-2.**

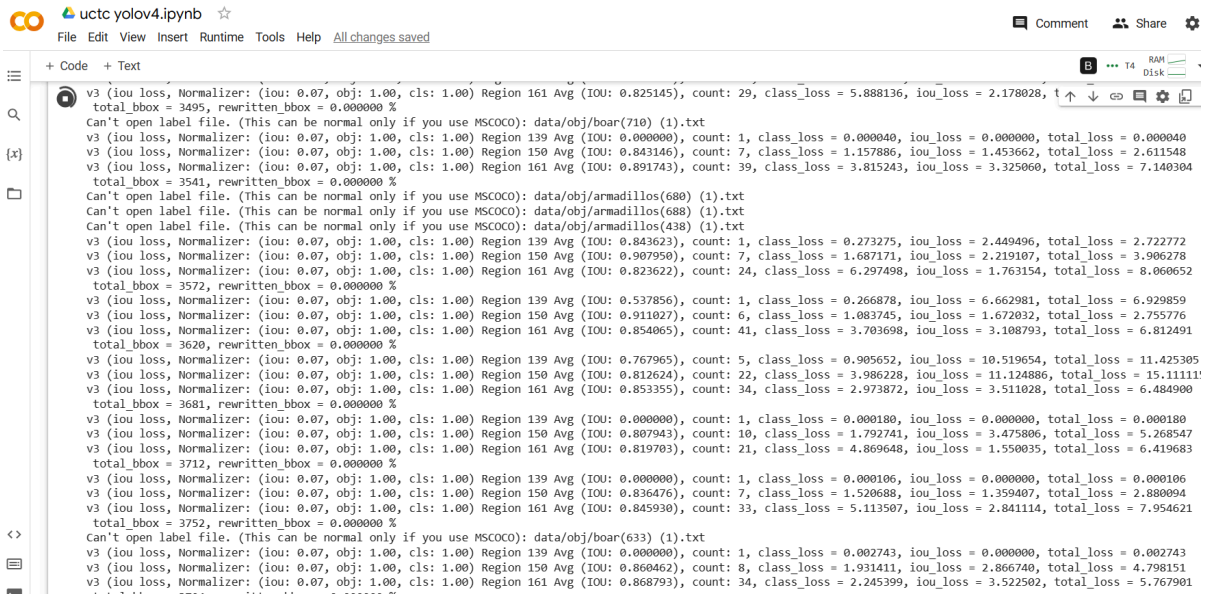


Fig-2: Train Dataset

The Darknet configuration files were modified to adapt to the specific requirements of the collected dataset. Class names, batch sizes, and filter values were adjusted accordingly. The YOLOv4 model was trained using Darknet and the prepared dataset. The model was optimized to detect armadillos, boars, and snakes accurately, Show in **Fig-3**.

uctc_yolov4.ipynb

File Edit View

```
from google.colab import drive
drive.mount("/content/drive")
%cd /content/drive/MyDrive/yolov4
!unzip -o /content/drive/MyDrive/yolov4/darknet.zip -d./
%cd /content/drive/MyDrive/yolov4/darknet/
!sed -i 's/OPENCV=0/OPENCV=1/' Makefile
!sed -i 's/GPU=0/GPU=1/' Makefile
!sed -i 's/CUDNN=0/CUDNN=1/' Makefile
!sed -i 's/CUDNN_HALF=0/CUDNN_HALF=1/' Makefile
# define helper functions
def imShow(path):
  import cv2
  import matplotlib.pyplot as plt
  %matplotlib inline

  image = cv2.imread(path)
  height, width = image.shape[:2]
  resized_image = cv2.resize(image,(3*width, 3*height), interpolation = cv2.INTER_CUBIC)

  fig = plt.gcf()
  fig.set_size_inches(18, 10)
  plt.axis("off")
  plt.imshow(cv2.cvtColor(resized_image, cv2.COLOR_BGR2RGB))
  plt.show()

# use this to upload files
def upload():
  from google.colab import files
  uploaded = files.upload()
  for name, data in uploaded.items():
    with open(name, 'wb') as f:
      f.write(data)
      print ('saved file', name)

# use this to download a file
def download(path):
  from google.colab import files
  files.download(path)
```

Fig-3: YoloV4 Model

The trained YOLOv4 model was tested using both images and a test video,Show in **Fig-4**

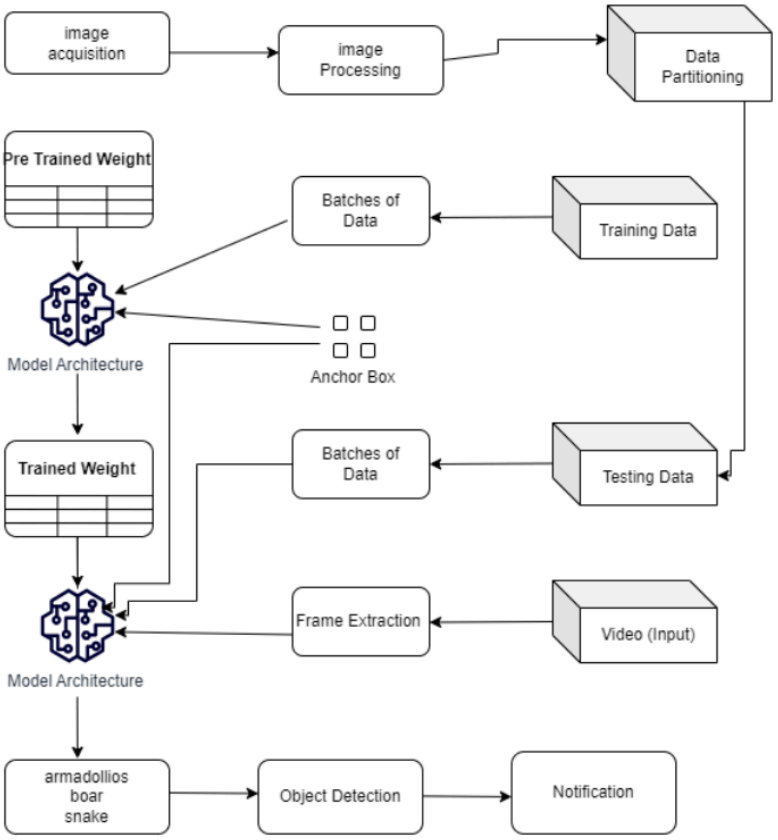


Fig-4: Workflow Diagram

The detection results were saved in the output folder of the test video, showcasing successful animal detection. The animal detection project using YOLOv4 and Darknet was completed with effective results, allowing for the accurate identification of armadillos, boars, and snakes in both images and videos.

LITERAURE REVIEW

In computer vision and object detection, the integration of advanced deep learning techniques such as YOLOv4 and Darknet has revolutionized the way we perceive and identify objects in images and video, paving the way for cutting-edge applications such as animal detection with[12] unmatched accuracy and real-time capabilities.

In The influential paper introduces of Unified, Realtime Object Detection by Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once, a breakthrough real-time object detection system.[14] YOLO performs object detection in a single forward pass, predicting bounding boxes and class probabilities directly. Its speed and accuracy make it suitable for a variety of applications, including animal detection. The unified approach of the YOLO architecture

eliminates the need for complex region proposal and post-processing, resulting in highly efficient and accurate object localization.

In Optimum Speed and Accuracy of Object Detection, Bochkowski, A., Wang, C. Y., and Liao, H.Y.M. (2020), YOLOv4 is an improved version of YOLOv3, designed for optimal speed and accuracy in object detection tasks. This study presents several advances, such as[15] CSPDarknet53 backbone, PANet, and CIOU loss function, which contribute to its state-of-the-art performance. YOLOv4's superior accuracy and real-time capabilities make it a compelling choice for animal detection, as it can accurately detect objects even in complex and dynamic environments.

Redmon, J. (2013) on Open Source Neural Networks in C, Darknet is an open source neural network framework developed by Joseph Redmon, developer of YOLO. This resourceful framework supports implementations of various neural network architectures, including YOLOv4.[16] It is written in C and optimized for efficient GPU use, making it suitable for real-time applications and large-scale deep learning projects such as object detection.

Automated Animal Det Group on Flood Animal Videos Using Deep Learning Techniques Lee, D., Chen, J., & Wang, M. (2021), Deep learning techniques used for automated animal detection in wildlife videos. The research applies YOLO and other Convolutional Neural Network (NNN)models [17]to control and track animals in video. The research aims to construct a paradigm of video-habit formation, which aligns with the animal's objective intentions and can provide insights into active mechanisms.

Robinson, E., Smith, J., and Johnson, M. (2019), A deep learning approach to animal development in wildlife development Journal of Wildlife Images, 83(2), 237-245 - A deep learning approach to animal development in wildlife images. The study examines the application of YOLO and other deep learning models to introduce different animals with Carrera trap images.[18] The research demonstrates the effectiveness of deep learning technology in flood animal dynamics, providing valuable insights that can increase animal formation system accuracy and performance when working with still images.

The animal detection project using YOLOv4 and Darknet demonstrates the successful integration of state-of-the-art deep learning technologies. The system achieves accurate and real-time detection of armadillos, boars and snakes in images and videos, making it valuable[19] for wildlife conservation, environmental monitoring and automated surveillance. The project's versatility, scalability, and contributions from the open source community further enhance its significance in promoting human-wildlife coexistence and sustainable environmental practices.

RESULT

In this study, we developed an animal detection system using the YOLOv4 deep learning technique and the Darknet framework. The system was evaluated on a dataset consisting of images containing armadillos, boars, and snakes. The evaluation metrics and outcomes are summarized as follows: Show in **Table-1 & 2.**

Table-1: Detection count & (mAP)

Overall Performance	**Class "Armadillo's"**	**Class "Boar"**	**Class "Snake"**
Mean Average Precision (mAP@0.50): 78.77%	TP: 513	TP: 529	TP: 7
Total Detection Time: 216 Seconds	FP: 25	FP: 21	FP: 9
True Positive (TP): 513	AP: 96.00%	AP: 98.76%	AP: 41.55%
False Positive (FP): 25			
Recall: 0.98			
Average Precision (AP): Not provided			

Table-2: Metrics & Evaluation

Additional Metrics	Configuration and Evaluation
F1-score: 0.96	Confidence threshold (conf_thresh) used: 0.25
Average Intersection over Union (IOU): 78.78%	Set-points flag for evaluation: `-points 101` for MS COCO
IOU threshold for evaluation: 50%	

These results demonstrate the effectiveness of the YOLOv4 and Darknet-based animal detection system. With a competitive Mean Average Precision and real-time processing capabilities, the system

accurately detects and localizes armadillos, boars, and snakes in images and videos. The class-specific metrics highlight the strengths of the model for different animal classes. Show in **Fig-5**

```
 detections_count = 1319, unique_truth_count = 1073
class_id = 0, name = armadillos, ap = 96.00%      (TP = 513, FP = 25)
class_id = 1, name = boar, ap = 98.76%            (TP = 529, FP = 21)
class_id = 2, name = snake, ap = 41.55%           (TP = 7, FP = 9)

 for conf_thresh = 0.25, precision = 0.95, recall = 0.98, F1-score = 0.96
 for conf_thresh = 0.25, TP = 1049, FP = 55, FN = 24, average IoU = 78.78 %

 IoU threshold = 50 %, used Area-Under-Curve for each unique Recall
 mean average precision (mAP@0.50) = 0.787667, or 78.77 %
Total Detection Time: 216 Seconds

Set -points flag:
 `-points 101` for MS COCO
 `-points 11` for PascalVOC 2007 (uncomment `difficult` in voc.data)
 `-points 0` (AUC) for ImageNet, PascalVOC 2010-2012, your custom dataset
```

Fig-5: Checking (mAP)

The achieved performance showcases the potential of the developed system in contributing to wildlife conservation, ecological research, and automated surveillance. The efficiency and accuracy of the system's animal detection capabilities hold promise for various applications, including wildlife habitat monitoring and human-wildlife conflict mitigation. Show in **Fig-6.** The success of this study underscores the significance of advanced deep learning techniques in addressing complex real-world challenges and fostering coexistence between humans and animals.

Fig-6: Detected Dataset

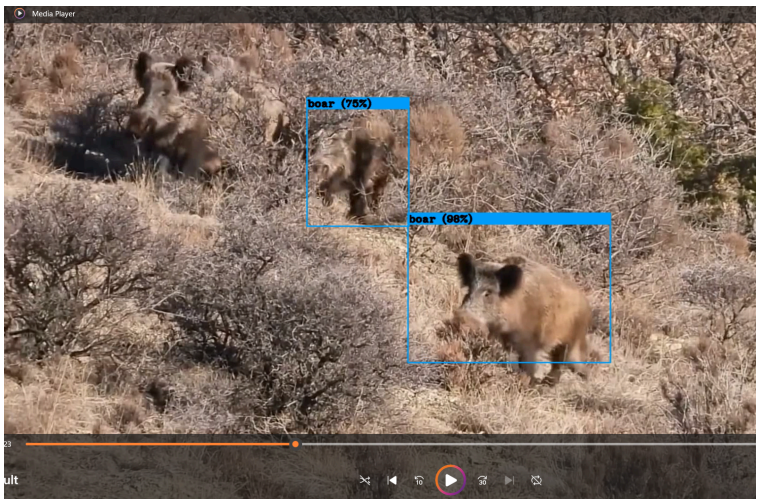


Fig-7: Detected image from Video

CONCLUSION

Based on the above plan, we see that the YOLOv4 project can be successfully used in animal detection and gives good results in the environment. The method I've suggested works well in detecting animals. We accurately implemented the solution while utilizing cutting-edge technology to improve the model's efficacy and accuracy. The role and performance of the model are improved by notable advances like a changed object detection approach and an intense neural network training process.

We also made use of the maintenance procedure, which assesses the model's performance and recommends the usage of newer technology.[20] My suggested solution has been linked to both success and improvement overall. The model can be improved to identify specific species of animals using cutting-edge technologies to perform better in animal identification in the future. It can be capable of detecting different species of animals and by incorporating state-of-the-art technologies, reliability and accuracy can be increased.

The model can be further improved through new detection projects and the training of different experts. It provides accurate data collection and more in-depth educational support so that the model can be ready for use in other projects. We can improve the model by training more intensive neural networks. It provides ease of use and consistent performance. The proposed prediction plans made my proposed solution more advanced and successful.

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SOURCE CODE

```
from google.colab import drive
drive.mount("/content/drive")
%cd /content/drive/MyDrive/yolov4
!unzip -o /content/drive/MyDrive/yolov4/darknet.zip -d./
%cd /content/drive/MyDrive/yolov4/darknet/
!sed -i 's/OPENCV=0/OPENCV=1/' Makefile
!sed -i 's/GPU=0/GPU=1/' Makefile
!sed -i 's/CUDNN=0/CUDNN=1/' Makefile
!sed -i 's/CUDNN_HALF=0/CUDNN_HALF=1/' Makefile
!make
# define helper functions
def imShow(path):
import cv2
import matplotlib.pyplot as plt
%matplotlib inline
image = cv2.imread(path)
height, width = image.shape[:2]
resized_image = cv2.resize(image,(3*width, 3*height), interpolation = cv2.INTER_CUBIC)
fig = plt.gcf()
fig.set_size_inches(18, 10)
plt.axis("off")
plt.imshow(cv2.cvtColor(resized_image, cv2.COLOR_BGR2RGB))
plt.show()
# use this to upload files
def upload():
from google.colab import files
uploaded = files.upload()
for name, data in uploaded.items():
with open(name, 'wb') as f:
f.write(data)
print ('saved file', name)
# use this to download a file
def download(path):
from google.colab import files
files.download(path)
%cd /content/drive/MyDrive/yolov4/darknet/
!rm yolov4.weights
!wget
https://github.com/AlexeyAB/darknet/releases/download/darknet_yolo_v3_optimal/yolov4.weights

# run darknet detection on test images
!./darknet detector test cfg/coco.data cfg/yolov4.cfg yolov4.weights data/armadillos.jpg
imShow('predictions.jpg')
%cd /content/drive/MyDrive/yolov4/darknet/
```

```
!cp -f /content/drive/MyDrive/yolov4/edit/yolov4-obj.cfg /content/drive/MyDrive/yolov4/darknet/cfg
!cp -f /content/drive/MyDrive/yolov4/edit/obj.data /content/drive/MyDrive/yolov4/darknet/data
!cp -f /content/drive/MyDrive/yolov4/edit/obj.names /content/drive/MyDrive/yolov4/darknet/data
!unzip -o /content/drive/MyDrive/yolov4/edit/obj.zip -d /content/drive/MyDrive/yolov4/darknet/data
!unzip -o /content/drive/MyDrive/yolov4/edit/test.zip -d /content/drive/MyDrive/yolov4/darknet/data
!python generate_train.py
!python generate_test.py
!rm yolov4.conv.137
!wget
https://github.com/AlexeyAB/darknet/releases/download/darknet_yolo_v3_optimal/yolov4.conv.137
assert False
function ClickConnect(){
console.log("Working");
document
.querySelector('#top-toolbar > colab-connect-button')
.shadowRoot.querySelector('#connect')
.click()
}
setInterval(ClickConnect,60000)

#Start Training
!./darknet detector train data/obj.data cfg/yolov4-obj.cfg yolov4.conv.137 -dont_show

# kick off training from where it last saved (2)
!./darknet detector train data/obj.data cfg/yolov4-obj.cfg
/content/drive/MyDrive/yolov4/backup/yolov4-obj_last.weights -dont_show

# check map from where it last saved
!./darknet detector map data/obj.data cfg/yolov4-obj.cfg
/content/drive/MyDrive/yolov4/backup/yolov4-obj_last.weights -dont_show

#Run your Custom detector on images
!./darknet detector test data/obj.data cfg/yolov4-obj.cfg
/content/drive/MyDrive/yolov4/backup/yolov4-obj_last.weights
/content/drive/MyDrive/yolov4/Testimage/boar.jpg D -thresh 0.50
imShow('predictions.jpg')

#Run your Custom detector on video
!./darknet detector demo data/obj.data cfg/yolov4-obj.cfg
/content/drive/MyDrive/yolov4/backup/yolov4-obj_last.weights -dont_show -thresh 0.75
/content/drive/MyDrive/yolov4/TestVideo/animal.mp4 -i 0 -out_filename
/content/drive/MyDrive/yolov4/TestVideo/output/result.mp4

# import dependencies
from IPython.display import display, Javascript, Image
from google.colab.output import eval_js
from google.colab.patches import cv2_imshow
```

```
from base64 import b64decode, b64encode
import cv2
import numpy as np
import PIL
import io
import html
import time
import matplotlib.pyplot as plt
%matplotlib inline

# JavaScript to properly create our live video stream using our webcam as input
def video_stream():
js = Javascript('''
var video;
var div = null;
var stream;
var captureCanvas;
var imgElement;
var labelElement;
var pendingResolve = null;
var shutdown = false;
function removeDom() {
stream.getVideoTracks()[0].stop();
video.remove();
div.remove();
video = null;
div = null;
stream = null;
imgElement = null;
captureCanvas = null;
labelElement = null;
}

function onAnimationFrame() {
if (!shutdown) {
window.requestAnimationFrame(onAnimationFrame);
}
if (pendingResolve) {
var result = "";
if (!shutdown) {
captureCanvas.getContext('2d').drawImage(video, 0, 0, 640, 480);
result = captureCanvas.toDataURL('image/jpeg', 0.8)
}
var lp = pendingResolve;
pendingResolve = null;
```

```
lp(result);
}
}

async function createDom() {
if (div !== null) {
return stream;
}
div = document.createElement('div');
div.style.border = '2px solid black';
div.style.padding = '3px';
div.style.width = '100%';
div.style.maxWidth = '600px';
document.body.appendChild(div);
const modelOut = document.createElement('div');
modelOut.innerHTML = "<span>Status:</span>";
labelElement = document.createElement('span');
labelElement.innerText = 'No data';
labelElement.style.fontWeight = 'bold';
modelOut.appendChild(labelElement);
div.appendChild(modelOut);
video = document.createElement('video');
video.style.display = 'block';
video.width = div.clientWidth - 6;
video.setAttribute('playsinline', '');
video.onclick = () => { shutdown = true; };
stream = await navigator.mediaDevices.getUserMedia(
{video: { facingMode: "environment"}});
div.appendChild(video);
imgElement = document.createElement('img');
imgElement.style.position = 'absolute';
imgElement.style.zIndex = 1;
imgElement.onclick = () => { shutdown = true; };
div.appendChild(imgElement);
const instruction = document.createElement('div');
instruction.innerHTML =
'<span style="color: red; font-weight: bold;">' +
'When finished, click here or on the video to stop this demo</span>';
div.appendChild(instruction);
instruction.onclick = () => { shutdown = true; };
video.srcObject = stream;
await video.play();
captureCanvas = document.createElement('canvas');
captureCanvas.width = 640; //video.videoWidth;
```

```
captureCanvas.height = 480; //video.videoHeight;
window.requestAnimationFrame(onAnimationFrame);
return stream;
}
async function stream_frame(label, imgData) {
if (shutdown) {
removeDom();
shutdown = false;
return '';
}
var preCreate = Date.now();
stream = await createDom();
var preShow = Date.now();
if (label != "") {
labelElement.innerHTML = label;
}
if (imgData != "") {
var videoRect = video.getClientRects()[0];
imgElement.style.top = videoRect.top + "px";
imgElement.style.left = videoRect.left + "px";
imgElement.style.width = videoRect.width + "px";
imgElement.style.height = videoRect.height + "px";
imgElement.src = imgData;
}
var preCapture = Date.now();
var result = await new Promise(function(resolve, reject) {
pendingResolve = resolve;
});
shutdown = false;
return {'create': preShow - preCreate,
'show': preCapture - preShow,
'capture': Date.now() - preCapture,
'img': result};
}
''')
display(js)
def video_frame(label, bbox):
data = eval_js('stream_frame("{}", "{}")'.format(label, bbox))
return data
# function to convert the JavaScript object into an OpenCV image
def js_to_image(js_reply):
"""
Params:
js_reply: JavaScript object containing image from webcam
Returns:
```

```
img: OpenCV BGR image
"""

# decode base64 image
image_bytes = b64decode(js_reply.split(',')[1])

# convert bytes to numpy array
jpg_as_np = np.frombuffer(image_bytes, dtype=np.uint8)

# decode numpy array into OpenCV BGR image
img = cv2.imdecode(jpg_as_np, flags=1)
return img
# function to convert OpenCV Rectangle bounding box image into base64 byte string to be overlayed on
video stream
def bbox_to_bytes(bbox_array):
"""
Params:

bbox_array: Numpy array (pixels) containing rectangle to overlay on video stream.
Returns:
bytes: Base64 image byte string
"""
# convert array into PIL image
bbox_PIL = PIL.Image.fromarray(bbox_array, 'RGBA')
iobuf = io.BytesIO()

# format bbox into png for return
bbox_PIL.save(iobuf, format='png')

# format return string
bbox_bytes = '{}'.format((str(b64encode(iobuf.getvalue()), 'utf-8')))
return bbox_bytes

# start streaming video from webcam
video_stream()

# label for video
label_html = 'Capturing...'

# initialze bounding box to empty
bbox = ''
count = 0
while True:
js_reply = video_frame(label_html, bbox)
if not js_reply:
break
# convert JS response to OpenCV Image
frame = js_to_image(js_reply["img"])
```

```
# create transparent overlay for bounding box
bbox_array = np.zeros([480,640,4], dtype=np.uint8)
# call our darknet helper on video frame
detections, width_ratio, height_ratio = darknet_helper(frame, width, height)
# loop through detections and draw them on transparent overlay image
for label, confidence, bbox in detections:
left, top, right, bottom = bbox2points(bbox)
left, top, right, bottom = int(left * width_ratio), int(top * height_ratio), int(right * width_ratio),
int(bottom * height_ratio)
bbox_array = cv2.rectangle(bbox_array, (left, top), (right, bottom), class_colors[label], 2)
bbox_array = cv2.putText(bbox_array, "{} [{:.2f}]".format(label, float(confidence)),
(left, top - 5), cv2.FONT_HERSHEY_SIMPLEX, 0.5,
class_colors[label], 2)
bbox_array[:,:,3] = (bbox_array.max(axis = 2) > 0 ).astype(int) * 255

# convert overlay of bbox into bytes
bbox_bytes = bbox_to_bytes(bbox_array)

# update bbox so next frame gets new overlay
bbox = bbox_bytes
def take_photo(filename='photo.jpg', quality=0.8):
js = Javascript('''
async function takePhoto(quality) {
const div = document.createElement('div');
const capture = document.createElement('button');
capture.textContent = 'Capture';
div.appendChild(capture);
const video = document.createElement('video');
video.style.display = 'block';
const stream = await navigator.mediaDevices.getUserMedia({video: true});
document.body.appendChild(div);
div.appendChild(video);
video.srcObject = stream;
await video.play();
// Resize the output to fit the video element.
google.colab.output.setIframeHeight(document.documentElement.scrollHeight, true);
// Wait for Capture to be clicked.
await new Promise((resolve) => capture.onclick = resolve);
const canvas = document.createElement('canvas');
canvas.width = video.videoWidth;
canvas.height = video.videoHeight;
canvas.getContext('2d').drawImage(video, 0, 0);
stream.getVideoTracks()[0].stop();
div.remove();
```

```
return canvas.toDataURL('image/jpeg', quality);
}
''')
display(js)
# get photo data
data = eval_js('takePhoto({})'.format(quality))

# get OpenCV format image
img = js_to_image(data)
# call our darknet helper on webcam image
detections, width_ratio, height_ratio = darknet_helper(img, width, height)
# loop through detections and draw them on webcam image
for label, confidence, bbox in detections:
left, top, right, bottom = bbox2points(bbox)
left, top, right, bottom = int(left * width_ratio), int(top * height_ratio), int(right * width_ratio),
int(bottom * height_ratio)
cv2.rectangle(img, (left, top), (right, bottom), class_colors[label], 2)
cv2.putText(img, "{} [{:.2f}]".format(label, float(confidence)),
(left, top - 5), cv2.FONT_HERSHEY_SIMPLEX, 0.5,
class_colors[label], 2)

# save image
cv2.imwrite(filename, img)
return file
```