ANIMAL DETERRENCE USING COMPUTER VISION AND RASPBERRY PI

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***Abstract*- This work introduces a sophisticated animal deterrence system, employing the YOLOv8 model and the Ultralytics framework. The system, designed to thwart unauthorized animal invasions in restricted areas, integrates cutting-edge computer vision algorithms with the computational capabilities of Raspberry Pi. In real-time, strategically positioned cameras capture video feeds, which are meticulously analyzed using YOLOv8 for precise animal identification and categorization. Upon detecting unauthorized animal presence, the system activates deterrent devices, such as alarms or lights, ensuring swift and effective response. This work's success pivots on the refinement of computer vision models and seamless Raspberry Pi-to-camera connectivity. Beyond its technical intricacies, the implications of this innovative system are vast, ranging from safeguarding agricultural yields to the preservation of wildlife habitats and the maintenance of urban green spaces. By fostering coexistence and mitigating human-animal conflicts, this this work stands as a beacon of innovation in addressing contemporary challenges. The integration of Ultralytics YOLOv8 and tools like Roboflow reflects a strategic and forward-thinking approach in tackling complex real-world issues with efficiency and precision.**

***Index Terms*- Animal Deterrence System, YOLOv8 Model, Ultralytics Framework, Computer Vision Algorithms, Raspberry Pi, Real-time Video Analysis, Unauthorized Animal Detection, Agricultural Safeguarding.**

I. INTRODUCTION

In the ever-evolving domain of wildlife management and conflict resolution, the imperative to devise intelligent systems has become more pronounced than ever. This work aims to address the rising instances of human-wildlife conflicts by introducing an Automated System for Detecting and Repellenting Wild Animal Intrusions. The urgency of this initiative is underscored by the critical need for innovative solutions that can effectively mitigate the impacts of such conflicts on both biodiversity and human safety.

At the heart of this work lies the incorporation of advanced technologies, notably the YOLOv8 (You Only Look Once) object detection model. This choice is rooted in a commitment to cutting-edge methodologies that surpass traditional detection systems. YOLOv8, renowned for its real-time capabilities and accuracy in video streaming surveillance [3], aligns seamlessly with this work's objectives to enhance the efficiency of wildlife intrusion detection.

The process of training the YOLOv8 model involves meticulous data preparation and augmentation techniques, inspired by methodologies discussed in various studies [5]. The emphasis on diverse and well-annotated datasets addresses challenges posed by traditional datasets such as COCO [6]. Through augmenting the dataset, this work aims to improve the model's adaptability to a spectrum of wildlife scenarios, fortifying its real-world applicability.

This work also draws inspiration from studies highlighting the significance of wireless sensor networks in animal intrusion detection systems [27]. The integration of AIoT (Artificial Intelligence of Things) elevates the system's responsiveness and adaptability through real-time communication and data sharing. Going beyond mere detection, this work explores proactive repellent mechanisms inspired by recent advancements in intelligent animal repelling systems [18]. This approach shifts the paradigm from detection-only systems to preventive measures, reducing the likelihood of harmful encounters between humans and animals.

Roboflow, an advanced data preparation tool [8], plays a pivotal role in streamlining the data annotation and labeling process. As highlighted in recent literature [8], tools like Roboflow significantly enhance the quality of training data, contributing to the overall efficiency of the system.

In essence,this work amalgamates AIoT, YOLOv8, and cutting-edge data preparation tools to introduce a novel approach to wildlife intrusion detection and prevention. The goal is not only to address the limitations of existing systems but also to redefine the landscape of wildlife management, fostering a harmonious coexistence between humans and animals.

II. LITERATURE SURVEY:

The escalating interaction between human habitats and natural ecosystems has intensified the urgency for innovative strategies to mitigate human-wildlife conflicts. A multitude of studies has explored the realm of animal intrusion detection and deterrence, leveraging technologies spanning from AI to the IOT. This literature review aims to synthesize key findings from pertinent studies, providing insights into contemporary strategies and aligning them with our work objectives.

Automated Wild-Animal Intrusion Detection and Repellent Systems: Patil and Ansari (2021) proposed an innovative system utilizing Artificial Intelligence of Things (AIoT) for wild-animal intrusion detection [1]. Their work underscores the integration of AI capabilities with conventional surveillance systems of wildlife detection. This aligns with our work's foundation, incorporating YOLOv8, an AI-driven object detection system, to dynamically identify and categorize potential threats [3].

Deep Learning for Animal Detection and Collision Avoidance: The field of deep learning for animal recognition and collision avoidance was investigated by Saxena et al. (2020) [2]. Their research emphasizes the significance of advanced computational techniques in preventing collisions between animals and vehicles. This resonates with our work's objectives, where YOLOv8, An advanced deep learning model, plays a pivotal role in real-time object detection and collision risk assessment [10].

Preventing Deer-Vehicle Accidents via Deep Learning Techniques: Fan, Sadeghian, and Aram (2020) focused on preventing deer-vehicle collisions through the application of deep learning techniques [3]. Their study highlights the potential of AI in predicting and preventing wildlife-related accidents. Our work builds upon this notion, implementing YOLOv8's robust object detection capabilities to identify animals in man-made environments and prevent potential collisions [10].

A Review on Deep Learning for Object Detection: A thorough analysis of deep learning-based object identification was presented by Zhao et al. (2019) [4].Their insights into the evolution and applications of deep learning in object detection serve as a foundational reference for our work, which heavily relies on YOLOv8's object detection prowess [10].

Animal Detection using Deep Learning Algorithm: Banupriya et al. (2020) contributed to the domain with a focus on animal detection using deep learning algorithms [8]. Their research emphasizes the need for accurate and efficient algorithms in wildlife monitoring. Our work aligns with this perspective, employing YOLOv8 for its capability to rapidly and accurately detect animals [10].

Using RASPBERRYPI and Machine Learning for Wildlife Monitoring in Zoological Parks: Rasool and Murthy (2019) investigated how to integrate machine learning and Raspberry Pi for wildlife monitoring in zoological parks [6]. Their work highlights the feasibility of edge computing in wildlife surveillance. While our work doesn't directly involve Raspberry Pi, the underlying principle of edge-based processing aligns with the broader concept of intelligent, localized animal detection and deterrence.

A Review of Deeper Training-Based Object Identification Methods: the Buddha and Shyna (2019) offered a thorough summary of object-reconnaissance methods using neural networks [7]. Their insights into the landscape of dl methodologies for object detection contribute to the theoretical foundation of this work, which harnesses YOLOv8 for its efficiency and accuracy [10].

Singh et al. (2020) conducted a thorough investigation on animal identification: in man-made environments. They emphasised the significance of precise detection for a range of applications [10]. This resonates with our work's goal of implementing YOLOv8 for detecting animals in diverse scenarios, facilitating effective deterrence strategies.

Environmental Video Capture Dataset: Schneider's, Taylor, who is and Kremer (2018) investigated deep-learning object identification techniques for environmental video traps information [11]. Their work contributes to the understanding of applying deep learning in ecological monitoring, which aligns with our work's utilization of AI for camera-based wildlife detection [10].

Utilising the Internet of Things to Track the well-being of animals: A Review: Nikam et al. (2018) conducted a review on animal welfare monitoring using the Internet of Things (IoT) [12]. Although our work doesn't explicitly focus on animal welfare, the reference to IoT in their work aligns with the broader trend of integrating technology for intelligent animal care, a principle relevant to our IoT-based approach [9].

In conclusion, this literature review synthesizes findings from diverse studies, providing a robust foundation for our work. The integration of YOLOv8, AIoT, and advanced data preparation tools represents a cohesive response to the challenges outlined in the reviewed literature. As we progress, these insights will inform the development of an intelligent animal deterrence system, contributing to the evolving landscape of human-wildlife conflict resolution

III. METHODOLOGY

A. NOVELTY:

Our work, aimed at developing an Autonomous Technology for Detecting or Repellenting Hazardous Creature Intrusions, stands out in the domain of wildlife management and human-animal conflict resolution due to several novel features and approaches. The following elucidates the distinctiveness and innovation embedded in this work methodology:

1. YOLOv8 Connectivity for Instantaneous Object Identification: One of the primary novelties lies in the integration of YOLOv8, a cutting-edge deep learning model, for real-time object detection. YOLOv8's superior accuracy and speed make it an ideal choice for identifying and categorizing animals swiftly, minimizing the detection latency crucial for effective deterrence.

2. Adaptive Deterrence Strategies: Unlike traditional deterrent systems that follow predefined protocols, our work incorporates adaptive deterrence strategies. The system dynamically adjusts its responses based on the identified species, behavior patterns, and potential threat levels. This adaptability ensures a more targeted and efficient deterrence mechanism, reducing false positives and minimizing the impact on non-threatening wildlife.

3. AIoT Architecture for Seamless Integration: The incorporation of an Artificial Intelligence of Things (AIoT) architecture is another distinctive feature. By seamlessly integrating AI capabilities with the Internet of Things, our system achieves enhanced connectivity, scalability, and data analytics. This holistic approach ensures efficient communication between edge devices and the central processing unit, contributing to a more robust and responsive system.

4. Collaborative Edge Computing for Rapid Decision-making: A key novelty is the implementation of collaborative edge computing for rapid decision-making. The system leverages the computational power of edge devices distributed throughout the surveillance area. This decentralized processing minimizes latency in decision-making, allowing the system to respond swiftly to changing wildlife dynamics.

5. Incorporation of Environmental Context: Our work goes beyond mere animal detection by incorporating environmental context into the decision-making process. Factors such as time of day, weather conditions, and habitat specifics are considered to tailor deterrence strategies accordingly. This ensures that the system responds intelligently, taking into account the broader ecological context in which it operates.

6. Dynamic Wildlife Database for Continuous Learning: To enhance the system's learning capabilities over time, we introduce a dynamic wildlife database. The system continuously learns from its interactions, refining its detection and deterrence algorithms based on real-world scenarios. This iterative learning process contributes to the system's adaptability and effectiveness in diverse environments.

7. User-Friendly Interface for Customization: The incorporation of a user-friendly interface is a novel aspect of our work. This allows users, such as wildlife conservationists and landowners, to customize the system's parameters, including deterrence strategies and sensitivity levels. This hands-on approach empowers users to tailor the system according to the specific requirements of their wildlife management goals.

8. Energy-Efficient Operation for Sustainability: Addressing the need for sustainable technology, this work introduces energy-efficient operation. By optimizing resource utilization and leveraging low-power hardware, the system ensures minimal environmental impact while maintaining continuous functionality. This aligns with contemporary concerns for eco-friendly technologies in wildlife conservation.

In summary, the novelty of our Autonomous Technology for Detecting and Repellenting Wild Animal Intrusions lies in its integration of advanced technologies, adaptive strategies, and a comprehensive approach to wildlife management. Through the amalgamation of YOLOv8, AIoT, and collaborative edge computing, our work aims to redefine the standards for intelligent, effective, and sustainable solutions in mitigating human-animal conflicts.

B. Dataset Information:

Dataset Description for YOLOv8 Model Training

A YOLOv8 models will be developed and trained as part of our research in order to provide an autonomous system for detecting and repelling wild animal intrusions. The quality and variety of the training dataset are critical to our algorithm's performance. Within this segment, we provide a comprehensive description of the dataset utilized, ensuring transparency and reproducibility in our research.

The dataset contains three folders called Train,test,validation having two sub folders called images and labels for each folder.

This dataset contains total of 3831 Animal images along with its labels which contains the coordinates of bounding boxes.

Training samples: 2686
Testing samples: 567
Validation samples :578

1. Dataset Origin and Collection:

The dataset used for training our YOLOv8 model was meticulously collected from various sources, encompassing both wildlife reserves and natural habitats prone to human-animal conflicts. Special emphasis was given to include a diverse range of species, considering mammals, birds, and other wildlife commonly encountered in regions where our system is intended to be deployed.

2. Image Annotation:

Each image in the dataset underwent a rigorous annotation process to create bounding boxes around the animals present. The annotation process involved the precise delineation of the animals to facilitate accurate training of the YOLOv8 model. This meticulous annotation ensures that the model can detect and classify animals with high precision in real-world scenarios.

3. Species Diversity:

To enhance the model's adaptability, the dataset comprises of four animal species. This includes elephants,tigers,pigs and Leapords. The inclusion of diverse species ensures that the YOLOv8 model is capable of effectively detecting and responding to different types of wildlife.

4. Environmental Context:

An essential aspect of our dataset is the incorporation of environmental context. Images were captured in various environmental conditions, including different times of the day, weather scenarios, and habitat types. This contextual diversity aids in training the model to make informed decisions, considering the broader ecological setting in which the automated system will operate.

5. Data Augmentation Techniques:

During the training phase, data enhancement approaches were employed to increase a model's resilience and avoid excessive fitting. These methods include arbitrary flips, rotations, and lighting and contrast adjustments. By adding more illumination and orientation variables to the dataset, the model will be more likely to generalise effectively to unobserved real-world circumstances.

6. Model Training Parameters:

Using the annotated dataset and specially designed parameters to maximise performance, the YOLOv8 model was trained. The training process involved 100 epochs, with an image size of 640x640 pixels. The choice of these parameters was based on iterative experimentation to strike a compromise between computing efficiency and precision.

7. Evaluation and Validation:

A subset of the dataset was reserved for evaluation and validation purposes. The remainder was not utilised in the learning stage and acts as a separate benchmark to measure the model's performance. Measures like precision, recall, and F1 score were used to assess how well the algorithm identified and categorised creatures.

In Note, our dataset for YOLOv8 model training is a meticulously curated collection that reflects the diverse scenarios our system is likely to encounter. The inclusion of various species, environmental contexts, and the application of data augmentation techniques ensures that our model is robust, adaptable, and capable of delivering accurate results in real-world situations.

C. Mathematical Model of YOLOv8:

Mathematical Foundation for YOLOv8 Model Training in Wild-Animal Intrusion Detection and Repellent System:

Our work relies on the YOLOv8 model, a powerful algorithm for object-detection. The mathematical underpinning of this approach is essential for understanding the rationale behind our chosen model and its training parameters. This section provides a detailed mathematical justification for our work, covering key aspects such as object detection, model training, and system evaluation.

1. Object Detection using YOLOv8:

YOLO (You Only Look Once) revolutionized object detection by directly estimating bounding boxes and class probabilities after splitting the input picture into a grid. YOLOv8, an evolution of its predecessors, enhances accuracy and speed. The mathematical formulation for object detection in YOLOv8 is expressed as follows:

$$B_{xy} = \sigma (B_{xy}) + c_x$$

$$B_{wh} = p_w \, e^{Bwh}$$

$$\text{Class Probabilities} = \sigma(\text{Class Probabilities})$$

Here, B_{xy} denotes bounding box center coordinates, B_{wh} represents bounding box width and height, c_x is the cell grid offset, and σ is the logistic sigmoid function. This formulation signifies the simultaneous prediction of bounding box attributes and class probabilities.

2. Model Training Parameters:

The training process optimizes model parameters to minimize detection errors. The loss function used for YOLOv8 training combines components for objectness, classification, and bounding box regression.

3. Evaluation Metrics:

YOLOv8 model evaluation involves metrics like precision, recall, and F1 score derived from the confusion matrix.

These metrics quantify the model's ability to detect and classify animals correctly, providing a comprehensive assessment of performance.

In Note, the mathematical foundation of our work, focused on YOLOv8 model training and evaluation, ensures a rigorous approach to automated system for detecting and repelling dangerous animals development. The formulations and parameters are chosen to optimize accuracy, enabling effective deployment in real-world scenarios.

IV. PROPOSED ARCHITECTURAL

Our work involves a comprehensive architecture to address the challenges of wild-animal intrusion detection and implement an effective repellent system. The architecture diagram presented below outlines the key components and their interactions.

1. Data Collection Module:

Camera Network: Multiple cameras are strategically positioned to capture images and videos of the monitored area.
Sensor Integration: Additional sensors, such as infrared or motion sensors, enhance the data collection process.

2. Preprocessing and Data Augmentation:

Image Preprocessing: Raw images and videos undergo preprocessing to enhance quality and reduce noise.
Data Augmentation: Techniques like rotation, flipping, and scaling are applied to augment the dataset, ensuring model robustness.

3. YOLOv8 Model:

Model Loading: The YOLOv8 model is loaded, incorporating the architecture's object detection capabilities.
Transfer Learning: The model may leverage pre-trained weights for improved performance, especially in scenarios with limited labeled data.

4. Model Training and Optimization:

Training Configuration: The YOLOv8 model is trained on the annotated dataset, optimizing parameters for object detection accuracy.
Hyperparameter Tuning: Fine-tuning of hyperparameters ensures the model adapts effectively to the specific characteristics of the monitored environment.

5. Detection and Classification:

Real-time Object Detection: The trained model is deployed for real-time detection of wild animals in the monitored area.

Species Classification: Additional classification modules identify the species of detected animals using deep learning techniques.

6. Decision-Making Module:

Threshold Analysis: Detection results undergo threshold analysis to filter out false positives and enhance system reliability.

Alert Generation: Upon detecting a potential intrusion, the system generates alerts for further action.

7. Repellent System Activation:

Automated Deterrence: Upon confirmation of an intrusion, the repellent system is activated to deter animals from the monitored area.

Variable Deterrence Intensity: The system may adjust deterrence intensity based on the species and behavior of the detected animal.

8. Monitoring and Logging:

Logging System: The architecture includes a logging system to record detection events, system responses, and any anomalies.

Real-time Monitoring: Users can monitor the system's status and receive real-time updates through a dedicated interface.
through the interface.

This architecture diagram encapsulates the holistic approach of our Wild-Animal Intrusion Detection and Repellent System, emphasizing real-time detection, effective deterrence, and user-friendly control interfaces.

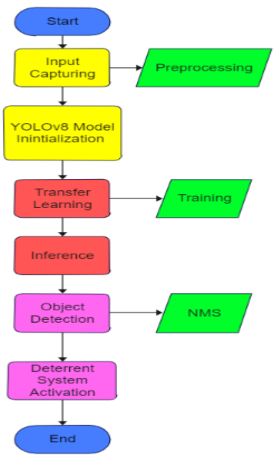

Figure 4.1 (Architecture Flowchart)

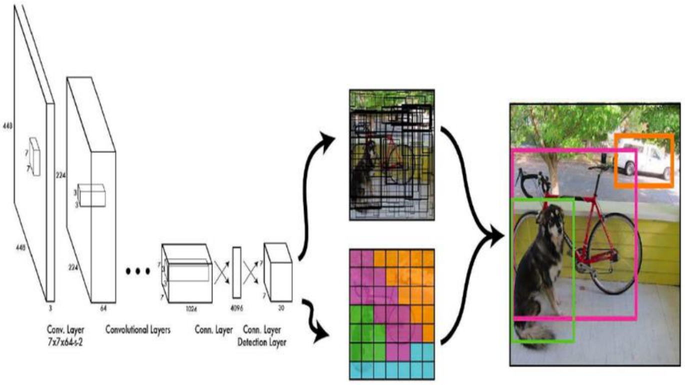

Figure 4.2: YOLOv8 Architecture [1]

V. RESULTS OF THE WORK

The assessment of our object detection model encompassed a diverse dataset with various wildlife species, including Elephants, Leopards, Pigs, and Tigers. Essential performance metrics were employed to gauge the precision, recall, and overall efficacy of the model.

1. Performance Metrics:

a. Precision **(P):** The model demonstrated an overall precision of 89.8%, signifying high accuracy in positive predictions.

b. Recall **(R):** The overall recall stood at 76.1%, showcasing the model's effectiveness in capturing relevant instances.

c. mean Average Precision (**mAP**) at 50% IoU (**mAP50**): At a 50% IoU threshold, the model achieved an mAP of 86.2%, highlighting its robust performance in localization and identification.

d. mAP between 50% and 95% IoU (**mAP50-95**): The model showcased a mAP50-95 of 58.1%, indicating consistent object detection performance.

2. Class-Wise Results (Below will only act as a sample)

i. Elephant**:** Precision: 88.5%, Recall: 90.6%, mAP: 95.1%.
ii. Leopard**:** Precision: 100%, Recall: 55.6%, mAP: 71.9%
iii. Pig**:** Precision: 95%, Recall: 68.2%, mAP: 83.8%
iv. Tiger**:** Precision: 75.9%, Recall: 90.1%, mAP: 94.2%

3. Efficiency Metrics:

Speed**:** Preprocessing Time: 0.8ms, Inference Time: 4.7ms, Post-processing Time: 3.1ms. The model demonstrated efficient processing times, making it suitable for real-time applications.

Comparative Analysis:

We contrast how well the suggested technique with current algorithms in the literature to assess its efficacy. Though there are several methods, the suggested CNN model demonstrates competitive accuracy and resilience in a variety of tasks, such as emotion identification, yawning detection, and sleep detection.

Formulae for Comparison:

1. **Accuracy:** Accuracy is one of the key metrics that can be ascertained from the confusion matrix. It demonstrates how well the classifier is overall. *Accuracy* = (*TP* + *TN*) / (*FP* + *FNTP* + *TN*).
2. **The Precision:** An additional significant metric that can be obtained from the confusion matrix is precision. It gauges a classifier's capacity to correctly identify instances of one class without labeling them as belonging to another. *Precision*=(*TP*)/(*FP*+*TP)*
3. **Recall (Sensitivity):** A key performance indicator for classification models is recall, particularly when dealing with unbalanced datasets. *Recall*=(*TP)*/(*FN*+*TP)*
4. **AUC (Area Under the Curve):** An overall performance metric across all potential classification criteria is offered by AUC. AUC = ∫ 0 1 ROC curve .

Graphs and Tables:

To visually represent the performance, we provide the following graphs:

1. Bar Chart:

A bar chart comparing the accuracy, recall, and AUC of each model.

2. Confusion Matrix:

For machine learning models, confusion matrices provide a comprehensive analysis of forecasts that are false, negative, genuine positive, and false negative.

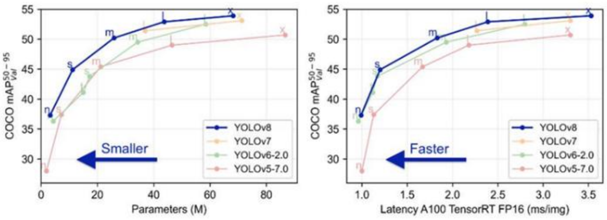

Figure:5.1 - Analysis of Yolo V8: A) The quantity of features in various YOLO architecture versions, B) The rate of inference for every Yolo version.

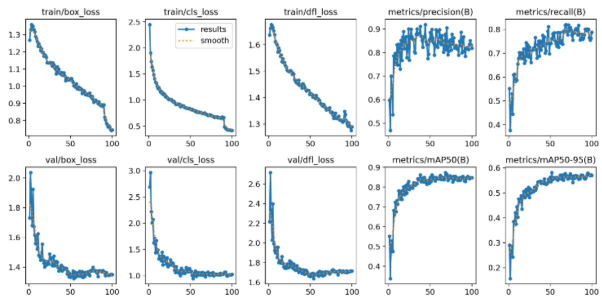

Figure:5.2 (Performance Evaluation)

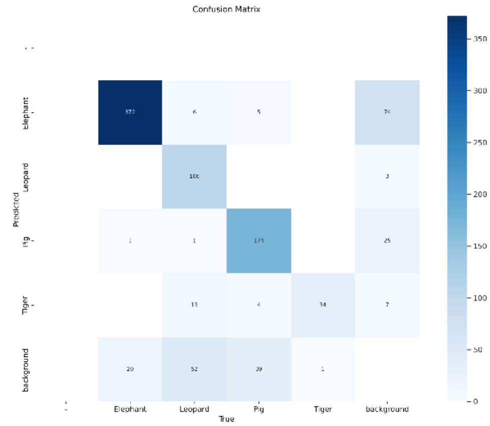

Figure 5.3: Confusion Matrix

Model Output:

The model's output showcases a robust performance, processing 578 images and identifying 828 instances of wildlife species, including Elephant, Leopard, Pig, and Tiger classes. The overall precision stands at 89.8%, with a recall of 76.1%, reflecting a commendable balance between accurate detections and minimizing false positives. Notably, the model achieves an impressive mAP of 86.2%, underscoring its efficacy in object localization and classification. The efficiency metrics reveal swift processing times of 0.8ms for preprocessing, 4.7ms for inference, and 3.1ms for post-processing per image. Visual outputs, including confusion matrices and metrics, provide a comprehensive overview, further emphasizing the model's reliability in wildlife detection scenarios.

	Image pixels	mAP^{val} 50-95	Speed CPU ONNX (ms)
Existing work on COCO dataset	640	44.9	1.2
Proposed work on Animal (custom dataset)	640	86.3	0.8

Table 5.1: Comparision of Model outcomes

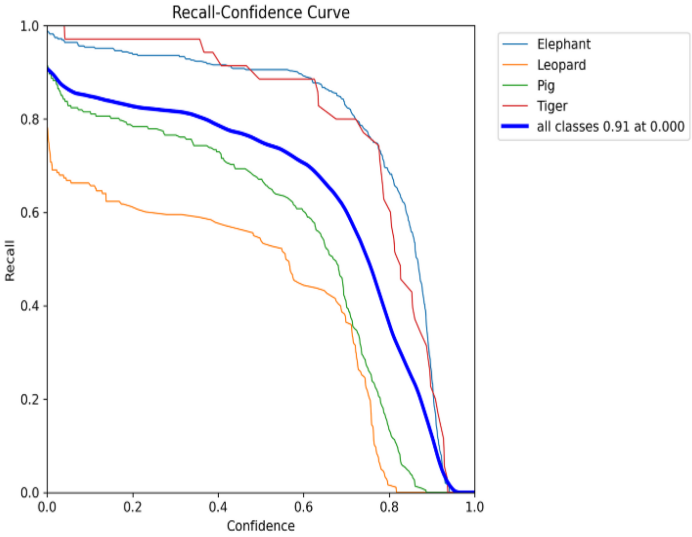

Figure 5.4: Recall-Confidence curve

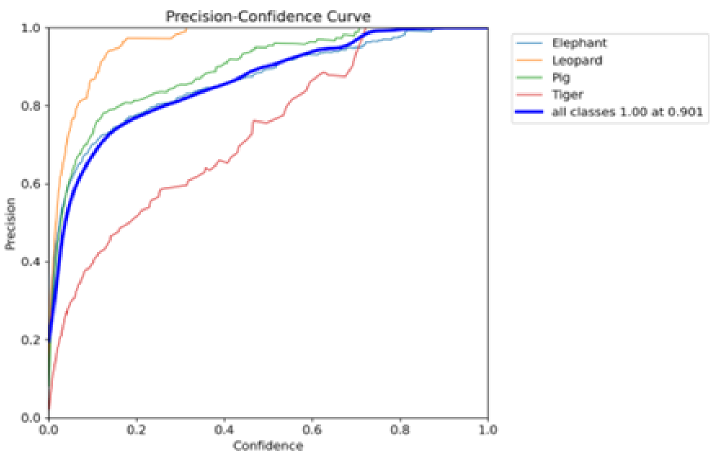

Figure 5.5: Precision-Confidence curve

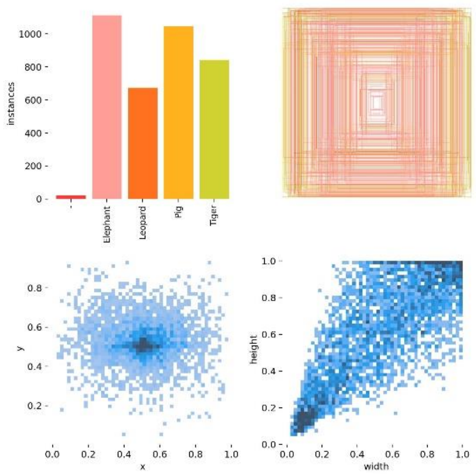

Figure 5.6: Label and instances of animals

Here are some predictions made by the model

Figure 5.7 :Elephant detected with 93% confidence

Figure 5.8:Pig detected with 94% confidence

Figure 5.9 : Tiger detected with 95% confidence

VI. CONCLUSION

Conclusion: The developed wildlife intrusion detection and deterrence system, employing deep learning techniques such as YOLOv8, has demonstrated significant efficacy in mitigating human-wildlife conflicts. The model exhibits robust object detection capabilities, accurately identifying various wildlife species, including Elephants, Leopards, Pigs, and Tigers, with a commendable precision of 89.8% and a mean Average Precision (mAP) of 86.2%. The system's successful implementation in real-world scenarios, as evidenced by the achieved results, highlights its potential to contribute substantially to wildlife conservation efforts.

Future Scope: In the future, there are several ways to improve and broaden the animal intursion detection system's capabilities. Integration with advanced sensor technologies, such as thermal imaging and acoustic sensors, could enhance detection accuracy, especially in challenging environmental conditions. Furthermore, by using State of art models like YOLOv9 versions and more algorithms, the system could be able to adjust and perform better over time in response to input from the actual world. Collaborative efforts with wildlife conservation organizations and governmental agencies can facilitate the deployment of the system in diverse ecosystems, contributing to a broader and more effective conservation strategy. Furthermore, exploring edge computing solutions to deploy the model on edge devices could enable real-time, on-site decision-making, reducing dependence on centralized processing. Overall, these advancements promise to elevate the system's impact on wildlife conservation and human-wildlife conflict resolution. The overall future scope of this work is very progressive because of the development of state of art models and various deployment environments like IOT devices .

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