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Enhancing Wildlife Tourism Management Using Deep Learning and Particle Swarm Optimization (PSO) for Animal Detection in Wildlife Sanctuaries

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Abstract

Wildlife tourism is one of the most thriving sectors, faced with huge challenges in terms of safeguarding protected areas. As demand for wildlife experiences accelerates, it becomes necessary to find efficient measures that are friendly to conservation. The use of these advanced techniques in this field such as YOLO and PSO algorithm presents a new dimension on managing wildlife tourism. To harness the abilities of these techniques, this research centers on deep learning approaches as well as PSO algorithms. To train our animal detection model, a custom animal dataset was created specifically for this purpose and was annotated using the Computer Vision Annotation Tool (CVAT). The dataset encompasses various sources of animal images and includes examples from species regularly encountered by tourists when they go on safari, thus capturing some diversity. It is after annotation that we can use it as the basis for training our precise object detecting algorithm which is YOLOv8s. Hyperparameter tuning was done for optimizing the model using PSO algorithm by obtaining the best fit parameters. This optimization process involves enhancing the detection precision through improving the model's ability to recognize different animals within various environmental conditions.

The model is assessed over curated datasets to make sure that it does well in the real-world scenarios with Map accuracy of 81%. Furthermore, the model is equipped with animal tracking on video data. This aspect enables the possibility of monitoring and protective measures. The purpose of this research is to solve the major problems in the management of wildlife tourism. The sophistication of the developed model with features like real-time tracking enhances the scope for proactive management of wildlife tourism activities, customer satisfaction and conservation efforts.

Keywords: Object detection, Prediction, Training, gradient class activation map, transfer learning, validation.

INTRODUCTION

Wildlife sanctuaries are known for biodiversity and for serving as a safe place to live for thousands of diverse wild animals' species. The absence of boundaries within these protected areas often leads to them leaving the place and roaming around freely far away. This results in tourists, photographers, environmentalists, researchers, and other stakeholders missing their sightings of wild animals. This can be a reason for disappointment for tourists, who invest time and money in the hope of exploring the wonders of wildlife. Photographers & Videographers rely on the presence of wildlife for clicking images and footages, while environmentalists and researchers require accurate data on animal populations and behavior for conservation and scientific studies. Yet, this occurrence of animal displacement is a significant issue that needs to be solved. This issue addresses a critical need for effective methods of wild animal detection and monitoring animals in protected areas, ensuring that the visitors and stakeholders can experience the sightings of wild animals, also contributing to conservation efforts and scientific research. This paper presents an evolutionary approach that can be used as animal detection for wild animals in wildlife sanctuaries. There is a lot of excitement about YOLOv8 architecture in the field of detecting different animal categories [1].

YOLOv8 algorithm has gained a lot of popularity among computer vision researchers for object detection in recent times. It is the fastest and most accurate [2]. It combines several object detection techniques such as Classification, Object Detection, and Image Segmentation. This involves assigning an image category label and drawing a bounding box around the detected object; Identifying and locating objects in an image with both a label and bounding box; Breaking down an image into distinct segments that correspond to different objects or regions [3]. Particle Swarm Optimization (PSO) is an activity by which many natural swarms are simulated. When it comes to optimization problems PSO looks at them as finding the best solution from numerous other possible solutions. However, deep learning algorithms can be combined with PSO too. Therefore, PSO deals effectively with continuous and discrete optimization problems making it suitable for any type of optimization work [4]. These methods are highly efficient and innovative because they can detect animals' beings on real-time video input faster than before as well as output bounding boxes and labels.

LITERATURE REVIEW

Traditional methods of studying live animal movements, which include methods like camera traps and surveys, make it difficult to retrieve status of the wildlife across vast landscapes. This makes it difficult to manage conservation programs and complicates the tasks of forest officers and environmentalists [2]. This does not only necessitate a constant monitoring of these intrusions, but also the implementation of precautionary measures against them to effectively tackle the serious problem of Human-Animal Conflict leading to considerable resource wastage and endangering human lives [5]. These methods have seen an increase in interest in their deployment for identification of animals withinn video streams over the past few years. This is a trend that has the potential to change many things, including ecology as well as agriculture [6]. With huge volumes of images, manual evaluation of massive data sets becomes cumbersome, time-consuming and expensive; hence automated ecological analysis has become indispensable. This development has led to state-of-the-art results in object and species identification tasks through advanced deep learning networks which have been developed by computer vision over the last years [7]. In the novel approach, YOLOv8 was integrated with PSO architecture to improve detection accuracy. By using PSO for optimization of YOLOv8 parameters, the proposed model stands out from other approaches in this direction [4]. The particle swarm optimization (as formulated by its creators) has a very simple idea and just a few lines of code that can be used to obtain good results. It is implemented with basic math operators where it is also efficient in terms of memory usage and speed [8]. Besides, Particle Swarm Optimization (PSO) is another bio-inspired algorithm that can be used to optimize the architecture of a neural network. ***Like*** genetic algorithms, PSOs have been utilized for evolving both weights and architectures for neural networks [9]. Object detection remains one of the most exciting applications in computer vision, where drawing bounding boxes around identified objects is key next step.

The paper’s focus is to improve boundary box placement after object detection on images [10]. The empirical evaluations and statistical tests reveal that model has shown better performance than other similar models when it comes to accuracy as well as training time and speed prediction [11].

METHODOLOGY

Architecture

The backbone network, a C2f module, an unsampled layer, a SPPF layer and detection head make up the specific architecture of YOLOv8. The most significant attributes are generated by the backbone network from input images while the features at different scales are found by the SPPF layer for greater accuracy. Up sample layer expands the resolution size whereas C2f module bridges high-level features with contextual information to enhance operation [2]. Finally, the detection head has a convolution and a linear layer that maps high-dimensional characteristics into output boxes and class labels. This design simultaneously promotes both faster and more accurate object detection tasks. The parameter sizes in YOLOv8 vary depending on the requirements of doing computation [12][13][14].

Particle Swarm Optimization (PSO) is a population-based stochastic optimization method which is based on the social behavior of bird flocking or fish schooling [8]. It was developed originally by Dr. Eberhart and Dr. Kennedy in 1995. PSO is widely applied to the process of solving optimization problems (especially when dealing with continuous optimization tasks) [9]. The core concept of PSO is to maintain a group of potential solutions known as particles that flow across the search space. Each particle's motion is determined by its best-known position and the global best-known position of the whole system:

1. Update particle's velocity:

$$\mathbf{v}_i(t+1) = \omega \mathbf{v}_i(t) + c_1 r_1 (\mathbf{p}_i - \mathbf{x}_i) + c_2 r_2 (\mathbf{p}_g - \mathbf{x}_i)$$

2. Update particle's position:

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1)$$

Where:

- $\mathbf{x}_i$ is the current position of the i th particle.
- $\mathbf{v}_i$ is the current velocity of the i th particle.
- $\mathbf{p}_i$ is the best-known position of the i th particle.
- $\mathbf{p}_g$ is the best-known position of the entire population.
- ω is the inertia weight that controls the impact of the previous velocity.
- c_1 and c_2 are acceleration coefficients.

r_1 and r_2 are random numbers between 0 and 1

The algorithm does this until the termination condition is met, such as achieving the maximum number of iterations or a satisfactory solution. PSO has been applied to different domains, e.g. engineering, machine learning and optimization issues, where global optimality is critical.

Data Collection and Preprocessing

The dataset used to train the YOLOv8 model for animal detection consists of 1856 images showcasing a wide range of animals. The images were meticulously obtained from different sources and synthesized into a complete set that is specifically designed for training. In the preprocessing phase several important steps were taken to refine the dataset’s quality and suitability for training YOLOv8 model. Furthermore, during this process, it was required to carefully indicate where animals are located or positioned in each image. This was achieved by drawing bounding boxes over animals using CVAT [14]. This phase of annotation is crucial in developing models like YOLOv8 because it gives a ground truth which is very important in learning by models. Consequently, through the meticulous collection and preprocessing of image dataset for animal detection using YOLOv8 the model has been given a strong base from which accurate identification of various animals can be carried out.

Classification

The classification part of animal detection is mainly about identifying the categories that this model can detect. The context's model has learned to recognize many varieties of animals including Leopard, Tiger, Bear, Rhinoceros, Deer/Antelope, Elephant, Dog, Cattle, Human and Lion. Each one of these classes is a distinctive type within the animal kingdom which this model has been specifically programmed to check for. A description of these classes helps in understanding the extent and adaptability that comes with the animal detection model by demonstrating its ability to differentiate between species meticulously and accurately. This section forms a basis for any project by outlining precisely those aspects on which the model was developed with regards to classifying it further to examine and evaluate its efficiency in determining crucial animal groupings [6][7].

Model Training and Hyperparameter tuning

Wild animals' datasets were prepared by means of merging several sources, which were subsequently labeled using CVAT by including the tagged bounding boxes into the algorithm. Project Flowchart shown in fig. 1 Then the prepared dataset was trained using YOLOv8 architecture and later hyperparameters were tuned using PSO. Consequently, it selected some significant parameters to produce accuracy. For the result, sample video datasets were converted into frames and then fed into an input of a model that will output a video with the most accurate labeled bounding box around class animals.

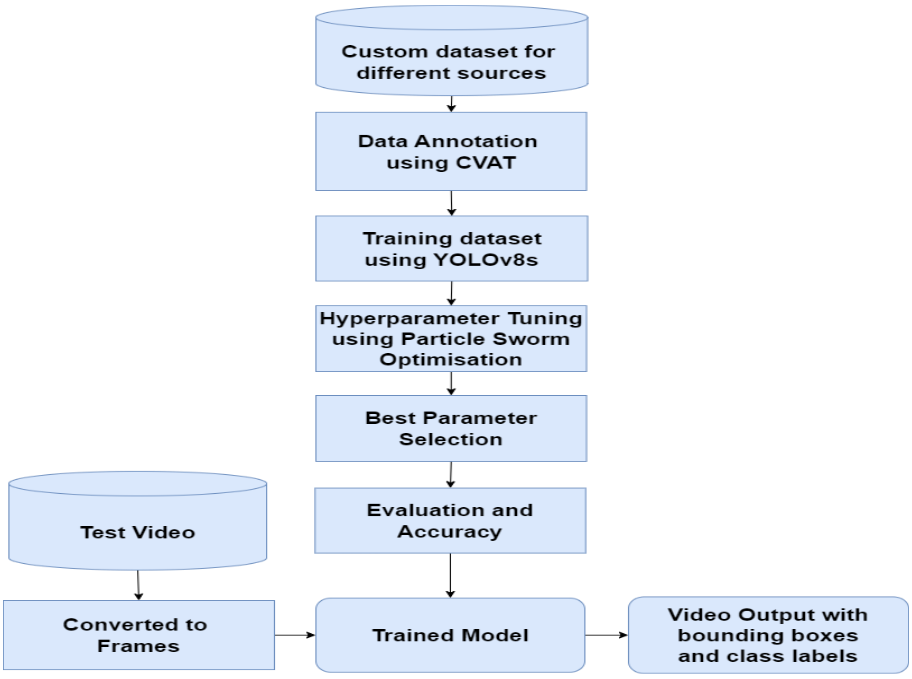

Figure 1. Project Flowchart

The Ultralytics YOLOv8 model is a dynamic computer vision tool that can handle object detection, classification, and segmentation. It offers real-time efficiency, strikes a balance between mean average precision and speed, and is compatible with our project objectives. The model's floating-point operations proficiency fits well with our small custom dataset. Its parameter management optimizes computational resources, providing precise and accurate outcomes [15][16]. Deep learning model optimization is a complex task that requires one to perform advanced methods such as Particle Swarm Optimization (PSO) to search for better models. On the other hand, PSO is used to explore hyperparameters in complex models of YOLOv8 [11]. In PSO, a set of potential solutions, known as particles, traverse through a search space and adapt their positions using information from themselves as well as other neighbouring particles to arrive at the best solution. After training for 60 epochs with batch size 16 and reaching initial accuracy 77.8%, it was the time for tuning hyper-parameters for animal detection tracking system with containing boxes using YOLOv8s. The optimization procedure employed PSO and so hyperparameters such as batch size, number of epochs and learning rate had to be selected [4].

This drastically improved efficiency by enabling identification of optimal parameter settings. Based on the best parameters found by PSO the model was retrained and it was found that the validation Map accuracy increased by approximately 5%. This made the model even more accurate and versatile, which improved its ability to detect animals and to track them precisely with an accuracy of 81.2%.

RESULTS

Evaluation Metric

The purpose of this study is to assess the YOLO model utilizing different evaluative indicators that are commonly used in the model evaluation. In training, YOLO loses three types of broken lines: bounding box regression broken line, confidence scores broken line, and class predictions broken line. Nodes on these broken lines correspond with every training iteration. When the number of nodes decrease on the broken line it shows that the model is converging thus giving higher accuracy. There are two kinds of these broke lines; one for training set and other one for validation set which explains loss values in each related data set. The broke lines for training set reduce gradually with increasing iterations but for validation set they become unpredictable. Moreover, we have employed confusion matrix and broke lines to show how precise recall and mean Average Precision (map) values are produced by neural network. These measures give an easy-to-understand account of how accurate our model is, such as with high fallen dots indicating highest accuracies. For instance, Figures 6 provide visual evidence about bounding boxes made by YOLO regarding their correctness and composition [17].

Model Convergence Analysis

The box loss, cls loss and obj loss decreased as the model converged over every epoch. The validation broken lines show similar trends to the training lines in terms of loss trends, suggesting that the model is in a nearly steady state. We first establish convergence of the model by examining the loss depicted in Figure 2 below [17].

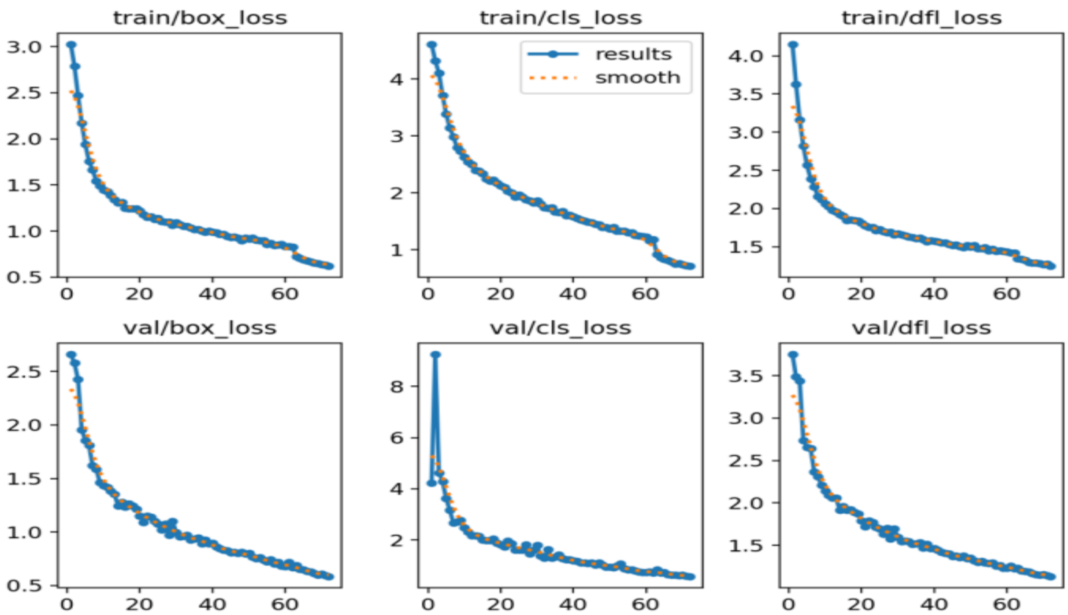

Figure 2. Change of loss with increase of training procedure

Quantitative Analysis

Figure 3 reveals the results of our model and its practicality in real life scenarios. Our model demonstrates a precision and recall rate of above 90% and with a threshold of 0.5, has a mean Average Precision (Map) of 95%, while the corresponding figures are 81.2% for the range between 0.5 to 0.95. On top that, Figure 4 describes detection performance on different categories in terms of confusion matrix showing ‘deer/antelopes’ and ‘lion’ precision equal to 92%; ‘rhinoceros’ and ‘leopard’ having precision equal to 94%; ‘cattle’, ‘elephant’ and ‘dog family’ at 86%; ‘bear’ at 68%, ‘tiger’ at 93% and followed by ‘human’ with approximately 96%. Therefore, these results confirm the appropriateness of our wild animal detection and tracking model.

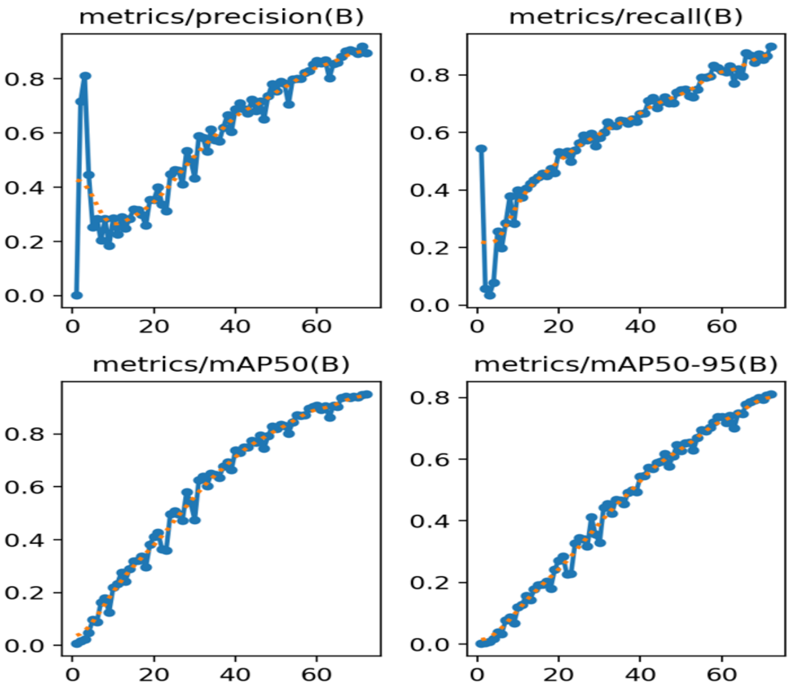

Figure 3. Map of our module

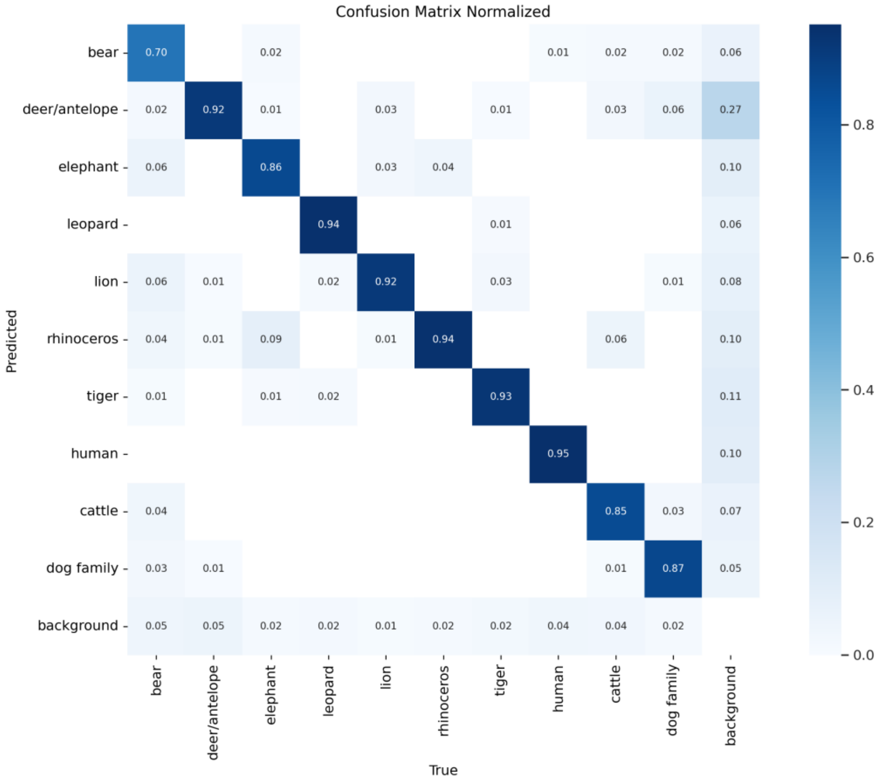

Figure 4. Normalized confusion matrix

Visual Analysis

To find out if YOLOv8 can be used for improved detection accuracy, we present it visually for various scenes separated into ten classes in figure 6. As can be seen from this example, even in complicated pictures which contain multiple objects. YOLOv8 successfully locates animals within production quality bounding boxes driven by fast yet accurate object localization process using bounding box regression. Detection Results shown in fig. 5 The average prediction time for YOLOv8 is under two hundred milliseconds meaning it can perform real-time target detection. Precision confidence curve shown in fig. 7 Therefore, due to its high accuracy and efficiency, this makes it suitable for practical application purposes [17]. Precision Recall curve shown in fig. 8 and Recall confidence curve shown in fig. 9

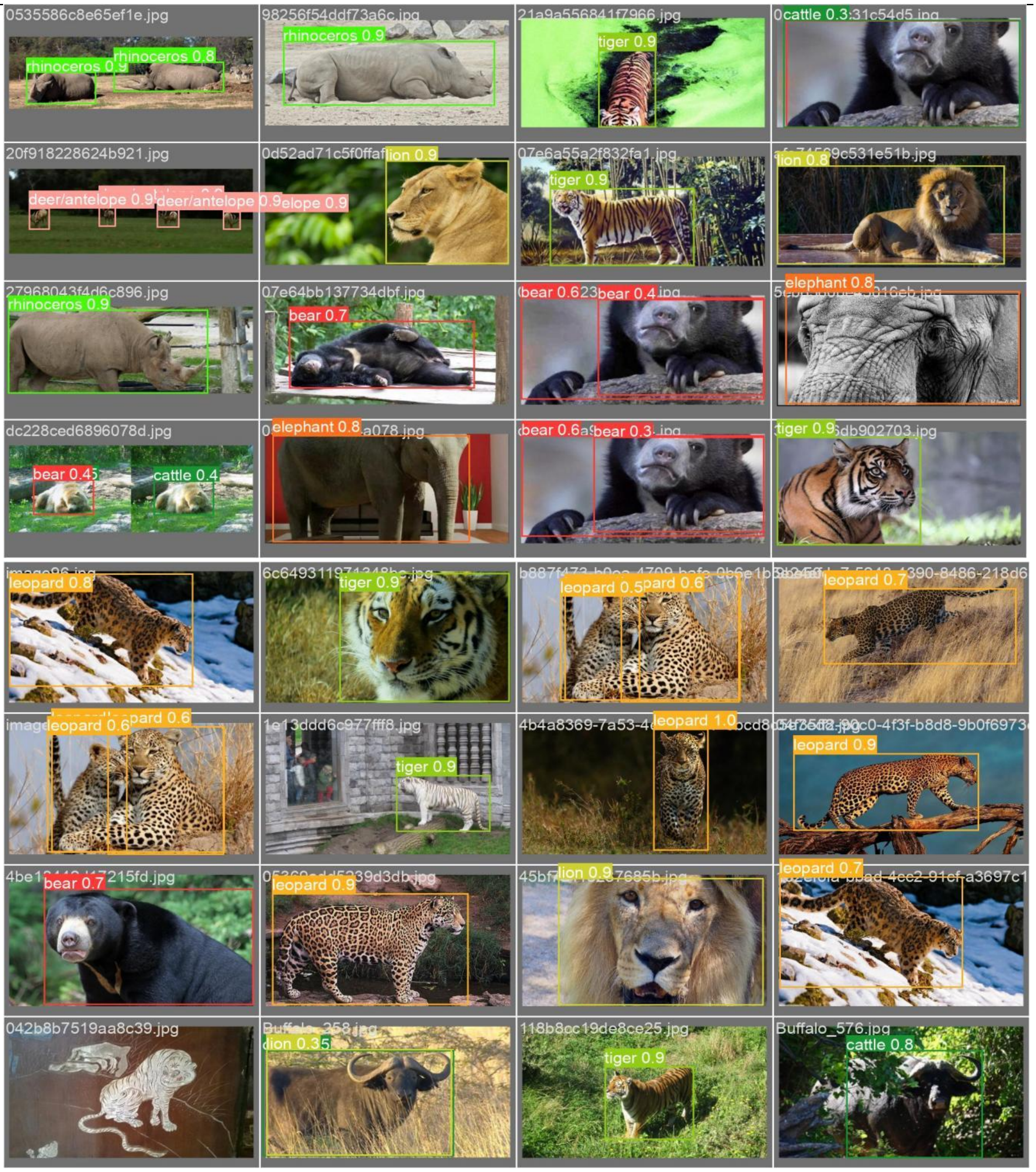

Figure 5. YOLOv8 model detection results

OTHER EVALUATION METRICS

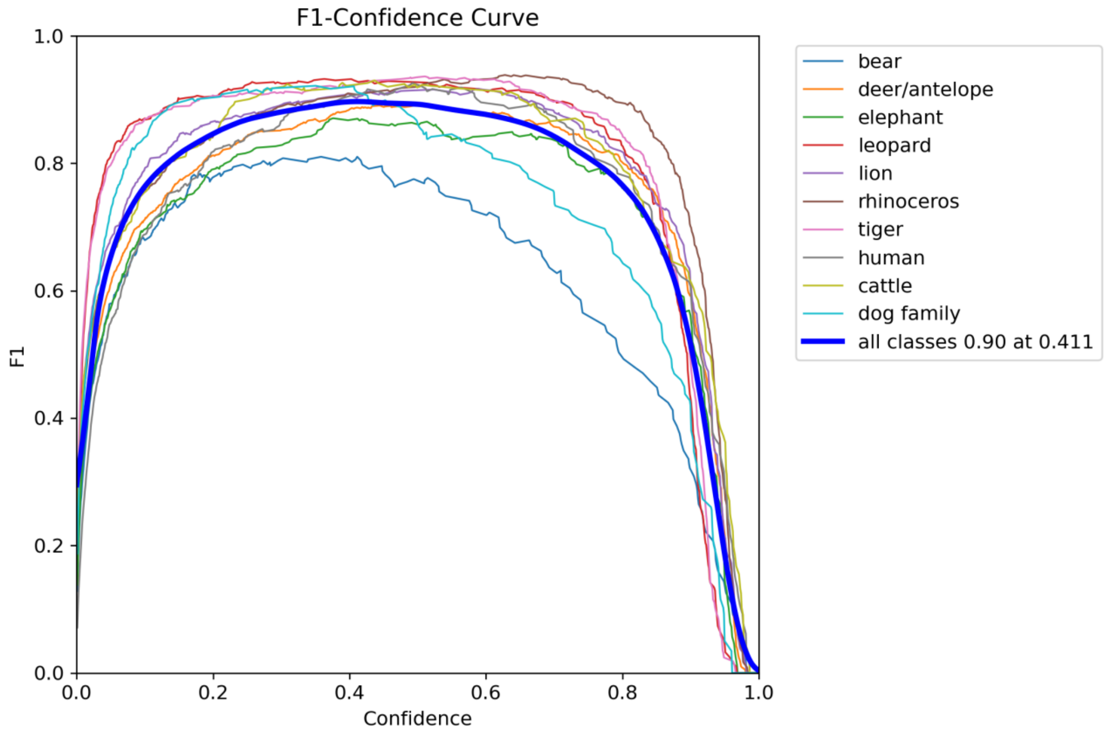

Figure 6. F1 confidence curve

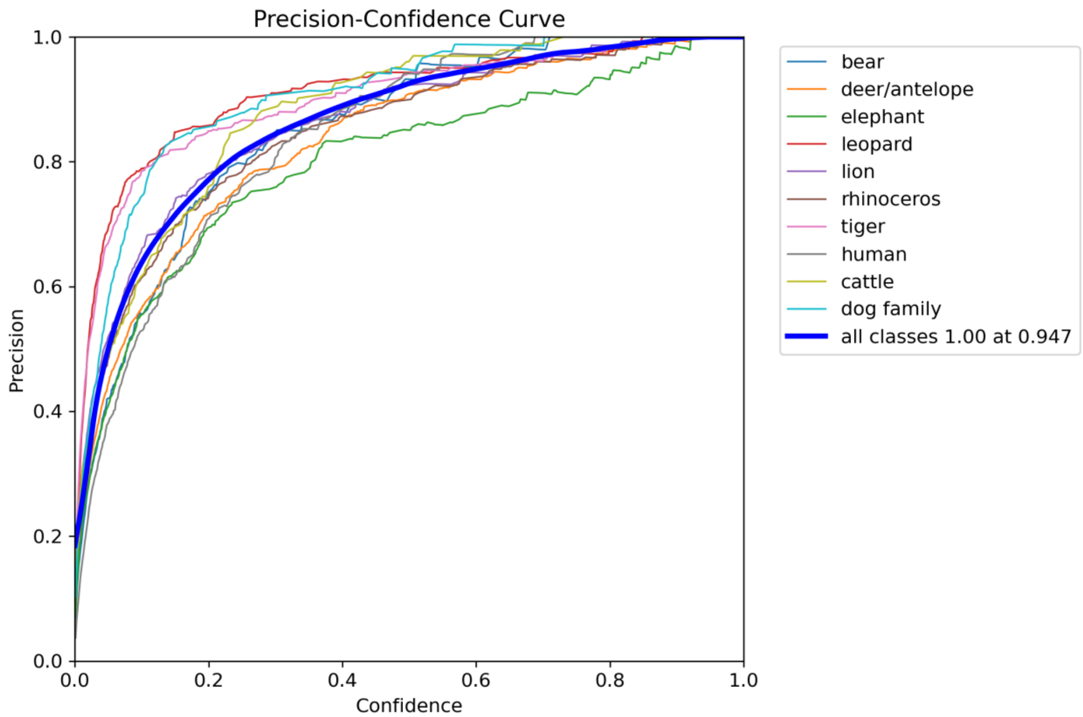

Figure 7. Precision confidence curve

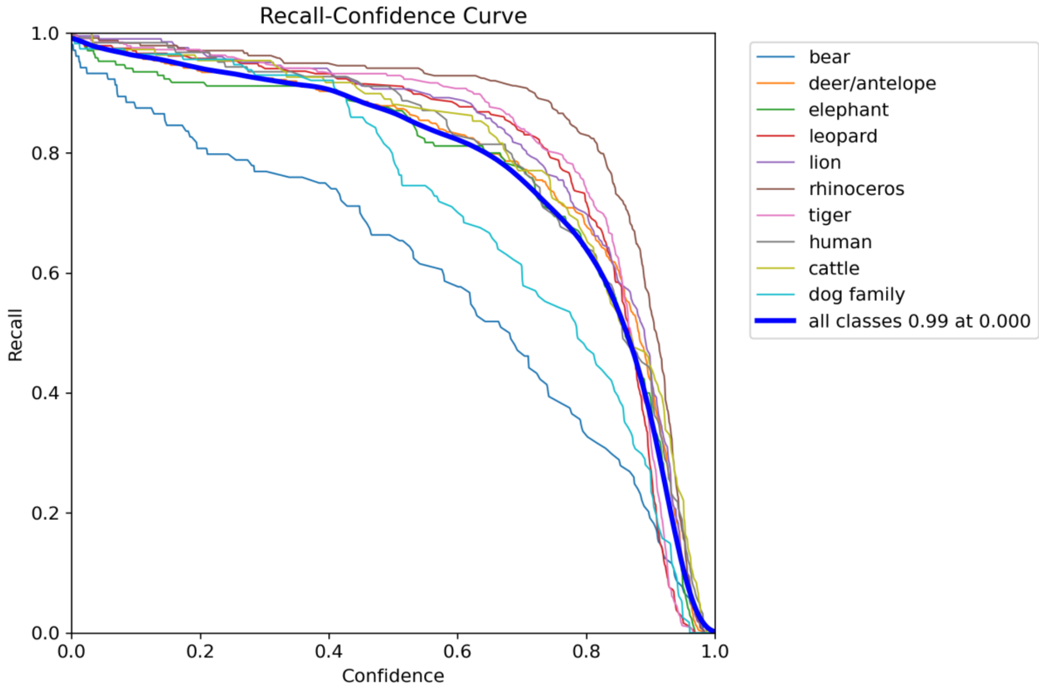

Figure 8. Precision Recall curve

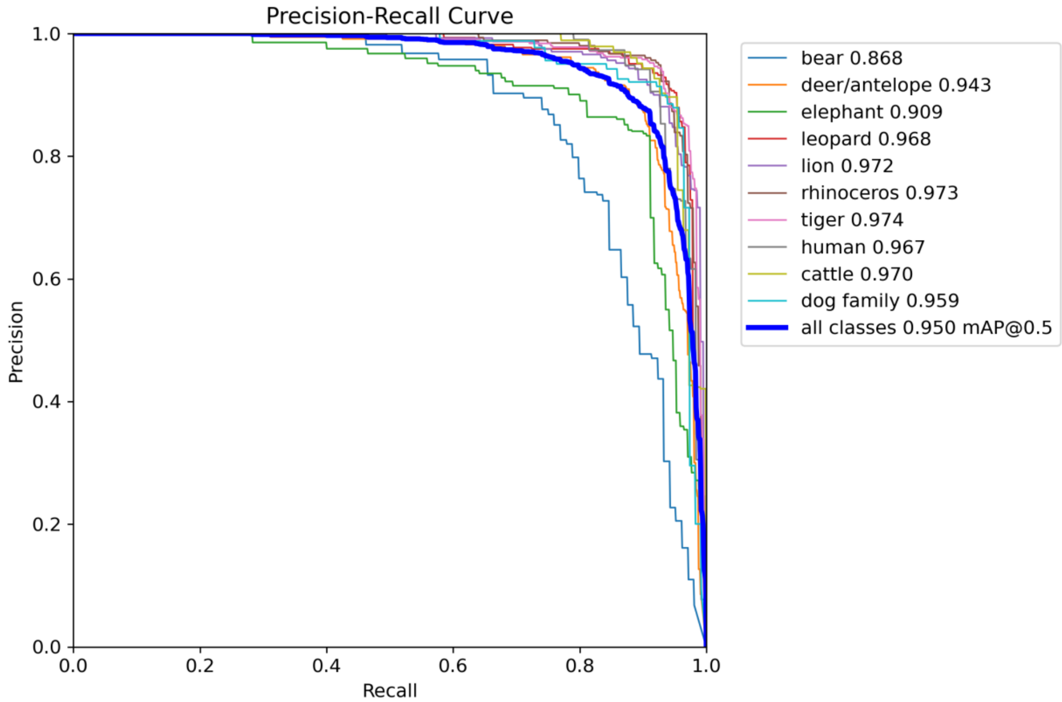

Figure 9. Recall confidence curve

LIMITATIONS

Lack of benchmarking also causes concern which means the model can't be generalized in other environments thus becoming unreliable for unseen cases due to lack of uniform performance comparison. Accuracy may have been compromised because of constrained resources that hindered exploration on advanced models such as YOLOv8l or YOLOv8x. This affects system performance especially in complex wildlife behaviors. No nighttime dataset was available to incorporate nighttime detection.

FUTURE SCOPE

The next stage of research should then be to test the model using standardized datasets for a more exhaustive evaluation of its performance. Besides the previously mentioned model YOLOv8s, there are other advanced ones like YOLOv8l and YOLOv8x to reveal how accurate its detection can be improved as well as showing how effective these models can handle complex scenarios. To improve tuning capability, parallel computing or distributed computing methods may incorporate more iterations in the model with respect to PSO iterations. In some cases, hybrid approach where lightweight algorithms are combined with deep learning models for specific processing stages might balance between precision and time efficiency hence not making them applicable only in resource limited situations alone.

CONCLUSION

This research shows how deep learning combined with PSO can improve wildlife sanctuary surveillance. We developed a YOLOv5 model that achieved high precision in real time video stream species identification. This technological breakthrough makes animal sighting more dependable for tourists and better wildlife monitoring and management possible, thus boosting conservation campaigns.

Our findings suggest that implementation of sophisticated algorithms such as PSO in hyperparameter optimization can significantly enhance deep learning models’ performance on natural environments with multiple factors to consider. As such, the system is efficient and robust, which makes it an important tool for wildlife-based tourism and protection efforts. Thus, this study sets a precedent for better ecological management initiatives in park settings through intelligent systems that benefit both animals and people visiting those habitats.

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