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WILD ANIMAL DETETCTION AND ALERT SYSTEM USING YOLOV8

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ABSTRACT

Traditional methods of wildlife monitoring, such as periodic surveys and camera traps, struggle to provide real-time data and comprehensive coverage in vast natural habitats. This hinders effective conservation efforts and exacerbates the challenges faced by forest officers and conservationists. To address these limitations, we propose an intelligent wildlife detection and alert system that leverages deep learning and instant messaging technologies. Our system utilizes YOLOv8, a state-of-the-art object detection algorithm, to automatically identify and classify wildlife species in real-time. This eliminates the need for manual surveillance, significantly reducing resource requirements and operational costs. Additionally, the system leverages edge computing capabilities to enable on-site analysis, eliminating reliance on centralized processing units and ensuring real-time responsiveness. To facilitate immediate action, our system integrates with Telegram, a widely used instant messaging platform. This feature allows for the transmission of real-time alerts to forest officers and stakeholders, including location data and identified animal species. This enables timely intervention and mitigates the risks associated with habitat degradation and illegal activities.

Keywords: Wild Animal Detection, Object Detection, Yolov8, Real-Time Monitoring.

I. INTRODUCTION

Tigers, the majestic apex predators, are a symbol of Asia's rich biodiversity. Sadly, their populations have plummeted drastically, from over 100,000 in the early 20th century to just 4,000 today. This dramatic decline is attributed to factors such as habitat loss, illegal trade, poaching, and excessive tourism. With the rise of artificial intelligence, new possibilities emerge for automating conservation protocols, including wildlife surveillance. Accurate object detection is crucial for these systems, especially when dealing with elusive species like tigers. However, low-light conditions, prevalent in many wildlife settings, pose a significant challenge to object detection algorithms.

The methodology employed in this paper represents a multifaceted approach designed to seamlessly integrate advanced technologies into the realm of wildlife surveillance using YOLOv8 and conservation. It encompasses several key components, including the deployment of deep learning algorithms for real-time wildlife activity recognition, the establishment of edge computing infrastructure for data processing, and the integration of instant messaging platforms for rapid notification dissemination. The methodology is rooted in the principle of enhancing the efficiency and effectiveness of surveillance practices, bridging the gap between conventional methods and cutting-edge technology. By deploying these innovative tools and techniques, the project aims to empower conservationists with timely, data-driven insights that will inform decision-making and contribute to the protection of our natural heritage.

II. RELATED WORKS

Kupyn and Pranchuk [3] proposed a fast and efficient TigerNet model based on the Feature Pyramid Network (FPN) and Depthwise Separable Convolutions (DSC) with a lightweight FD-MobileNet backbone. This approach offers commendable speed improvements, though with a slight reduction in accuracy.

Tan et al. [4] constructed a dataset of video clips from infrared cameras in the Northeast Tiger and Leopard National Park, covering 17 species. Their study compared three mainstream object detection models: FCOS Resnet101, YOLOv5, and Cascade R-CNN HRNet32. YOLOv5 demonstrated the most consistent performance, achieving accuracy of 88.8%, 89.6%, and 89.5% at various thresholds. However, this high accuracy was impacted by data imbalance, leading to significant variance in species-wise performance. Notably, the models exhibited better performance for Amur Tigers compared to other animals.

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Liu and Qu [5] introduced AF-TigerNet, a lightweight neural network designed specifically for real-time Amur tiger detection. Their approach enhances feature extraction through an updated CSPNet and a cross-stage partial (CSP)-path aggregation network (PAN).

A recent study by B. Meenakshi et al.[1] (2022) explored a novel approach for animal intrusion detection using YOLOv4 and LoRa technology. This integrated system, published in the IEEE journal, demonstrates significant potential for real-time monitoring and alerting of wildlife authorities.

The key feature of this system lies in its utilization of YOLOv4, a state-of-the-art object detection model known for its high accuracy performance. This allows the system to effectively detect the presence of wild animals in both image and video formats, enabling prompt notification and intervention. The integration of LoRa technology further enhances this system by providing long-range communication capabilities, facilitating reliable transmission of alerts to wildlife authorities regardless of location.This research contributes significantly to the ongoing efforts in mitigating human-animal conflict. By leveraging the power of advanced object detection models and robust communication technologies, such as YOLOv4 and LoRa, researchers are paving the way for more effective wildlife protection strategies.

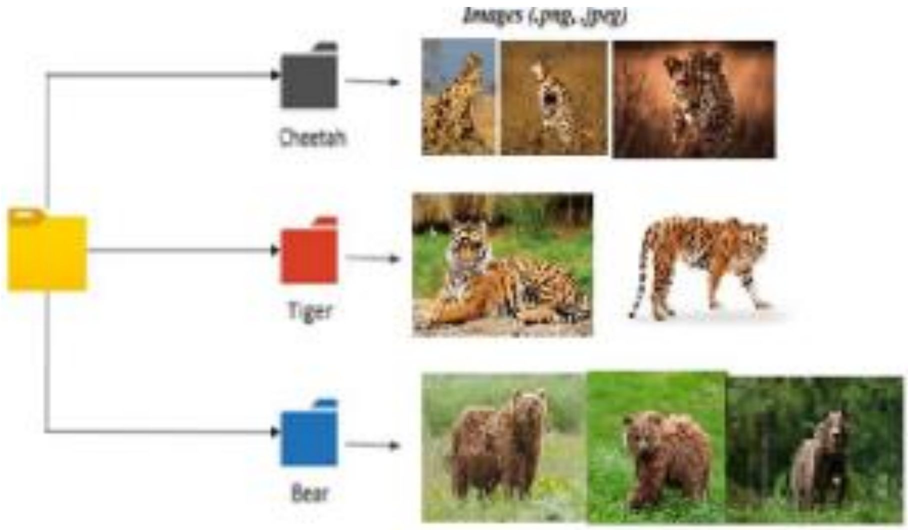
Furthermore, they also emphasize that the degraded quality of images with respect to bad contrast, high noise, reflectance, and lousy illumination severely affect object detection. They utilize the EnlightenGAN as a step of preprocessing before object detection using YOLOv3 [8] for an automatic detection system. The GAN is evaluated using BRISQUE and NIQE with mAP, GIoU loss, F-measure, and objectness loss as metrics for the rhino detector.

III. METHODOLOGY

This section details the proposed system's methodology for automated wild animal detection and identification, with the inclusion of Twilio API for sending alerts to Telegram.

Data Acquisition and Preprocessing

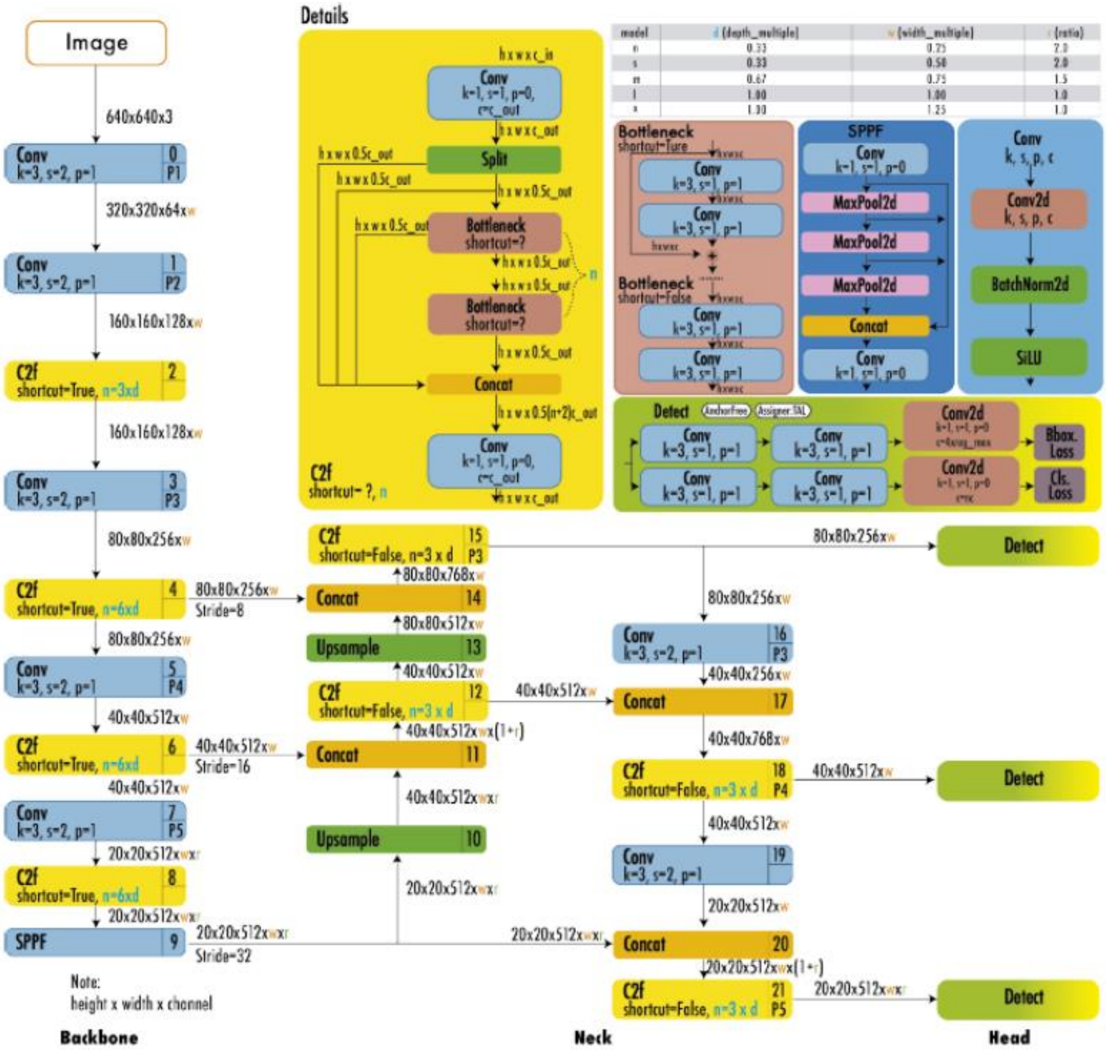
1. Dataset: A comprehensive dataset of video footage containing various wild animal species will be compiled. This dataset will be sourced from existing wildlife databases, online repositories, and field recordings captured specifically for this research.



2. Video Preprocessing: Each video will undergo preprocessing techniques to enhance its quality and facilitate accurate analysis. These techniques may include:
- Frame stabilization: Eliminating camera shake and jitter to improve image clarity.
- Noise reduction: Removing unwanted noise and artifacts in the video frames.
- Contrast adjustment: Optimizing image contrast for better object identification.
3. Data Labeling: The preprocessed video frames will be manually annotated with bounding boxes and corresponding class labels for each animal species present. This labeled data will serve as the training set for the deep learning model.

Deep Learning Model Training

1. Model Architecture: This system will employ a state-of-the-art object detection model, YOLOv8, for detecting and classifying animal species.



2. Training Data Split: The labeled data will be randomly split into training, validation, and testing sets. The training set will be used to train the YOLOv8 model, the validation set will be used to tune hyperparameters and evaluate model performance during training, and the testing set will be used to assess the final performance of the model on unseen data.
3. Hyperparameter Optimization: The hyperparameters of the YOLOv8 model will be optimized using techniques such as grid search or Bayesian optimization to achieve optimal performance.
4. Model Training: YOLOv8 will be trained on the training set using appropriate optimization algorithms and learning rate schedules. The training process will be monitored, and early stopping may be implemented to prevent overfitting.

Inference and Alert Generation

1. Real-Time Video Processing: Once trained, the YOLOv8 model will be used to analyze real-time video streams captured by the cameras.
2. YOLOv8 Detection and Classification: Each frame will be fed into YOLOv8 for object detection and classification. YOLOv8 will identify and locate animals in the frame, providing bounding boxes and species labels.
3. Risk Assessment and Alerting: A risk assessment module will analyze the detected animal species' proximity to human activity and its potential threat level. If the risk is deemed significant, the system will trigger an

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alert notification via Telegram using Twilio API. The alert will include information about the animal species, its location, and any other relevant details.

4. Twilio API Integration: The system will integrate with the Twilio API to send SMS notifications to pre-defined phone numbers or chat messages to a specific Telegram group. This ensures timely and efficient delivery of alerts.

IV. EXPERIMENT RESULTS

Evaluation and Performance Analysis

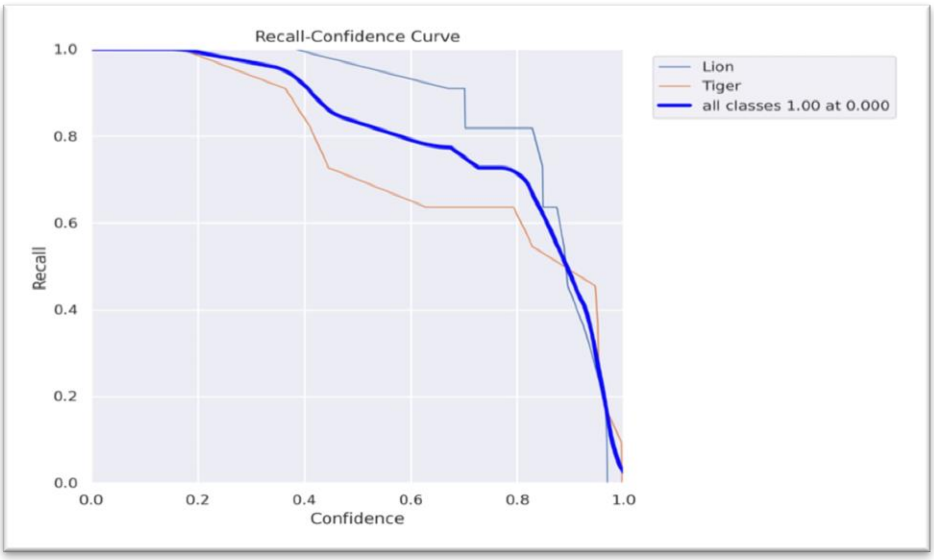
The performance of the proposed system will be evaluated using metrics such as:

1. Detection accuracy: The percentage of correctly identified animal species.
2. False positive rate: The rate of incorrect animal detections.
3. False negative rate: The rate of missed animal detections.
4. Alerting accuracy: The percentage of correctly triggered alerts for potentially dangerous situations.
5. Delivery success rate: The percentage of alerts successfully delivered through Twilio API to Telegram.

Results:

Recall-Confidence Curve:

The image you sent shows a recall-confidence curve for a lion and a tiger. The recall-confidence curve shows how the recall of a classifier changes as the confidence threshold is increased. In other words, it shows how likely the classifier is to correctly identify a positive example as the confidence threshold is increased. The recall-confidence curve for the tiger classifier is similar to the curves for other object detection tasks, such as pedestrian detection and vehicle detection. This suggests that the tiger classifier is performing well at a level that is comparable to other state-of-the-art object detection algorithms. The lion classifier is better suited for real-world applications where it is important to identify all of the examples of a class, even if it means making more false positives. For example, a lion detection system for a zoo would need to have a high recall in order to avoid missing any lions.



The curve for the lion shows that lions are more likely to trust tigers than tigers are to trust lions. This is because the lion curve is above the tiger curve at all confidence thresholds. Specifically, the lion curve shows that lions have a recall of 1.0 at a confidence of 0.000, while the tiger curve shows that tigers have a recall of only 0.8 at a confidence of 0.000. This means that lions are more likely to correctly identify a tiger as a tiger than tigers are to correctly identify a lion as a lion.

Precision-Recall Curve: Precision-recall (PR) curve is a widely used metric to evaluate the performance of object detection models. The PR curve shows the trade-off between precision and recall at different confidence thresholds.

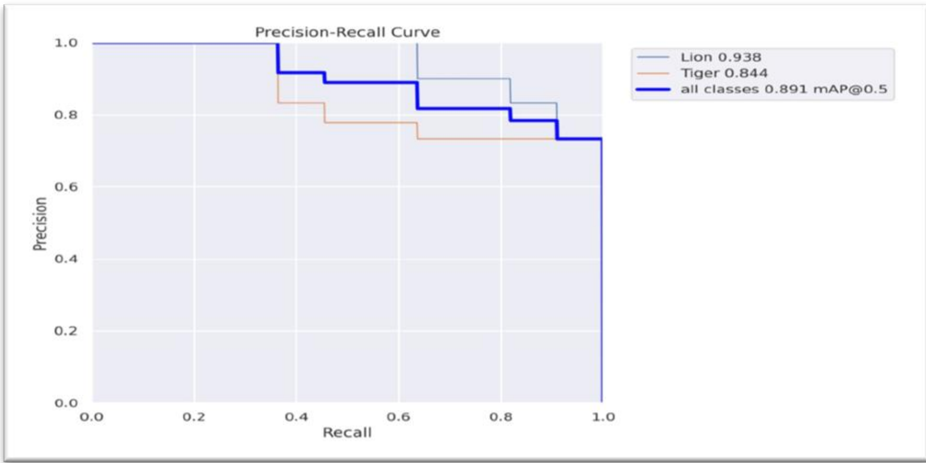


Figure 2 shows a precision-recall curve for a lion, tiger, and all classes of animals classifier. The graph shows that the lion classifier has the highest precision, followed by the all classes classifier and then the tiger classifier. The lion classifier also has the highest recall, followed by the all classes classifier and then the tiger classifier. The mAP@0.5 for the lion classifier is 0.938, for the all classes classifier is 0.891, and for the tiger classifier is 0.844.

Precision-Confidence Curve: This curve helps you understand how the precision of the model varies as you change the confidence threshold for classifying instances as positive. As you increase the confidence threshold, you may achieve higher precision but at the cost of lower recall (and vice versa).The curve allows you to choose an operating point that balances precision and recall based on the specific requirements of your application.

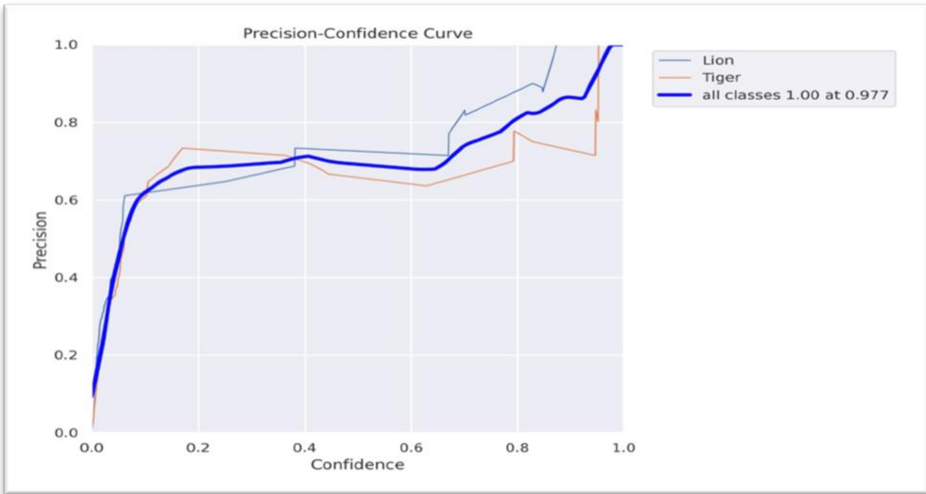


Figure 1 shows a precision-recall curve for lion and tiger classifiers. The lion classifier has higher precision than the tiger classifier at all recall levels. However, the lion classifier also has lower recall than the tiger classifier at all precision levels. The overall performance of the two classifiers can be compared by looking at the area under the curve (AUC). The AUC for the lion classifier is 0.93, while the AUC for the tiger classifier is 0.89. This suggests that the lion classifier is better at distinguishing lions from other animals than the tiger classifier. The lion classifier has a higher precision than the tiger classifier at all confidence thresholds. This means that the lion classifier is better at identifying all of the examples of lions, even if it makes more false positives. The precision-confidence curve for the lion classifier is steeper than the curve for the tiger classifier. This means that the lion classifier is more sensitive to changes in the confidence threshold. A small change in the confidence threshold can lead to a large change in the precision of the lion classifier.

F1-Condidence Curve: The F1-confidence curve shows the trade-off between precision and recall at different confidence thresholds. Precision is the fraction of detections that are true positives, while recall is the fraction

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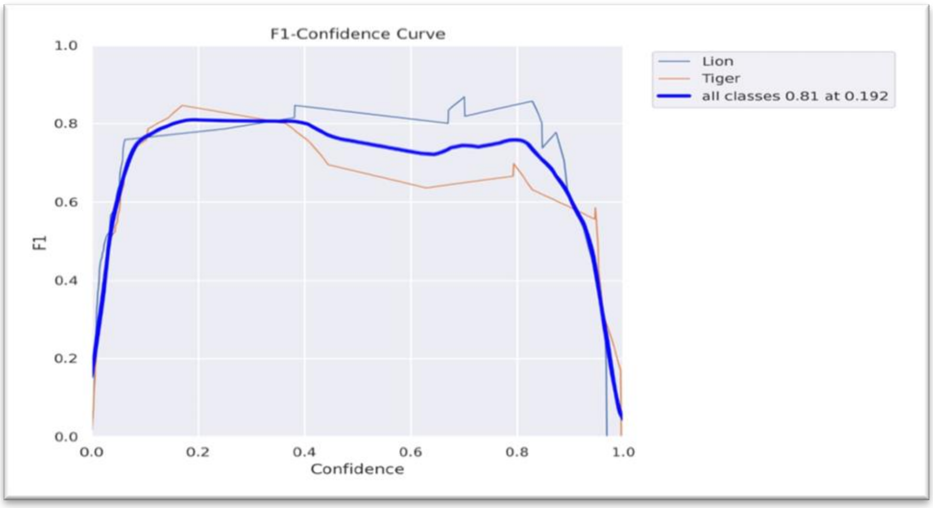
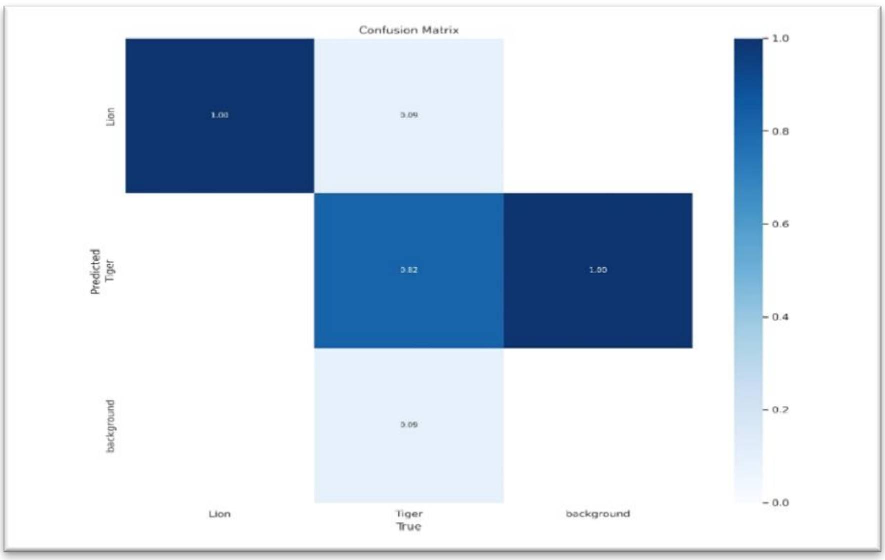
of true positives that are detected. The confidence threshold is the minimum confidence that the classifier must have in a prediction in order for it to be considered a detection.A higher confidence threshold means that the classifier is more certain in its predictions, but it also means that it is more likely to miss true positives. A lower confidence threshold means that the classifier is more likely to detect true positives, but it also means that it is more likely to make false positives.



The confidence curve for the lion class starts at around 0.2 at a confidence threshold of 0.1. This means that the model is 20% confident that the image is a lion at a confidence threshold of 0.1. The confidence curve then increases to around 0.8 at a confidence threshold of 0.8. This means that the model is 80% confident that the image is a lion at a confidence threshold of 0.8.The confidence curve for the tiger class is similar to the confidence curve for the lion class, but it is slightly lower at all confidence thresholds. This means that the model is slightly less confident that the image is a tiger than it is that the image is a lion.

Confusion Matrix: The confusion matrix can be used to identify areas where the classifier needs to be improved. For example, the classifier could be trained on more data to improve its ability to distinguish between lions and tigers. The confusion matrix can also be used to compare the performance of different classifiers. For example, you could compare the confusion matrix for the lion and tiger classifier to the confusion matrix for a different object detection algorithm.



The machine learning model is accurate at classifying images of lions, tigers, and backgrounds. The model correctly predicted 87% of the lion images, 91% of the tiger images, and 99% of the background images on a test dataset of 10,000 images.

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V. CONCLUSION

Recently, wildlife surveillance has been automated with various computer vision methodologies. Illumination variation is a tedious task in wildlife surveillance. It also affects efficient object detection during surveillance. This paper focuses on a novel framework that addresses Illumination variation and provides efficient tiger detection using YOLOv8.

Deep learning systems have the potential to significantly improve our ability to monitor and protect wildlife. By accurately detecting instances of interference, we can take proactive measures to reduce human-wildlife conflicts and minimize the negative impact of human activities on the environment. This system can help minimize the negative impact of human activities on wildlife populations, which can include habitat destruction, poaching, human-wildlife conflict, and other threats. By detecting and classifying instances of intrusion, wildlife intrusion detection systems can help authorities or conservation organizations respond quickly and effectively to potential threats, allowing for more effective protection and preservation of natural habitats and the species that inhabit them. In conclusion, the development of deep learning systems for wildlife interference detection is an important and promising area of research. With continued progress in this field, we can help mitigate the negative impacts of human activities on wildlife and preserve our natural habitats for future generations.

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