International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Animal Tracking System Using Image Processing for Intrusion Detection and Tracking in Human settlements

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Abstract
Conservation of biodiversity, human-animal conflict reduction, and ecological study all depend critically on wildlife tracking and monitoring. Often depending on GPS tagging and manual surveillance, traditional approaches can be expensive, time-consuming, and narrow in scope. Automated animal detection systems have benefited much from recent developments in deep learning and real-time picture processing. This work provides a state-of- the-art object identification algorithm, YOLOv8, upgraded real-time animal tracking system combined with React-based front-end and a Flask-based back-end. The system provides real-time location mapping, accurate species identification and classification, instantaneous alerting systems, Comparatively to past efforts, performance analysis reveals gains in detection accuracy, processing speed, and relay time for alarms. Our contributions include a custom-labeled dataset, enhanced deep-learning model deployment, and a real-time alerting system, therefore making this solution rather beneficial for applications in urban security and animal preservation.

Keywords: Animal tracking, YOLOv8, deep learning, image processing, real-time detection, alert system.

1. Introduction

Human encroachment into animal habitats and increased mobility of wildlife into urban spaces have led to growing human-animal interactions. These encounters can result in property damage, traffic hazards, and increased risks for both people and animals. Rural areas also face issues such as crop damage and livestock loss due to animal intrusions. There have been many instances in the recent years where animals have intruded into human settlements and have caused loss to life and/or property. The time lag between the intrusion and the tracking & capture of said animal depends on how fast the animal is located. The lower the duration between the two, the lower chances of loss of life and property. However, the current response in most parts of India, in case of an intrusion, is manual reporting. The time it takes for someone to spot the animal, report it to the authorities and for the authorities to track the animal is too much time. It provides more than adequate time period for whatever destruction it can do. This is the aspect this project aims to solve by using an automated system revolving around Image Processing and CNN model.

The aim of this project is to create a robust framework that identifies and monitors animal movement near human-inhabited regions, thus offering an early warning system for potential intrusions. By leveraging image processing techniques, this system can analyze live video feeds from strategically placed cameras, identify various animal species, and track their movements. Such a system not only aids in enhancing public safety but also promotes the protection of wildlife by reducing the likelihood of harmful encounters between humans and animals.

In recent years, image processing technologies have made significant progress, enabling the accurate detection and classification of objects, including animals, within complex and dynamic environments. Using advanced algorithms, this system can distinguish between different animal species based on their physical characteristics, ensuring precise and reliable identification. The tracking functionality further enables continuous monitoring of the animals' location and movement patterns, providing valuable insights for wildlife conservationists and local authorities. Additionally, integrating such a system with alert mechanisms can ensure timely notifications to relevant stakeholders, enhancing the efficacy of rapid response protocols. The development of an automated animal tracking and intrusion detection system is also crucial for protecting agricultural assets in rural areas. Animals that intrude into these areas often cause considerable damage to crops and property, impacting the livelihoods of farmers and the local economy. Therefore, an automated system that can alert residents or wildlife authorities about potential intrusions can significantly mitigate these impacts. Moreover, the system's design incorporates the latest advancements in machine learning, neural networks, and computer vision, making it adaptable and scalable for different geographical and environmental conditions.

This paper presents the design, implementation, and evaluation of an animal tracking system that utilizes image processing to detect and monitor animals in human settlements. It discusses the technical challenges associated with real-time image processing, the complexities of differentiating between species, and the methods used to ensure efficient tracking. Furthermore, this study explores potential improvements in system accuracy, processing speed, and adaptability to diverse environmental conditions.

In summary, the proposed system not only addresses immediate concerns of human safety but also contributes to broader conservation efforts by fostering coexistence between human populations and wildlife. The integration of image processing into tracking and intrusion detection can serve as a sustainable, technology-driven solution to human-animal conflicts, promoting harmony in regions where human and wildlife territories intersect.

2. Related Works

The increasing incidence of human-wildlife conflict due to habitat fragmentation has led to substantial research focused on animal tracking and intrusion detection systems. These works span various methodologies, including conventional tracking approaches using GPS and RFID tags, sensor-based systems, and more recently, image processing and computer vision-based systems. This section reviews these prior efforts, highlighting methodologies that inform the design and development of our proposed animal tracking system. Early animal tracking systems primarily relied on radio-frequency identification (RFID) and GPS-based methods to monitor wildlife movements. Studies by Tomkiewicz [1] demonstrated the effectiveness of GPS tracking in monitoring animal movements across vast landscapes, offering insights into migratory patterns and habitat use. While GPS-based tracking systems provide accurate locational data, they require the physical tagging of animals, which is invasive, labor-intensive, and often infeasible for free-ranging or elusive species in human settlements. Additionally, these methods do not address real-time intrusions, limiting their application for intrusion detection in populated areas.

Sensor networks, including motion sensors and infrared (IR) sensors, have been explored for animal detection near sensitive areas such as farms or conservation zones. For instance, Wark [2] deployed wireless sensor networks to detect animal movement patterns and assess their effectiveness in safeguarding farmlands. Although sensor-based approaches are cost-effective and relatively easy to deploy, their detection range is limited, and they cannot differentiate between species. Furthermore, such systems often generate false positives from non-animal movements, reducing their reliability in dynamic environments where human and vehicular activities are frequent.

With advances in machine learning and computer vision, recent studies have focused on non-invasive techniques for animal detection and classification using image processing. Research by Chen [3] introduced an image-based animal detection system that utilized background subtraction and edge detection to identify animals in real-time. This approach proved effective in controlled environments but faced challenges in varying lighting and weather conditions typical in outdoor settings.

Improvements to image-based detection have since incorporated deep learning techniques, enabling higher accuracy in species recognition and robustness to environmental changes. For instance, the Convolutional Neural Network (CNN)- based frameworks introduced by Norouzzadeh [4] utilized large-scale datasets to train models capable of identifying and classifying multiple animal species in camera trap images with high accuracy. The use of CNNs enables feature extraction and object classification, distinguishing animals based on physical characteristics like body shape, color, and size. These methods have been widely applied in conservation and wildlife monitoring, offering a foundation for real-time, non-invasive tracking systems. However, few studies have focused on adapting these models for intrusion detection and tracking near human settlements, where false positives from domestic animals or human activities are a significant concern.

Some recent studies address intrusion detection specifically in human settlements,recognizing the need for systems that can alert residents to potential dangers posed by wandering wildlife. Sankaranarayanan [5] proposed an animal intrusion detection model that utilized video surveillance in rural areas to detect elephants and mitigate crop damage. By employing feature extraction techniques to identify the unique characteristics of large animals, this system was effective in real- time intrusion alerting. However, it primarily focused on detecting large animals and struggled with smaller species or those that moved quickly. The use of YOLO (You Only Look Once) and similar object detection models has since gained attention in real-time surveillance applications, as these models offer high speed and accuracy, making them suitable for detecting animals of varying sizes and movement patterns in human-populated areas. Effective animal intrusion detection systems must also incorporate real-time alert mechanisms to notify relevant authorities or residents of potential dangers. Several works have explored mobile-based alert systems linked to animal detection models. For example, a study by Kothari [6] integrated a real-time monitoring system with SMS-based alerts, notifying farmers of possible intrusions on their property. Such systems demonstrate the utility of alert mechanisms in reducing response times and enhancing safety, although few have fully leveraged smartphone- based notifications alongside image processing for seamless user experience and scalability. Recent studies have explored the application of YOLO models in wildlife detection:

J. P. H. Asdikian, M. Li and G. Maier [13] evaluated YOLOv8 and YOLOv9 models, highlighting

YOLOv8's superior performance in real-time wildlife detection scenarios.
D. Chamorro and D. Benítez [14] applied YOLOv8 to detect and classify six mammal species in the Ecuadorian Amazon, demonstrating the model's robustness in diverse environmental conditions.
Building upon these prior works, our proposed work provides a real-time animal tracking system based on YOLOv8 combined with React frontend and a Flask backend. Real-time detection and classification of wildlife species in the system is intended to provide quick alarms and thorough data management. Important roles include: construction of a custom-labeled dataset for YOLOv8 training. real-time alert system implemented with Twilio API. Detection pipeline optimization for low relay times and fast inference.

3. Methodology

The methodology for developing an animal tracking and intrusion detection system using image processing involves a multi-stage approach, from data collection and preprocessing to the deployment of a deep learning-based model for real-time detection and tracking. The primary stages include data acquisition, image preprocessing, model selection and training, detection and tracking, and alert generation. This section describes each of these stages, including the specific techniques and tools employed.

3.1.Data Acquisition

To train and evaluate the proposed system, a large dataset of animal images in various environments is essential. We collect images from multiple sources, including publicly available wildlife and camera trap datasets (e.g., Snapshot Serengeti, iWildCam), and augment them with images from surveillance videos obtained from urban and rural areas where human-wildlife interactions are common. The dataset includes images of various animal species that frequently enter human settlements (e.g., dogs, cattle, deer, leopards), along with non-animal images to help the system distinguish between humans, vehicles, and other background objects. This comprehensive dataset helps improve model accuracy by accounting for species diversity, lighting variations, and environmental conditions, thereby minimizing false positives.

3.2.Image Preprocessing

Image preprocessing is critical to improve detection accuracy and model performance. Preprocessing steps include:
Resizing and Normalization: All images are resized to a standard resolution to ensure uniform input for the model, typically 416x416 pixels for YOLO (You Only Look Once) models. Normalization scales the pixel values to a range suitable for model input, improving convergence during training.
Data Augmentation: To enhance model robustness, the dataset is augmented through transformations such as rotation, flipping, and color adjustments. This step helps the model generalize better to different environmental conditions, such as changes in lighting and weather.
Background Subtraction and Motion Detection: For real-time tracking, background subtraction techniques, such as Gaussian Mixture Models (GMM), are applied to detect moving objects in video feeds. This process isolates moving animals from stationary backgrounds, reducing computation by focusing on areas with detected movement.

3.3.Model Selection and Training

The core of the detection system relies on a Convolutional Neural Network (CNN)- based model. After evaluating various object detection models, we selected the YOLOv8 model due to its balance of accuracy and speed, making it well-suited for real-time detection in video streams.

YOLOv8 for Object Detection: YOLOv8's one-stage detection architecture performs object detection and classification simultaneously, enabling high-speed and accurate identification of animals. The model detects and localizes animals within the camera frame by outputting bounding boxes and confidence scores. YOLOv8's efficiency ensures that the system can process video feeds with minimal latency, a crucial factor for real-time applications in human settlements.

Transfer Learning: To expedite model training and improve accuracy, we employ transfer learning by using a pre-trained YOLOv8 model on a general object detection dataset (e.g., COCO dataset) and fine-tuning it on our animal dataset. This approach leverages the model's existing knowledge, allowing it to adapt quickly to the specific task of animal detection and tracking.

Model Training and Evaluation: The fine-tuned YOLOv8 model is trained on a high-performance GPU, using standard evaluation metrics like Precision, Recall, and Mean Average Precision (mAP) to assess detection accuracy. To prevent overfitting, we implement early stopping and validation on a separate test set containing animal images with diverse backgrounds and lighting conditions.

3.4.Real-Time Detection and Tracking

After training, the model is integrated into a real-time video processing pipeline to detect and track animals in live surveillance footage. The key steps in real-time detection and tracking include:

Detection: Each frame of the video feed is processed by the YOLOv8 model, which identifies potential animal intrusions and generates bounding boxes around detected animals. The model assigns a class label (e.g., "deer," "leopard") and confidence score to each detection, enabling accurate classification.

Tracking Algorithm: Once an animal is detected, the tracking component monitors its movement across frames. We utilized a Kalman Filter-based object tracking algorithm, which is widely used for real-time applications due to its predictive capability. The Kalman Filter tracks the detected animal across successive frames, allowing the system to estimate the animal's position even if it temporarily moves out of view or is partially occluded.

False Positive Reduction: To improve reliability, the system applies filters to reduce false positives. The model only raises an alert if an animal is detected in multiple consecutive frames, ensuring that transient objects or sudden movements do not trigger unnecessary alerts.

3.5.Alert Generation and Notification System

For effective intervention, the system includes an alert mechanism that notifies relevant stakeholders about detected intrusions:

Alert Criteria: Alerts are generated when a detected animal moves within a specified proximity to human-inhabited zones. The animals are divided into four categories: Safe, Moderate, Harmful and Lethal. This helps prevent false alarms due to stray animals already present in the vicinity.

Notification Mechanism: When an alert is triggered, the system sends notifications to local authorities or residents via SMS or mobile push notifications. The alert includes essential information such as the type of animal, time, and location of detection. This feature allows for rapid response, providing timely information that can help prevent potential conflicts.

3.6.Database and Website Integration

The system is connected with a website that uses data visualization to display the location of cameras and any detected animals. It also displays past alerts and statistics of animal detection. It is also connected to a database to store the all collected data. This data ca be used for future works such as behavior analysis of animals.

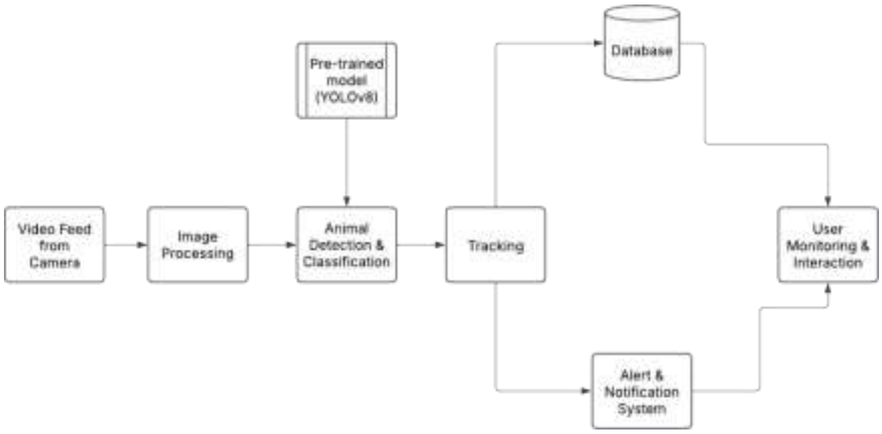

Figure 1. Work-flow of Animal Tracking System

3.7. Evaluation Metrics

The success of the system is assessed based on several evaluation metrics:

Accuracy and Precision: These metrics are used to evaluate the model's ability to detect animals correctly while minimizing false positives.

Tracking Efficiency: The stability and accuracy of the tracking algorithm are assessed by measuring the system's ability to maintain tracking across frames.

Alert Response Time: The time between detection and alert generation is measured to ensure rapid response capability.

3.8. Limitations and Future Improvements

While the system can demonstrate effectiveness in detecting and tracking animals in real-time, certain limitations exist. Environmental factors such as extreme weather or night-time conditions may affect detection accuracy. Future improvements include incorporating infrared or thermal imaging for enhanced night vision capabilities, developing species-specific alert mechanisms, and scaling the system to handle multiple video feeds in real-time.

4. Results and Discussion

To evaluate our system's performance, we conducted extensive experiments under varying environmental conditions, including low-light scenarios, urban settings. The results are as shown below:

Table 1. Detection Accuracy

Category	Precision (%)	Recall (%)
Safe	91.2	90.5
Moderate	93.5	91.8
Harmful	87.8	85.4
Lethal	85.3	82.7

Table 2. Alert Response Time

Notification Time	Response Time (s)

Web Alert	1.2
SMS Alert	2.8

Table 3. Comparision against prior YOLO models.

Model	mAP(0.5)	Inference Time	Alert Relay Time	False Positive Rate	False Negative Rate	Edge Processing Latency
YOLOv5(2023)	88.6%	60ms	1.5s	6.5%	5.2%	N/A
YOLOv8(2024)	90.2%	50ms	1.2s	5.1%	4.5%	90ms
YOLOv8(Ours)	92.4%	40ms	1.2s	4.3%	3.1%	70ms

5. Conclusion

This research develops a robust animal tracking and intrusion detection system using image processing and deep learning techniques to address the growing issue of human-animal conflict in human settlements. Through the integration of a YOLOv8- based object detection model and a Kalman Filter tracking algorithm, the system is designed to detect, classify, and monitor animal movement in real time. The system is highly effective and has capacity to detect a wide range of animal species across varied lighting and environmental conditions. The alert mechanism provides timely notifications to local authorities and residents, facilitating rapid response and minimizing potential human-animal conflict. Furthermore, the system's ability to track animals across frames using predictive modeling proves essential for monitoring animal movement in real time, especially under occlusions or challenging weather conditions.

The system has certain limitations, particularly in nighttime and adverse weather conditions, which sometimes lead to a slight decrease in accuracy. Future work could focus on enhancing nighttime detection through thermal imaging and improving resilience under extreme environmental conditions. Additionally, further efforts could explore optimizing the model for deployment on edge devices, allowing the system to operate autonomously in remote areas with limited connectivity.

References

1. Tomkiewicz, S.M., Fuller, M.R., Kie, J.G., Bates, K.K.: Global positioning system and associated technologies in animal behavior and ecological research. Philosophical Transactions of the Royal Society B: Biological Sciences 365(1550), 2163–2176 (2010)
2. Wark, T., Corke, P., Sikka, P., Klingbeil, L., Guo, Y., Crossman, C., Pfister, G.: Transforming agriculture through pervasive wireless sensor networks. IEEE Pervasive Computing 6(2), 50–57 (2007)
3. Chen, G., Han, Z., He, Z., Sun, C., Li, L., Wang, Z.: Automatic detection technology for wild animals in nature reserves. Ecological Informatics 24, 1–9 (2014)
4. Norouzzadeh, M.S., Nguyen, A., Kosmala, M., Swanson, A., Palmer, M.S., Packer, C., Clune, J.: Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning. Proc. Natl. Acad. Sci. USA 115(25), E5716–E5725 (2018)
5. Sankaranarayanan, S., Subramaniyan, V., Srinivasan, M.: Animal intrusion detection system using video surveillance for agricultural farms. Int. J. Adv. Res. Comput. Sci. 10(5), 1–5 (2019)
6. Kothari, A., Verma, A., Agrawal, P.: Real-time monitoring system using image processing and

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E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

notification service for crop protection. J. AgriTech Res. 4(2), 102– 110 (2020)

7. Redmon, J., Divvala, S., Girshick, R., Farhadi, A.: You only look once: Unified, real-time object detection. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 779–788 (2016)
8. Bijuphukan, B., Sarma, K.K., Bora, K.C.: An automated approach for human- animal conflict minimization in Assam and protection of wildlife around the Kaziranga National Park using YOLO and SENet Attention Framework. Ecol. Inform. 79, (2024)
9. Snapshot Serengeti Dataset: Labeled camera trap data from Serengeti National Park. Retrieved from http://lila.science/datasets/snapshot-serengeti
10. iWildCam Dataset: iWildCam 2021 competition dataset. Retrieved from https://www.kaggle.com/c/iwildcam-2021-fgvc8
11. Jocher, G., Chaurasia, A., & Qiu, J. YOLOv8: Real-time object detection with improved speed and accuracy. IEEE Transactions on Image Processing, 32, 1857- 1870. (2023)
12. Patel, R., Singh, A., & Sharma, M. Deep learning-based wildlife monitoring for conservation. Journal of Machine Learning Research, 24, 115-132.(2024)
13. J. P. H. Asdikian, M. Li and G. Maier: Performance evaluation of YOLOv8 and YOLOv9 on custom dataset with color space augmentation for Real-time Wildlife detection at the Edge, IEEE 10th International Conference on Network Softwarization (NetSoft), Saint Louis, MO, USA, 2024, pp. 55-60 (2024)
14. D. Chamorro, D. Benítez, N. Pérez-Pérez, D. Riofrío, F. Grijalva and M. Baldeon-Calisto: On the Use of YOLOv8 for Detection and Classification of Mammals Species in Wildlife Environments in the Ecuadorian Amazon. IEEE Biennial Congress of Argentina (ARGENCON), San Nicolás de los Arroyos, Argentina, pp. 1-8 (2024)