2024 Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM) | 979-8-3503-6509-2/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICONSTEM60960.2024.10568876

Strategies and Technologies for Alleviating Human Wildlife Conflict: A Technical Analysis and Comparative Study

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Abstract- The preservation of wildlife and forests is paramount for maintaining ecological balance, biodiversity, and ensuring the sustenance of life on Earth. The challenge of mitigating human-wildlife conflict demands a proactive approach, leveraging technology to detect and prevent territorial encroachment, thus safeguarding biodiversity and enhancing safety in forest ecosystems. Machine learning algorithms, such as YOLOv5, play a pivotal role in revolutionizing forest conservation efforts, offering real-time monitoring capabilities to detect and classify human and animal movements accurately. The role of machine learning algorithms in preventing human-wildlife conflict is explored through this literature review. This work explores the larger application of machine learning algorithms in mitigating human-wildlife encounters, fostering a sustainable coexistence between humans and wildlife in critical ecosystems.

Keywords—Human-wildllife, Machine Learning, YOLOv5

I. Introduction

Human-wildlife conflicts have been escalating in recent times, spurred by factors such as urbanization, industrialization, and habitat loss. As human populations expand into previously uninhabited areas, encounters with wildlife become inevitable, leading to clashes over resources and space. Rapid urban development encroaches upon natural habitats, disrupting ecosystems and forcing wildlife into closer proximity with human settlements. This intensification of conflicts not only threatens biodiversity but also jeopardizes human livelihoods and safety. These conflicts pose significant challenges for conservation efforts and require sustainable solutions that balance human needs with wildlife conservation goals. Addressing the root causes of these conflicts is essential for promoting harmonious coexistence between humans and wildlife.

A. Why monitor human and wildlife?

Human-wildlife conflict leads to human and animal fatalities, agricultural losses, destruction of assets, habitat degradation, and decline in wildlife populations along with shrinking habitats[11]. Animal-vehicle collisions emphasize the critical need for proactive measures to mitigate road hazards and safeguard both human and wildlife populations[12]. The complex wildlife poaching dynamics in rural areas, driven by economic concerns, livestock protection, and human-wildlife conflict, underscores the need for comprehensive conservation strategies[13].

B. Use of machine learning in mitigating conflict

Machine learning enhances animal detection systems for tackling wildlife-vehicle collisions and human-wildlife encounters. Adopting recent breakthroughs in machine learning minimizes false detections and optimizes model performance. Challenges like detecting hotspot areas and improving training datasets highlight the importance of machine learning in mitigating human-wildlife conflicts[14].

C. Why use YOLO algorithm?

The YOLO algorithm, integrated with an IP camera, Raspberry Pi, and deep learning technology, effectively addresses human-animal conflicts by swiftly detecting wildlife intrusion. YOLO's real-time object detection capabilities allow for quick identification of animals in images captured by the IP camera, enabling timely intervention to prevent conflicts. The Raspberry Pi serves as a compact computing platform for running YOLO locally, minimizing latency and facilitating rapid alarm generation upon detection. Deep learning technology, particularly YOLOv3, ensures high accuracy in identifying animals under varying conditions, enhancing the system's reliability in assessing threats and alerting relevant authorities. Overall, this integrated system provides a proactive approach to mitigating human-animal conflicts and promoting coexistence in shared habitats[15].

II. LITERATURE REVIEW

[1] Emmanuel Onwuka focused on the prevalent issue of crop vandalization occurring between farmers and herdsmen in Nigeria. It introduces an innovative solution in the form of an IoT-based farm intrusion detection model employing RFID and image recognition technology. The system utilizes sensors to read workers' tags for identification purposes, alongside cameras to capture user images for further identification. These images are then transmitted to a Convolutional Neural Network for recognition. The model boasts impressive performance metrics, with reported accuracy of 90%, precision of 70%, and a recall rate of 80%. Through the implementation of this technology, the paper claims to effectively control the incidence of illegal encroachment into farmland.

[2] Lewis explore the diverse impacts of mobile phone use in mitigating human wildlife conflict among Maasai communities, revealing the multifaceted roles of mobile technology. Which is a much traditional approach as it utilized the general calling feature of the mobile phone to alert communities via call from a forest officer, doesn't deal much into the process of detection of the animals as this paper makes the assumption that the forest officers have their own system of detecting animals. Hence the paper doesn't cover the concept of animal detection as it mostly deals in second phase which is efficient communication post detection. More over the paper has limited geographical scope as they are approach is limited to the villages in and around areas in Northern Tanzania.

[3] Nguyen significantly advances ecological research by revolutionizing wildlife monitoring through the utilization of deep convolutional neural networks for precise and automated animal recognition in camera trap images. Using the Wildlife Spotter Project dataset, a collaborative effort engaging citizen scientists, highlighting the significance of community involvement in gaining valuable insights. The paper delves deeply into the intricacies of CNN algorithms, offering a comprehensive comparative analysis of different CNN architectures tailored for image classification tasks.

AlexNet with 8 trainable layers out of which 5 are convolution layers and 3 are fully connected layers. VGG-16 with 16 Trainable layers out of which are 13 convolution layers with 3x3 filters and 3 fully-connected layers. GoogLeNet with 22 Trainable layers which reduces the number of parameter while achieving high accuracy and uses an Average pooling layer instead of a fully connected layer. ResNet-50 which has 50 trainable layers which is load intensive but have a lower complexity and a higher performance

On Evaluation of the above models, it was found that AlexNet performed rather poorly with a lower F-measure and accuracy of 91.48% and 94.91%. While VGG-16 's F-measure and accuracy was 93.70% and 91.48%, which was slightly greater than that of ResNet-50 whose F-measure was 93.36% and accuracy was 96.11%. Hence VGG-16 seemed to be more efficient as the computation cost of ResNet-50 was far greater than that of VGG-16.

[4] Shanmugasundaram introduced an IoT-based animal tracking system tailored for zoo environments, integrating sensors and GPS technology to comprehensively monitor animal locations and health status. This comprehensive approach utilizes a tech stack comprising a PIC microcontroller, temperature sensor (LM35), PIR sensor, and GPS device. The system is divided into two main components: the sensing part, which incorporates the temperature and PIR sensors to gather data, and the monitoring part, which processes this data in real-time. The GPS modem is employed to retrieve longitude and latitude information, communicating with the microcontroller via serial communication. The PIC 16F877 microcontroller, known for its advanced features and widespread use in experimental and modern applications due to its affordability, versatility, and availability, serves as the central processing unit of the system, facilitating efficient data management and ensuring the animals' well-being and safety with minimal human intervention.

[5] Wang's research focuses on movement ecology through the integration of GPS and accelerometers with machine learning techniques. By utilizing state space models, the study provides valuable insights into animal behavior. Predominantly, state space models and hidden Markov models are applied for unsupervised learning on GPS data, allowing for the inference of distinct behavioral patterns. Additionally, supervised learning algorithms like random forests and support vector machines are employed to classify behaviors using synchronized observations of animal behavior alongside location and acceleration data. However, it is important to note that the paper primarily focuses on mathematical and theoretical approaches based on probabilities, lacking real-world accuracy or test results.

[6] Pitman introduces a novel approach by integrating convolutional neural networks with the efforts of citizen scientists, significantly reducing the manual labor required for species identification in camera trap images. The paper addresses the challenge faced by ecologists who deploy camera traps for wildlife studies, resulting in vast datasets that are cumbersome to evaluate manually. To tackle volunteer shortages, the study employs machine learning, particularly deep learning techniques, to automate image classification using datasets annotated by citizen scientists. The results demonstrate high accuracies ranging from 91.2% to 98.0% for identifying empty images and between 88.7% and 92.7% for specific species. Furthermore, leveraging transfer learning from

CNNs trained on large datasets proves increasingly advantageous as the size of the training dataset decreases, resulting in accuracy improvements of up to 10.3%.

[7] Ibraheam achieve an exceptional 99.8% accuracy in wildlife-vehicle detection using deep learning, leveraging British Columbia Ministry of Transportation and Infrastructure (BCMOTI) and Snapshot Wisconsin data for robust training. The Reconyx Hyperfire™ PC900 camera was used for their research. The proposed recognition system in comprises two CNN image classification models, with the first model acting as a binary classifier for detecting animals or humans and the second CNN model is designed as a multi-class classifier, identifying seven possible animal species, including bear, elk, deer, moose, etc. The 2 CNNs in used in a 'cascade filtering' approach enables hierarchical learning, reducing testing time through feature compression in the fully-connected layers. Training and evaluation were conducted on the BCMOTI and Snapshot Wisconsin datasets, split into 70% for training, 15% for validation, and 15% for testing.

[8] Jeremy paper's main goal aims for the preservation of Tiger population in India, which was once on the verge of extinction. To achieve the same the TrailGuard AI camera-alert system, developed by Nightjar in Washington, DC, USA, represents a groundbreaking approach to wildlife conservation in India, which houses approximately 66% of the world's wild tiger population, and 35% of this increasing population permanently resides outside designated tiger reserves.

It provided a better alternative to traditional camera traps which face challenges such as false triggers, data processing costs, and theft. TrailGuard AI addressed these issues by employing embedded artificial intelligence via an advanced computer vision chip from Intel to autonomously identify and filter wildlife and human detections in real-time. This advanced system, validated using camera trap photos and three-dimensional species renderings, not only improves the accuracy of species identification but also conserves battery life as when it is not in action, the entire system is powered off and draws only 7–10 microamps, allowing for more transmissions on a single charge. It had undergone its physical trial and testing in Kanha–Pench corridor in India. Though on the physical level its advantages are mentioned there is no mention of the algorithm or model which is being used nor is there a measure of the accuracy or f1 score.

[9] Emmanuel Kipchumba addresses the escalating human-wildlife conflict in Tanzania by proposing an innovative solution leveraging IoT technology and SMS for prompt response. Their system integrates sensing, processing, and alerting units, utilizing PIR sensors, GPS, and Raspberry Pi cameras for wildlife detection. With more than 1,000 deaths and 20,000 injuries in Tanzania from 2012-2019 due to human-wildlife conflict, it is clear that urgent action is needed to address this issue. Processing is streamlined through a Raspberry Pi microcomputer running the YOLO algorithm, achieving impressive training accuracy of 90% and validation accuracy of 78%. Notably, the system sends SMS alerts to response teams upon animal detection, showcasing the transformative potential of technology in mitigating human-wildlife conflict while bolstering support for local communities.

[10] Mengyu presents a thorough study where researchers create the Northeast Tiger and Leopard National Park wildlife dataset (NTLNP dataset) to evaluate the effectiveness of three mainstream object detection models: YOLOv5, FCOS, and Cascade R-CNN. Their rigorous assessment, conducted on both day and night imagery, demonstrates satisfactory performance, with YOLOv5m exhibiting the highest recognition accuracy. These results highlight the potential of AI technology to transform wildlife research and conservation efforts by efficiently processing large volumes of camera trap imagery, thereby saving time and resources for ecologists. Additionally, the study achieves notable metrics, including a mean average precision (mAP) of 0.98 in animal image detection, 88% accuracy in animal video classification, and an average recall rate of 0.90 across all tested models.

III. Technologies

Paper	**Main Focus**	**Technology/Methodology**	**Key Findings/Results**
Emmanuel Onwuka	Crop vandalization, IoT-based farm intrusion detection.	RFID, Convolutional Neural Network.	Reported accuracy of 90%, precision of 70%, recall rate of 80% in controlling illegal encroachment into farmland.
Lewis	Impact of mobile phone use in mitigating human-wildlife conflict.	Utilized general calling feature of mobile phones for community alerts.	Limited geographical scope in Northern Tanzania, emphasis on efficient communication post detection.
Nguyen	Wildlife monitoring using deep CNN.	CNN algorithms: AlexNet, VGG-16, ResNet-50;	Comparative analysis of CNN architectures, highlighted

		Dataset: Wildlife Spotter Project dataset.	importance of community involvement.
Shanmugasundaram	IoT-based animal tracking system for zoos.	PIC microcontroller, temperature sensor (LM35), PIR sensor, GPS device.	Real-time monitoring of animal locations and health status.
Wang	Movement ecology using GPS and accelerometers with machine learning.	State space models, hidden Markov models, supervised learning algorithms.	Mathematical and theoretical approach focusing on behavioural patterns.
Pitman	Species identification in camera trap images using CNNs and citizen scientists.	Transfer Learning on CNNs, citizen science annotations.	High accuracies (91.2% to 98.0% for empty images, 88.7% to 92.7% for specific species) with reduced manual labour.
Ibraheam	Wildlife-vehicle detection using deep learning.	Reconyx Hyperfire™ PC900 camera, binary classifier and multi-class classifier CNNs with cascade filtering.	99.8% accuracy achieved, hierarchical learning approach.
Jeremy	Wildlife conservation using TrailGuard AI camera-alert system.	Embedded AI, computer vision chip, physical trial in India.	Improved species identification, conservation benefits, no algorithm/model specifics provided.
Emmanuel Kipchumba	IoT-Based Early Warning System for Human-Wildlife.	Integrated IoT, SMS module, PIR sensors, GPS, Raspberry Pi cameras, YOLO algorithm for processing.	90% training accuracy and 78% validation accuracy with YOLO algorithm. SMS alerts upon animal detection.
Mengyu	Animal Detection and Classification.	CNN algorithms: YOLOv5, FCOS, and Cascade R-CNN Dataset: NTLNP dataset.	YOLOv5 achieved highest recognition accuracy, mean average precision of 0.98 in animal image detection, 88% accuracy in animal video classification.

IV. CONCLUSION

This literature summarises the pivotal role of AI, particularly YOLO algorithm, in mitigating human-wildlife conflict through efficient detection and prevention measures. While various AI technologies like CNNs and object detection models have been explored, YOLO stands out for its real-time monitoring capabilities, high accuracy in animal detection, and ability to swiftly alert relevant authorities, thus fostering proactive conservation strategies and promoting coexistence between humans and wildlife in critical ecosystems.

While AI technologies offer transformative capabilities, it is still really important to recognize that humans play a vital role too, especially for dealing with complex aspects that AI might not fully understand.

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