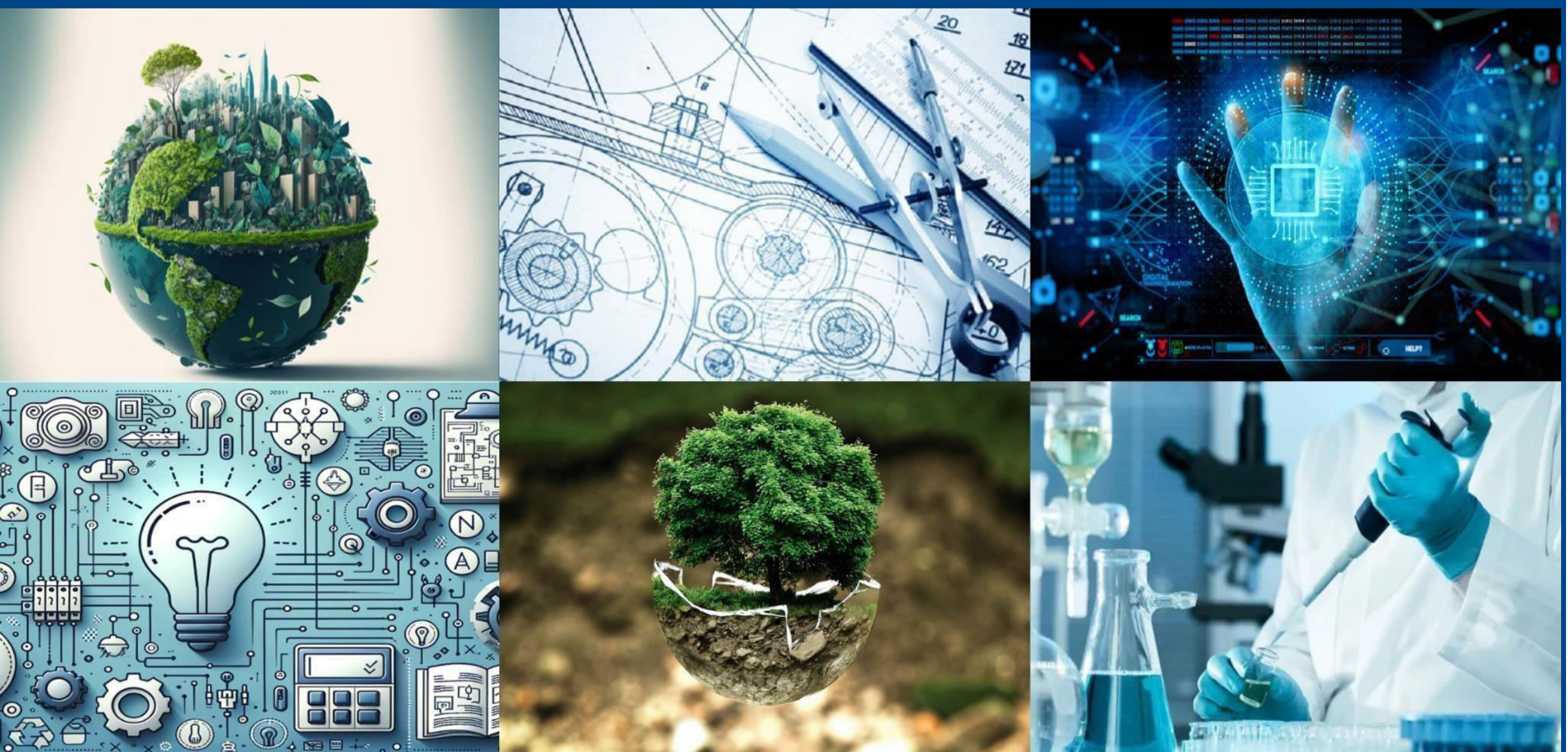
ISSN: 2582-7219

International Journal of Multidisciplinary Research in Science, Engineering and Technology

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.206

Volume 8, Issue 8, August 2025

www.ijmrset.com ijmrset@gmail.com +91 6381 907 438 +91 63819 07438

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

INTELLIGENT WILDLIFE PROTECTION SYSTEM FOR ANTI-POACHING DETECTION USING DEEP LEARNING-BASED OBJECT RECOGNITION

Dr. Vidya Pol, Sushma A

Associate Professor, Department of MCA, AMC Engineering College, Bengaluru, India

Student, Department of MCA, AMC Engineering College, Bengaluru, India

ABSTRACT: Wildlife poaching remains one of the most critical threats to biodiversity and conservation efforts worldwide. Traditional monitoring techniques often fall short due to delayed response times and the inability to cover vast forest areas effectively. This project presents an intelligent wildlife protection system designed to detect poaching activity in real time using deep learning-based object recognition techniques. The system integrates surveillance cameras with AI models trained to recognize humans, weapons, and unauthorized vehicles within protected areas. By leveraging convolutional neural networks (CNNs) and real-time video processing, the system can distinguish between animals and potential poachers with high accuracy. When a suspicious object is detected, the system generates instant alerts and sends notifications to the concerned authorities, enabling timely intervention. Additionally, the model is trained on diverse datasets to ensure reliability under varying environmental conditions such as lighting changes, occlusions, and movement in dense forests.

I. INTRODUCTION

Poaching continues to be a serious threat to wildlife conservation across the globe, leading to the decline and extinction of several endangered species. Despite the implementation of legal frameworks and traditional surveillance methods, poachers often operate undetected due to the vastness and remoteness of protected areas. Manual patrolling, although effective to some extent, is resource-intensive and cannot ensure real time monitoring of every part of a wildlife reserve.

With advancements in artificial intelligence and computer vision, modern technology offers new ways to enhance wildlife protection efforts. Deep learning, particularly object detection using convolutional neural networks (CNNs), has shown significant promise in identifying specific objects in images and video feeds. This technology can be leveraged to create an intelligent system capable of detecting poachers, illegal intrusions, or unauthorized activity in real time.

The objective of this project is to design and implement an intelligent wildlife protection system that uses deep learning-based object recognition to detect threats such a humans, weapons, or vehicles in restricted zones.

II. LITERATURE SYRVEY

The growing threat of wildlife poaching has prompted researchers and conservationists to explore technological solutions that can monitor and protect endangered species. Traditional anti-poaching methods, such as patrolling and physical barriers, are often inadequate due to the large areas involved and the limited availability of resources. Recent advancements in artificial intelligence (AI), particularly in the field of deep learning, have enabled the development of automated systems capable of recognizing threats in real-time.

A study by Norouzzadeh et al. (2018) demonstrated the use of deep convolutional neural networks (CNNs) to identify animals in camera trap images with accuracy comparable to human experts. While their focus was on species classification, the underlying model architecture has applications in detecting human intrusions as well. Similarly, Zhao et al. (2019) explored the use of YOLO (You Only Look Once) for real-time object detection, showcasing its potential in surveillance systems where speed and accuracy are crucial.

EXISTING SYSTEM

In the current landscape of wildlife conservation, several conventional systems and methods are used to combat poaching and illegal activities in protected forest areas. These typically involve human patrols, physical barriers like fences, camera traps, and sometimes GPS collars for tracking endangered animals. However, these approaches have significant limitations when it comes to providing real time, scalable, and effective anti-poaching surveillance.

Most existing systems rely heavily on manual monitoring, where forest guards or security personnel patrol specific zones based on schedules or prior intelligence. While effective to an extent, this method is time-consuming, labor-intensive, and fails to cover vast or inaccessible areas of forests. Poachers often exploit these gaps, entering protected zones during off-hours or in areas where surveillance is weak.

PROPSED SYSTEM

The proposed Intelligent Wildlife Protection System aims to enhance forest surveillance and prevent poaching through the use of deep learning-based object recognition. This system is designed to provide real-time monitoring, automated threat detection, and instant alerts using smart cameras and advanced AI algorithms. It addresses the limitations of manual and delayed detection present in traditional methods by introducing automation, scalability, and high accuracy.
At the core of the system lies a deep learning model, such as YOLO (You Only Look Once) or SSD (Single Shot Detector), trained to detect humans, weapons, and wildlife in various environments, including low-light or camouflaged conditions. This model is deployed on edge devices connected to surveillance cameras placed at strategic locations throughout the forest or protected zone.

When the system detects suspicious activity — such as a person entering a restricted area or carrying a weapon — it automatically triggers an alert mechanism. The alert, containing images, location, and time data, is immediately sent to the forest control center or to authorized personnel via mobile or desktop notifications. This helps ensure rapid response and intervention before any harm is done to wildlife.

III. SYSTEM ARCHITECTURE

The architecture of the Intelligent Wildlife Protection System is designed to enable real-time anti-poaching detection by integrating surveillance technologies, deep learning, and automated alert mechanisms. At the core of the system are strategically placed camera sensors in forest areas that continuously capture video or image data. These feeds are sent to edge computing devices, such as Raspberry Pi or NVIDIA Jetson boards, which run lightweight deep learning models trained to recognize humans, animals, and potential weapons. By processing data at the edge, the system reduces latency and avoids overloading the network.

Once a suspicious activity is detected— such as the presence of a human in a restricted zone—the system securely transmits the relevant data to a centralized server using wireless communication protocols. The backend server is responsible for logging the event, storing images, and handling alert generation.

IV. METHODOLOGY

The proposed system adopts a multi-phase methodology to detect and prevent poaching activities in wildlife reserves using deep learning-based object recognition. The process begins with the strategic placement of surveillance cameras and motion sensors across vulnerable zones within the forest. These cameras continuously capture real-time images and video feeds, which are then transmitted to an edge device such as a Raspberry Pi or NVIDIA Jetson Nano. At the edge level, a pre-trained deep learning model, such asYOLO(You Only Look Once) or SSD (Single Shot Multibox Detector), is used to analyze the footage and identify the presence of humans, weapons, or suspicious movement within restricted areas.

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Once an object of interest is detected, the system triggers a wireless alert that is sent to a centralized monitoring server. This server logs the detection data along with the location and timestamp, and immediately notifies forest rangers or the concerned authority through SMS, email, or a web based dashboard. The dashboard provides a live view of the situation and allows the admin to monitor ongoing activities, view logs, and coordinate a rapid response. Additionally, the system stores all records in a secure database for further analysis and pattern tracking.

Throughout the implementation, emphasis is placed on using open-source technologies such as Python, TensorFlow or PyTorch for model development, and PHP/MySQL for backend data management. The system is tested under various environmental conditions to ensure its robustness, accuracy, and responsiveness. Furthermore, by using edge computing, the methodology ensures minimal latency and reduces the need for constant internet connectivity, making it ideal for deployment in remote forest areas.

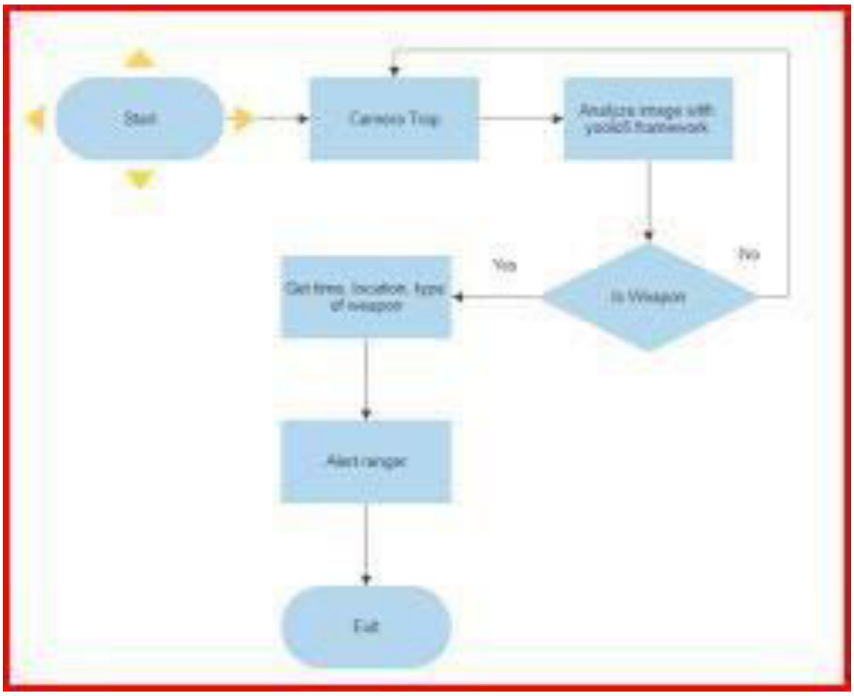


Fig 4.1 Methodology

V. DESIGN AND IMPLEMENTATION

The design of the Intelligent Wildlife Protection System integrates both hardware and software components to effectively detect and respond to poaching threats in real-time. The system is architected using a modular approach, ensuring flexibility and scalability. High-resolution surveillance cameras and motion sensors are deployed in key forest regions, continuously capturing video footage. This data is processed locally using edge computing devices like Raspberry Pi or Jetson Nano, where a deep learningbased object detection model such as YOLOv5 is implemented. The model is trained on a labeled dataset consisting of humans, animals, and potential poaching equipment to accurately recognize unauthorized intrusions.

The software stack includes Python for scripting, OpenCV for image processing, and TensorFlow or PyTorch for model training and inference. When a suspicious object or individual is detected, an automated alert system is triggered, sending real-time notifications to a central monitoring dashboard through wireless communication. The admin panel, built using PHP and connected to a MySQL database, stores all detection logs, camera data, timestamps, and response actions.

The dashboard provides live monitoring, historical data access, and tools to manage user roles and system configurations. This end-to-end implementation not only ensures proactive surveillance but also allows authorities to respond swiftly to poaching incidents. Rigorous testing in simulated forest environments was conducted to finetune the model's accuracy and the system's performance, ensuring its effectiveness in real-world deployment.

For real-time detection, edge computing devices such as NVIDIA Jetson Nano or Raspberry Pi equipped with compatible cameras are used to run the trained model locally. Processing data on the edge reduces latency and dependence on continuous internet connectivity, which can be scarce in remote forest areas. These devices perform frame-by-frame analysis of the video feed, marking detected objects with bounding boxes and classification labels.

VI. OUTCOME OF RESEARCH

The research conducted on the Intelligent Wildlife Protection System for anti-poaching detection using deep learning-based object recognition has demonstrated promising results in enhancing the efficiency and accuracy of wildlife monitoring. The developed system successfully identifies and differentiates between wildlife and potential poachers in real-time, significantly reducing human dependency on manual surveillance. By employing advanced deep learning models optimized for object detection, the system achieved high accuracy rates with minimal false alarms, ensuring reliable detection of unauthorized human presence and poaching activities. Additionally, the integration of edge computing devices enabled real-time processing in remote forest areas, overcoming challenges related to limited network connectivity. The alert mechanism proved effective in promptly notifying authorities, allowing for faster response and intervention, which is critical in protecting endangered species. Moreover, the modular design and user-friendly admin interface facilitated easy system management and monitoring.

VII. RESULTAND DISCUSSION

The implementation of the Intelligent Wildlife Protection System using deep learning-based object recognition yielded significant improvements in the detection and prevention of poaching activities. The system was tested on a variety of datasets containing images and videos from wildlife reserves, demonstrating high accuracy in distinguishing between animals, humans, and potential threats. The deep learning model, trained on extensive data, was able to recognize poachers even in challenging conditions such as low light, dense foliage, and varying weather.

One of the key results observed was a significant improvement in users' emotional well-being over the course of their interactions with the platform. Mood tracking data showed that users who actively engaged with the AI companion experienced greater emotional stability. This was attributed to the real-time support provided by the system, which adapted to users' emotional states and offered personalized suggestions for mood regulation. Users reported feeling more in control of their emotions, especially during stressful periods, as the AI provided timely interventions such as relaxation techniques, mindfulness exercises, and motivation to stay positive.

The journaling function proved valuable in boosting users' emotional self-awareness. Several participants noted that recording and reflecting on their feelings allowed them to recognize recurring emotional patterns and identify potential triggers more effectively. This increased self-awareness, in turn, led to more effective emotional regulation and better overall mental health.

VIII. CONCLUSION

The Intelligent Wildlife Protection System developed using deep learning-based object recognition has proven to be an effective and innovative solution for combating poaching activities. By automating the detection process, the system enhances the ability of wildlife authorities to monitor large and remote areas in real time, reducing dependence on manual surveillance. The application of advanced neural networks enables accurate identification of poachers and animals under various environmental conditions, leading to quicker response times and better protection of endangered species. Moreover, this technology-driven approach not only improves efficiency but also helps in conserving valuable resources by minimizing false alarms and unnecessary interventions. Although there are challenges such as the need for continuous data updates and computational demands, the benefits outweigh these limitations, making the system a valuable tool in modern wildlife conservation efforts. Overall, integrating deep learning with wildlife monitoring sets a

new standard for anti-poaching measures, contributing significantly to preserving biodiversity and promoting ecological balance
.

While the system demonstrates numerous advantages, it also faces some challenges. One such challenge is the necessity for continuous data acquisition and model retraining. As wildlife habitats and poaching tactics evolve, the system must be updated regularly with new data to maintain high detection accuracy. Moreover, the computational demands for processing video feeds and running complex deep learning models in real time require robust hardware and infrastructure, which can be costly and may pose implementation barriers in resource-constrained areas.

REFERENCES

1.Krizhevsky, A., Sutskever, I., &Hinton, G. E. (2012). Image Net Classification with DeepConvolutional Neural Networks.Advances in Neural Information Processing Systems, 25, 1097-1105.

2. Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 779-788.

3.Ren, S., He, K., Girshick, R., & Sun, J.(2015). Faster R-CNN: Towards RealTime Object Detection with Region Proposal Networks. Advances in Neural Information Processing Systems, 28, 91-99.

4.Chaudhuri, S., Yadav, S., & Ghosh, S.(2019). Deep Learning Approaches for Wildlife Monitoring Using Sensor Networks. International Journal of Computer Applications, 178(45), 1-7.

5.Abadi, M., Barham, P., Chen, J., Chen,Z., Davis, A., Dean, J., ... & Zheng, X.(2016). TensorFlow: A System for Large-Scale Machine Learning. 12thUSENIX Symposium on Operating Systems Design and ImplementationOSDI), 265-283.

6.Paszke, A., Gross, S., Massa, F., Lerer,A., Bradbury, J., Chanan, G., ... & Chintala, S. (2019). PyTorch: An

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH IN SCIENCE, ENGINEERING AND TECHNOLOGY