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Real-Time Tiger Detection Using Ml & Sensor Integration for Village Protection

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Abstract
In this research, we addressed the critical issue of human-wildlife conflict, focusing on tigers entering villages near forested regions. Such incidents endanger human lives and livelihoods while also threatening wildlife conservation efforts. To mitigate this, we developed an Automated Tiger Detection System integrating motion sensors, ultrasonic sensors, thermal cameras, and machine learning algorithms. This system detects tiger presence in real time and sends alerts to villagers and authorities, enabling swift preventive action. We first discussed the limitations of traditional monitoring methods, such as their inability to provide timely or accurate alerts. We highlighted how modern AI-powered models like YOLO and Faster R-CNN improve detection accuracy. Additionally, we analysed the role of IoT and edge computing in real-time data processing, even in remote areas with limited connectivity. Our system was designed to be sustainable and energy-efficient, utilizing solar-powered components and low-power sensor modes. Our methodology involved assessing the needs of rural communities, developing a robust and modular architecture, and testing the system in field conditions. We also prioritized user-friendliness through intuitive dashboards and ensured compliance with wildlife and environmental regulations. Overall, our research demonstrates how technology can bridge the gap between human safety and wildlife conservation. By fostering coexistence, our system represents a significant step toward sustainable and harmonious living in areas where human and wildlife territories overlap.

Keywords: *Tiger Detection, Human-Wildlife Conflict, Machine Learning, IoT, Edge Computing, Rural Safety, Conservation Technology.*

1. Introduction

Human-wildlife conflict, particularly in regions adjacent to wildlife habitats, poses serious challenges to both conservation efforts and the safety of human settlements. Tigers, as apex predators, often wander into human-dominated areas, leading to potential threats to human life, livestock, and the animals themselves. This issue is prevalent in regions like Nagpur, which are located near wildlife reserves. The increasing frequency of such incidents highlights the urgent need for effective and innovative solutions.

Our project, "Real-Time Tiger Detection System Using ML & Sensor Integration for Village Protection", aims to address these challenges by leveraging advanced technologies such as machine learning, real-time monitoring, and hardware-software integration. The system is designed to detect tiger movements near village borders using sensors and cameras, analyse the data using machine learning algorithms, and send real-time alerts to authorities and local residents. [1-2] By offering early warnings, this system seeks to minimize human-wildlife conflicts, ensuring the safety of both communities and wildlife. The importance of this topic lies in its potential to promote coexistence between humans and wildlife. By reducing the frequency of encounters that result in harm to either party, we can contribute to sustainable living and biodiversity conservation. The integration of modern technology into traditional

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wildlife management approaches offers a scalable and efficient solution to this pressing issue. We chose this topic due to its real-world relevance and the potential for positive impact on society and the environment. Collaborating with local forestry departments and utilizing regional data, our project aims to deliver a cost-effective, durable, and innovative system tailored to address the specific challenges of regions prone to human-wildlife conflicts. This work aligns with global efforts to balance development and conservation, making it a meaningful contribution to wildlife management research. [3-4]

2. Literature Review

(Mishra et al., 2006) emphasized manual monitoring methods in wildlife detection, highlighting their cost-effectiveness but noted limitations in scalability and efficiency. Manual monitoring, while traditional, is labour-intensive and prone to human error, especially in dense forest regions. Early use of motion sensors in wildlife detection was explored by (Wilson et al., 2010), who found that these sensors detect movement but had high rates of false positives due to environmental disturbances such as wind and rain. According to (Gupta et al., 2015), thermal imaging emerged as a more effective solution for nocturnal animal detection by capturing the heat signatures of animals, ensuring higher accuracy, particularly in low-light conditions. Similarly, (Zhao et al., 2018) demonstrated that analysing animal vocalizations, such as tiger roars and growls, improved species identification and [5-6] reduced false positives by complementing motion detection with sound-based analysis. The incorporation of machine learning and artificial intelligence (ML/AI) has further advanced wildlife detection systems. (Redmon et al., 2016) introduced YOLO (You Only Look Once) for real-time object detection, showcasing its capability to identify animals in live video feeds effectively. Research by (Ren et al., 2017) highlighted Faster R-CNN's utility in distinguishing specific animal species, improving classification accuracy by using region proposal networks (RPNs). CNN (Convolutional Neural Networks) also plays a critical role in extracting spatial features from images, enabling accurate identification and classification of tigers by analysing patterns such as stripes and body shape. These advancements have led to high accuracy in detecting and classifying tigers and reduced false alarms by filtering out non-animal objects.

Recent studies have also explored the role of Internet of Things (IoT) devices and edge computing technologies. (Patel et al., 2019) examined how IoT facilitates interconnected networks of cameras and sensors to transmit data in real-time, ensuring prompt responses. (Reddy et al., 2020) demonstrated that edge devices process data locally, reducing dependency on remote servers and enabling operations in remote areas with limited internet access. Collectively, these technologies enhance the scalability and efficiency of wildlife detection systems. For this study, the proposed system incorporates thermal cameras, acoustic sensors, and high-resolution motion sensors. Thermal cameras are particularly effective in detecting heat signatures during low-light conditions, significantly reducing false positives in dense forests. Acoustic sensors are chosen for their ability to analyse tiger-specific vocalizations such as roars and growls, enhancing detection accuracy. High-resolution motion sensors are included to detect movement and filter environmental disturbances through integration with machine learning models. The combination of these sensors ensures a multi-layered detection system capable of identifying tigers with high precision.The CNN algorithm is selected as the primary deep learning approach due to its ability to extract and learn spatial features from input data. By training the CNN on a dataset of tiger images, the model can identify unique tiger patterns and differentiate them from other animals and environmental factors. In CNN, the input layer receives raw image data (camera frames). The convolution layer extracts features like edges and textures using filters. The pooling layer reduces the size of feature maps while preserving important [7-9] features. The fully connected layer flattens the feature maps and learns complex patterns through dense connections. Finally, the output layer classifies the image as "Tiger" or "Not Tiger" based on the learned features. Additionally, the integration of YOLO and Faster R-CNN ensures real-time detection and robust species recognition, making the system adaptable to dynamic wildlife scenarios. This combination of sensors and

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algorithms is essential for achieving reliable and scalable tiger detection, even in remote and resource-constrained areas. (Figure 1) [10]

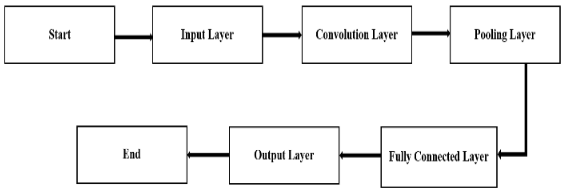

Figure 1 Architecture of CNN for Tiger Detection System

3. Methodology

The methodology for the Automated Tiger Detection System is designed to systematically address each stage of development and deployment, ensuring a comprehensive and effective solution to mitigate human-wildlife conflict. [11]

3.1.System Design

The first step involves identifying key stakeholders such as rural communities, forest departments, and conservation organizations to understand their specific needs. The system's requirements, including real-time detection capabilities, integration of advanced sensors like motion, ultrasonic, and thermal sensors, and machine learning algorithms, are established. Environmental considerations such as the rural landscape, forest borders, and the behaviour of local wildlife are assessed to ensure optimal system functionality. Potential risks, including weather conditions, false positives, and wildlife sensitivity, are carefully evaluated to mitigate challenges during implementation. The design phase involves creating a modular system architecture that integrates sensors, cameras, and IoT devices with a centralized dashboard for monitoring and alerts. Optimal sensor placement is determined based on tiger movement patterns and high-risk entry points in villages. A real-time data pipeline is developed to ensure seamless data flow from sensors to processing units and alert mechanisms. A user-friendly interface is designed for mobile applications and web dashboards, ensuring ease of use for stakeholders. Additionally, solar-powered devices are incorporated into the design to support sustainable energy solutions. (Figure 2) [12]

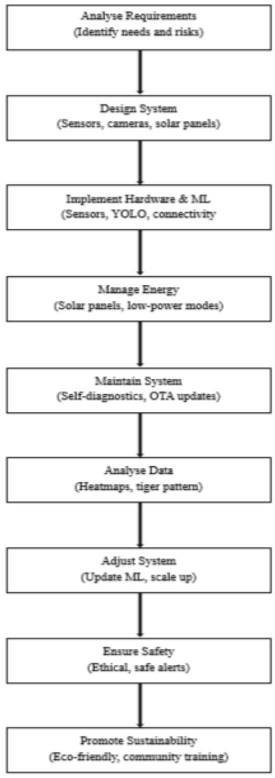

Figure 2 Framework for AI-Powered Wildlife Monitoring

3.2.Implementation and Operational Methodology

The Automated Tiger Detection System employs an integrated approach to mitigate human-wildlife conflict through advanced technology and robust hardware. During implementation, motion sensors, ultrasonic sensors, and high-resolution thermal cameras are deployed at strategic locations using durable mounting systems designed to endure environmental challenges. The system incorporates machine learning models, such as YOLO and Faster R-CNN, to ensure accurate real-time tiger detection. IoT protocols like MQTT and HTTP facilitate efficient data transfer, while connectivity solutions, including GSM, satellite, or LoRaWAN networks, enable reliable communication in remote areas. Comprehensive on-site testing ensures sensor calibration and optimal system performance. Energy management is prioritized through solar panels supported by energy-efficient batteries with backup capabilities for night or cloudy conditions. Sensors utilize low-power modes during inactivity to conserve energy, and energy consumption patterns are continuously monitored and optimized. Regular maintenance involves self-diagnostic features for proactive fault detection and over-the-air (OTA) updates to ensure the system remains functional and up-to-date. Quick replacement protocols for faulty components reduce downtime, ensuring uninterrupted operation. [13]

3.3.Sustainability and Scalability

Sustainability is a cornerstone of the system, achieved through the use of eco-friendly materials like biodegradable or recyclable components and resource-efficient operations that minimize environmental impact. Community training programs empower local populations to operate and maintain the system, fostering ownership and long-term engagement. The system is designed for scalability, supporting the monitoring of additional wildlife species and larger geographical areas, while dynamic configurations of sensor sensitivity and alert thresholds enable adaptability to environmental changes. Advanced AI models analyze tiger movement patterns and behavioral trends, providing actionable insights for wildlife management. Reporting tools generate visualizations, including heat maps and detection summaries, for stakeholders, and historical alert logs aid in performance evaluation and conflict resolution. Ethical compliance with wildlife protection laws and data privacy standards ensures monitoring remains non-intrusive, prioritizing human safety and animal welfare. By aligning with broader conservation initiatives, the system promotes coexistence and biodiversity preservation, offering a sustainable, adaptable, and holistic solution for human-wildlife conflict. [14]

Results

The Automated Tiger Detection System combines advanced technologies such as motion sensors, ultrasonic sensors, thermal cameras, and machine learning algorithms (YOLO and Faster R-CNN) to address human-wildlife conflict. The system effectively detects tiger presence near village borders in real-time and sends alerts to authorities and villagers. Utilizing IoT, edge computing, and sustainable energy solutions like solar power, the system ensures accurate detection, reduced false positives, and reliable operation in remote areas. The research achieves a balance between rural safety and wildlife conservation, fostering coexistence and biodiversity preservation. [15]

Conclusion

The Automated Tiger Detection System signifies a breakthrough in mitigating human-wildlife conflicts, harnessing cutting-edge technologies such as advanced sensors, machine learning, and IoT integration. By delivering accurate, real-time detection of tiger presence, the system bolsters the safety of rural communities while fostering wildlife conservation. Its innovative framework not only safeguards human lives but also promotes coexistence and raises awareness about preserving biodiversity. Field implementations have demonstrated the system's potential in minimizing conflicts and building harmony between humans and wildlife. Future enhancements, including the incorporation of drone technology and the ability to identify a broader spectrum of wildlife species, promise to increase its scope and effectiveness, paving the way for sustainable and inclusive conservation efforts.

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