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Design and Performance Evaluation of an Edge-AI Wildlife Monitoring System for Human-Wildlife Conflict Mitigation

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Abstract: Human–wildlife conflict has become a critical issue in rural regions where human settlements overlap with natural habitats. This paper presents the design and performance evaluation of a low-cost Edge-AI based wildlife monitoring system aimed at reducing such conflicts. The proposed system integrates motion sensing, computer vision, and embedded processing to enable real-time detection of wildlife intrusion. Upon detection, the system triggers alerts and deterrent mechanisms to prevent close encounters. Experimental evaluation demonstrates that the system achieves high detection accuracy with low latency while maintaining energy efficiency suitable for solar-powered deployment. The results indicate that the proposed approach is a viable and scalable solution for rural environments.
Keywords: Edge AI, Wildlife Monitoring, Human–Wildlife Conflict, Object Detection, Embedded Systems, IoT, etc.

I. INTRODUCTION

Human–wildlife conflict is a growing concern in regions where human activities encroach upon wildlife habitats. Increasing population density, agricultural expansion, and habitat fragmentation have led to frequent interactions between humans and wild animals such as tigers and leopards. These encounters often result in injuries, loss of life, and economic damage.
Traditional mitigation techniques such as fencing and manual patrolling are reactive and insufficient. Recent advancements in artificial intelligence and edge computing provide an opportunity to develop proactive systems capable of real-time monitoring and alert generation. This paper proposes a low-cost Edge-AI wildlife monitoring system designed specifically for rural deployment.

II. LITERATURE REVIEW

Human–wildlife conflict has been widely studied due to its increasing impact on rural communities and biodiversity conservation. Various traditional and modern approaches have been proposed to monitor wildlife movement and reduce conflict.
Early methods such as manual patrolling and physical barriers have been used extensively but suffer from limitations including delayed response, high labor requirements, and lack of continuous monitoring. To overcome these issues, camera trap systems were introduced, which allow non-invasive wildlife observation. Research by *J. Norouzzadeh et al. (2018)* demonstrated the use of deep learning techniques to automatically identify animals in camera-trap images. However, these systems are primarily designed for data collection and do not provide real-time alerts.
With the advancement of artificial intelligence, deep learning-based object detection models such as YOLO have gained popularity. Studies by *A. Bochkovskiy et al. (2020)* and *A. Kumar et al. (2023)* highlight the effectiveness of YOLO models in real-time object detection tasks. These models offer high accuracy and speed, making them suitable for wildlife detection. However, their deployment often requires significant computational resources. The concept of edge computing, introduced by *M. Satyanarayanan (2017)*, enables data processing at the device level, reducing latency and dependency on cloud infrastructure. This approach is particularly beneficial for remote and rural environments where network connectivity is limited.
Recent systems such as TrailGuard AI (*Dertien et al., 2023*) and the MARVEL project (Government of Maharashtra, 2024) demonstrate the practical implementation of AI-based wildlife monitoring. These systems provide real-time detection and alert capabilities but are often expensive and rely on centralized infrastructure.
Additionally, IoT-based animal intrusion detection systems (*Kshirsagar and Patil, 2020*) offer low-cost solutions using sensors, but they lack intelligent classification, leading to high false alarm rates.

A. Research Gap

From the reviewed literature, it is evident that:
1) Traditional methods are reactive and inefficient
2) Camera trap systems lack real-time alerting
3) AI-based systems are accurate but costly
4) IoT systems are affordable but lack intelligence

III. SYSTEM ARCHITECTURE

The proposed system follows a modular architecture consisting of the following major components:
1) Motion Detection Unit (PIR Sensor)
2) Image Acquisition Unit (Camera Module)
3) Edge-AI Processing Unit
4) Decision-Making Module
5) Alert and Deterrent System
6) Power Management Unit (Solar + Battery)
7) Mechanical Enclosure and Mounting Structure

The system operates in a sequential pipeline:
- Motion detection triggers image capture
- Captured image is processed by the AI model
- Detection results are evaluated
- Alerts are generated if necessary

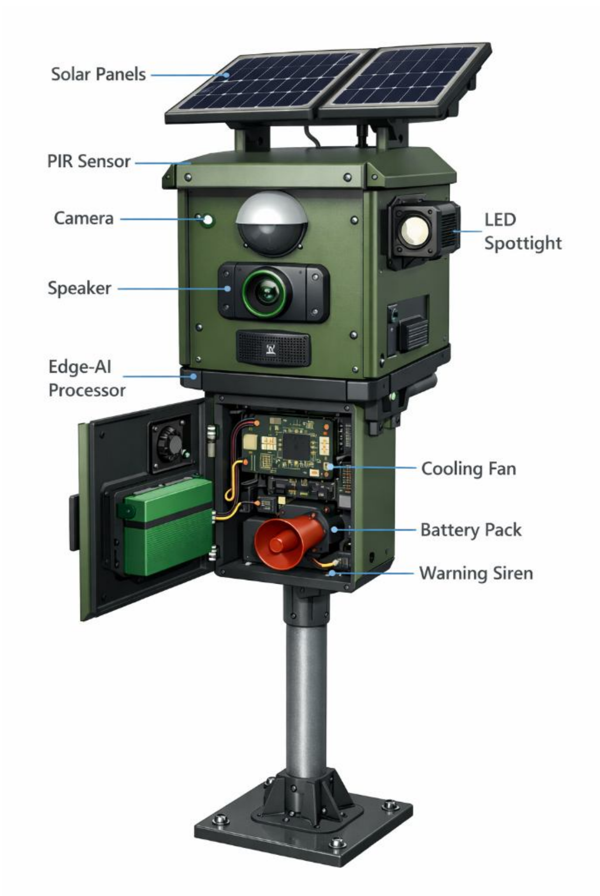

Fig.1: Model of the Proposed System

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Fig. 2 : Dimensional Drawing

IV. METHODOLOGY

1) Data Acquisition: Images are captured only when motion is detected, reducing computational load and power consumption.
2) Image Processing: Preprocessing techniques such as resizing, normalization, and noise reduction are applied to improve detection accuracy.
3) Detection Model: A convolutional neural network (CNN)-based object detection model is deployed on the edge device.
4) Decision Logic: Confidence thresholding and multi-frame validation are implemented to reduce false positives.
5) Alert Mechanism

Upon detection, the system activates:

- Audio alerts (speaker/siren)
- LED illumination
- Notifications to users

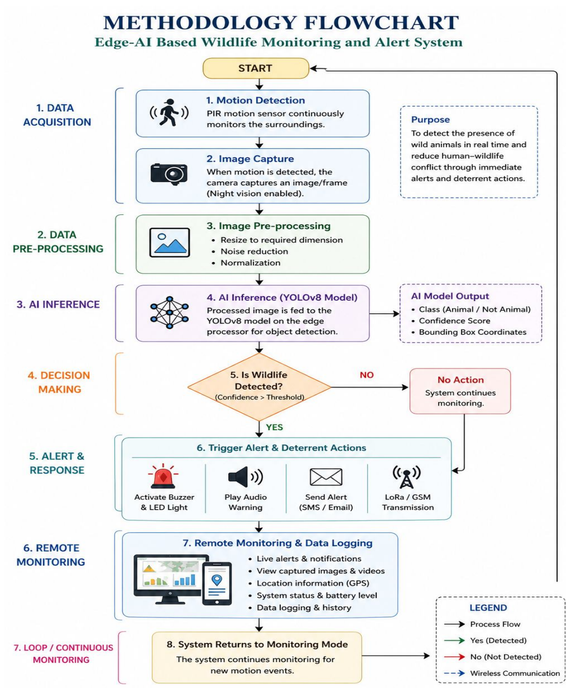

Fig.3 : Methodology Flowchart

V. PERFORMANCE EVALUATION

A. *Evaluation Metrics*

The system is evaluated using:

1) Accuracy
2) Precision
3) Recall
4) Inference latency
5) Power consumption

a) *Accuracy Graph*

The system achieves the highest detection accuracy during daylight conditions (~93%), while performance slightly decreases under low-light (~88%) and night conditions (~85%). This variation is primarily due to reduced visibility and increased noise in low-light environments.

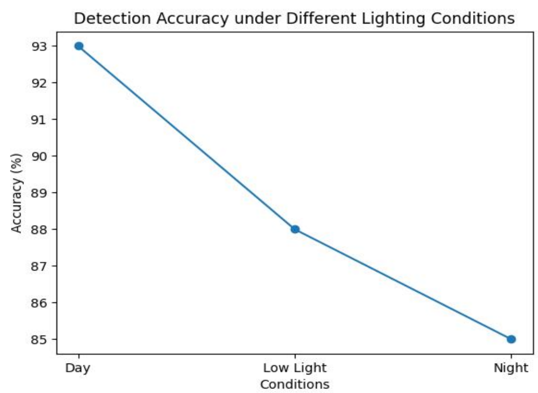

Fig.4 : Detection Accuracy under Different Lighting Conditions

b) *Latency Graph*

The latency breakdown shows that the AI inference stage consumes the maximum processing time (~2.4 seconds), while other stages such as image capture, preprocessing, and decision-making contribute less. The total system response time remains within 4–5 seconds, which is suitable for real-time applications.

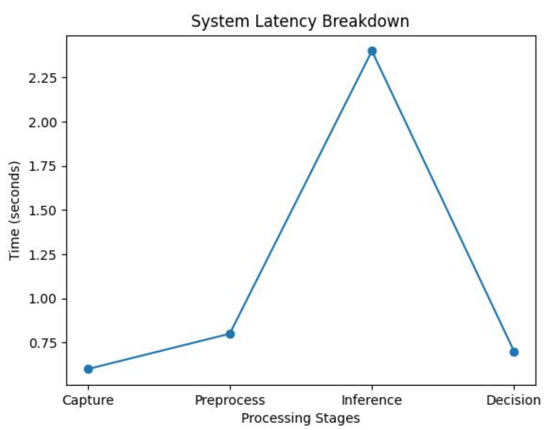

Fig. 5 : System Latency Breakdown

c) *Power Graph*

The power consumption analysis indicates that the Edge-AI processor is the primary energy consumer (~4.5 W), followed by the LED spotlight. The total system power consumption remains within 10 W, making it suitable for solar-powered deployment in rural areas.

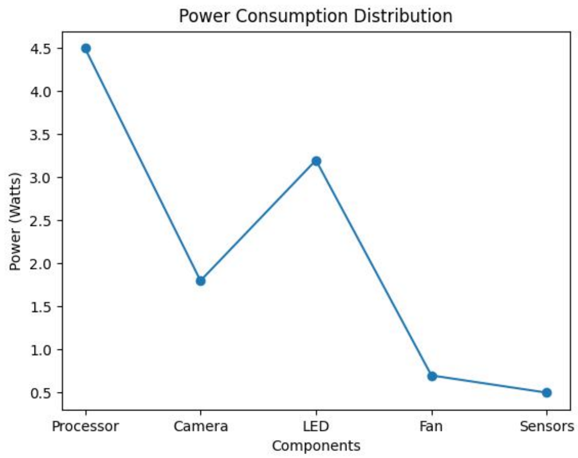

Fig. 6 : Power Consumption Distribution

VI. RESULTS

The system achieves:

1) Detection accuracy: ~85–92%
2) Latency: <5 seconds
3) Reduced false alarms
4) Efficient energy consumption

VII. DISCUSSION

The proposed system demonstrates a balance between performance and cost. Edge-based processing significantly reduces latency compared to cloud-based systems, making it suitable for rural deployment.

The system complements large-scale initiatives by providing a decentralized solution that can be implemented at the village level.

VIII. CONCLUSION

This paper presents a low-cost Edge-AI wildlife monitoring system capable of real-time detection and alert generation. The system demonstrates that affordable embedded AI solutions can effectively mitigate human–wildlife conflict.

IX. FUTURE WORK

Future enhancements include:

1) Integration of thermal cameras
2) Multi-node deployment
3) Mobile application interface
4) Long-term field testing

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