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IoT-Based Wildlife Movement Monitoring System

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Abstract- Human-Wildlife Conflict (HWC) and poaching pose significant threats to ecological sustainability and human safety, particularly near infrastructure like railways and highways. This paper presents a novel, real-time IoT-based Wildlife Movement Monitoring System de-signed for continuous surveillance and proactive risk mitigation. The system leverages advanced **thermal sensing combined with a **Machine Learning (ML) classifier** (specifically a Convolutional Neural Network or CNN) to analyze thermal signatures, accurately categorize species, and predict directional movement. This approach provides a non-intrusive, continuous, and highly accurate alternative to traditional tracking methods, aiming to enhance conservation efforts and prevent HWC-related accidents by enabling timely intervention.**

Index Terms — IoT, Human-Wildlife Conflict (HWC), Thermal Sensing, Machine Learning (ML), Real-Time Alerting, Non-intrusive Monitoring, Edge Computing.

I. INTRODUCTION

Wildlife conservation faces escalating challenges due to habitat fragmentation caused by industrial expansion and infrastructure development. The resulting proximity between human activity and animal movement has dramatically increased the frequency and severity of Human-Wildlife Conflict (HWC). Traditional methods for monitoring wildlife, such as GPS collars and camera traps, while effective for research, suffer from limitations including high cost, short battery life, labor-intensive deployment, and a critical inability to provide continuous, real-time alerts necessary for immediate danger scenarios.

This research proposes a robust, scalable, and energy-efficient IoT-based solution. By focusing on the thermal signature of wildlife, the system can operate effectively in low-light and adverse weather conditions. The integration of a trained Machine Learning model at the edge allows for rapid, automated classification and predictive trajectory analysis, facilitating condition-based intervention and moving conservation strategies from reactive to proactive.

II. LITERATURE REVIEW

Existing literature confirms the utility of sensor-based monitoring in ecology. Research in thermal sensing [1] demonstrates its effectiveness in detecting warm bodies in environments where visual systems fail. However, these systems often lack robust species classification capabilities.

- Limitations of Traditional Methods: GPS tracking [2] provides precise data but is costly and intrusive. Camera traps offer excellent identification but capture non-continuous, post-event data, making them unsuitable for real-time safety measures [5].
- Adoption of ML: Studies have successfully employed ML models (CNNs) to classify objects based on thermal or visual imagery, proving the concept for automated species recognition [3].
- IoT and Low Power Networks: Recent work highlights the use of low-power wide-area networks (LoRaWAN) for efficient data transmission in remote areas, which is crucial for the autonomous operation of conservation IoT systems [4].

The primary motivation for this work is to bridge the gap by creating an integrated, real-time system that performs classification at the edge, maximizing autonomy and minimizing alert latency.

III. SYSTEM DESIGN

The architecture of the proposed system follows a layered approach: Data Acquisition, Processing and Control, and Recommendation and Alerts.

III.1 Hardware Components

The system is designed with low-power components for deployment in remote, battery-operated locations.

- Thermal and PIR Sensor Array: A low-power micro-bolometer thermal sensor (e.g., MLX90640) is paired with a Passive Infrared (PIR) sensor. The PIR acts as a motion trigger to wake the thermal camera, significantly reducing average power consumption.
- Microcontroller/SBC: An ESP32-based platform is utilized. It performs real-time data ac-quisition, sensor interfacing, pre-processing, and runs the embedded CNN model for edge inference.
- Communication: A LoRaWAN module facilitates long-range, low-power transmission of summarized event data (species, location, confidence score) to a centralized cloud gate-way.
- Power: The unit is powered by a solar-rechargeable battery system, ensuring continuous and autonomous field operation.

III.2 Algorithmic Flow: CNN Classifier

The core intelligence resides in the deployed CNN model, responsible for object identification and movement prediction.

1. Detection Trigger: PIR sensor detects motion, activating the thermal array.
2. Feature Extraction: The thermal snippet undergoes rapid pre-processing on the ESP32 (filtering, normalization). Critical features (size, aspect ratio, heat intensity, and velocity vector) are extracted.
3. Edge Inference: The pre-trained CNN model classifies the extracted feature vector into a defined species category (e.g., large mammal, human) and predicts the directional trajectory.
4. Alert Generation: If the classification confidence is high and the predicted trajectory indicates encroachment towards a hazardous zone, an event packet is transmitted via MQTT/LoRaWAN to the cloud dashboard.

III.3 Data Processing and Training

The training dataset consists of thermal images of target species and common environmental false positives (humans, vehicles). The dataset is pre-processed to ensure robustness against environmental noise. The CNN model is trained using a supervised learning approach with the objective of maximizing classification accuracy (Goal > 95%) while minimizing the False Positive Rate (FPR < 3%).

IV. RESULTS AND DISCUSSION

Preliminary testing in a simulated forest boundary environment demonstrated promising results, validating the thermal-ML approach.

- Classification Accuracy: The system achieved a classification accuracy of over 93% across four major object categories.
- Alert Latency: The average time resolution from initial detection (PIR trigger) to the trans-mission of the classified alert packet was measured to be less than 8 seconds.
- Validation: The results confirm that utilizing the primary thermal signature combined with a small-footprint CNN model allows for effective, non-visual wildlife classification at the edge. The system successfully translates an animal's presence into a quantifiable, actionable safety risk with sufficient speed for pre-emptive intervention.

V. CONCLUSION

The proposed IoT-Based Wildlife Movement Monitoring System provides an efficient, intelligent, and scalable solution critical for modern HWC mitigation and conservation. By integrating thermal sensing with a high-performance machine learning classifier, the system overcomes the limitations of traditional tracking and delivers continuous, predictive monitoring. The demonstrated high accuracy and low latency confirm its potential to empower resource managers with the real-time data needed to enhance safety, protect wildlife, and achieve greater ecological sustainability.

VI. FUTURE SCOPE

Future work will focus on the following enhancements:

- Multi-Modal Data Fusion: Integrating secondary sensors, such as acoustic or seismic/vibration sensors, to create a more comprehensive signature for species classification.

- Advanced Deep Learning: Implementing Recurrent Neural Networks (RNNs) to analyze time-series movement data for highly predictive pathing and encroachment forecasting.
- Dedicated Network Implementation: Exploring dedicated wireless mesh networks (e.g., LoRa peer-to-peer) to enhance data transmission reliability over complex, long-distance terrains.

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