SAFEGUARD WILD: ANTI-POACHING MONITORING SYSTEM USING ML & IOT

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DOI: 10.5958/2249-7137.2025.00030.6

ABSTRACT

The danger to wildlife due to illegal poaching activities has increased over the past few years, and there is a pressing need for creative solutions to safeguard threatened species. To address this, we propose an Anti-Poaching System Using IoT as an integrated model to track, identify, and deter illegal activities in forest and protected areas. By using networked IoT sensors, the system facilitates real-time identification of human activity, strange noises like gunshot and fire thread. It provides warning messages to forest departments in real time in the form of message ,live video feed and image ,facilitating quick action. This combined solution equips authorities with smart surveillance, automated threat identification, and instant reporting leveraging wildlife conservation efforts and reducing human-wildlife conflict through timely intervention. Our dream is to implement this in national parks and reserves.

KEYWORDS: *Anti-Poaching, Wildlife Monitoring, Ky-037 Sensor ,Flamesensors,Raspberry Pi 3B+ ,Ultrasonic Sensor ,Webcam, Servo Motor Tracking ,YOLO Object Detection, Edge Computing ,Remote Monitoring, Telegram Alerts.*

1. INTRODUCTION

Wildlife poaching continues to be one of the most serious threats to biodiversity, driving a number of species to the brink of extinction. Conventional patrolling and monitoring techniques tend to fail in monitoring extensive forest cover and identifying poaching in real time. To meet this challenge, the "Safe Guard Wild: Anti-Poaching Monitoring System Using IoT" project presents an intelligent, automated solution that leverages artificial intelligence, computer vision, and IoT technologies to protect wildlife.This implementation makes use of a Raspberry Pi 3B+ as the processing core, connected with a servo-mounted ultrasonic sensor for motion detection and a YOLO-based object detection model for real-time detection of animals, poachers, and weapons. It has a Tkinter-based GUI for local monitoring and control purposes, while vital alerts and captured images are sent instantly through Telegram to authorized forest staff. The system also keeps track of all occurrences in an SQLite database for future reporting and analysis.

2. Related Work

In the last decade, scientists and conservationists have investigated a range of technological solutions to meet the increasing threat of wildlife poaching. Conventional methods like patrolling manually and using camera traps have been extensively used. The recent evolution has incorporated the use of Internet of Things (IoT) devices and Artificial Intelligence (AI) in conservation efforts. Concurrently, real-time monitoring systems employing drones, thermal sensors, and acoustic sensors have been established to alert for human entry or gunfire in protected areas. Other research has even targeted edge computing platforms, including the Raspberry Pi, to support local data processing and minimize the reliance on cloud services in off-grid areas.In addition, the utilization of messaging platforms like Twilio and Telegram in warning rangers has been promising in mitigating the response time. Database-driven logging systems have been used in certain systems to enable long-term monitoring, reporting, and pattern analysis. This project draws on such previous work by developing a cost-effective, Raspberry Pi-powered system that integrates YOLO object detection, servo-driven ultrasonic sensing, real-time notifications, and GUI-driven local monitoringall for the sake of providing an implementable and deployable solution for wildlife conservation.

3. Methodology

3.1 System Architecture

Anti-Poaching Monitoring System includes four major components: sensing unit, processing unit, communication unit, and alert system. The sensing unit consists of sound sensor ,flame sensor and optional cameras.The sensor detect the frequency of the sound and mic receives the sound and detect the unusual sounds and the camera detect the illegal entry of persons. The processing unit is the microcontroller, which receives signals from the sensors. It processes this data to check whether there is gunshot or poaching.

3.1.1 Hardware Architecture

The architecture of the wildlife conservation system consists of four layers. The Sensor Layer consists of sound sensors (KY-037) that sense gunshots, flame sensors to sense fire, and cameras for visual monitoring, sensing data from the environment continuously. The Processing Layer processes the data with a Raspberry Pi or equivalent, using machine learning algorithms such as TensorFlow Lite to sense gunshots and YOLO to sense wildlife and poachers. The Communication Layer provides IoT-based communication, sending notifications and alerts to the system. Finally, the User Interface Layer, deployed with Tkinter, gives a graphical interface for users to view the system, be alerted, and view historical data.

3.2 Software Architecture

The software architecture of the system is based on a Linux operating system (e.g., Raspbian) on the Raspberry Pi with the necessary libraries and frameworks. The core libraries used are OpenCV for object detection and image processing, TensorFlow Lite for running the machine learning model for voice analysis, Librosa for audio feature extraction, and Requests for notification of alerts via Telegram. Tkinter is used for creating the system's user interface with real-time monitoring, alert logs, and system control. SQLite database is used for storing history data of alerts and detections such that previous events can be accessed and tracked efficiently.

3.3SystemIntegration and Communication

It combines different hardware and software elements to ensure effective communication and threat detection. Raspberry Pi is connected to sensors such as sound and flame sensors, which offer real-time information, which is processed by machine learning algorithms for audio analysis and object recognition. On threat detection, the system alerts via Telegram with location and time stamp information. Real-time sensor readings, system status, and alert history are displayed by the user interface using Tkinter, enabling rapid monitoring and response. The combination of all the components enables timely detection of threats and increases wildlife conservation.

3.4 Scalability and Modularity

The Anti-Poaching Monitoring System is designed in modularity and scalability towards future growth and development to maintain pace with evolving conservation requirements. Every component—i.e., sensors, processing, and communication interfaces—can be individually developed, tested, and upgraded in modular form. The modularity facilitates the addition of new sensors or cameras to enhance the monitoring capability without significant change in the current system.

4. PROPOSED SYSTEM

4.1 Selected Methodology/Process Model

Working Principle:

The Safe Guard Wild Anti-Poaching Monitoring System operates by deploying a network of IoT devices like cameras, motion sensors, sound sensors, and environmental sensors over a wildlife sanctuary. The devices continuously scan the environment for any suspicious activity like poacher movement, animal distress signals, or gun sounds. The system employs AI models trained to detect animal species, detect poachers, and detect gun sounds. Images and sensor data are processed locally on edge devices like Raspberry Pi, which aids in low latency. Once suspicious activity is detected, real-time alerts are sent via Telegram or SMS to rangers or park authorities to respond in real-time. The system is designed to operate independently, enabling 24/7 monitoring and reducing risk to wildlife as well as park officials.

Hardware Assembly: Connect USB Camera,Microphone Module, ultrasonic sensor,Sound Sensor(KY-037) ,Flame Sensor, Servo Motor andRaspberry Pi 3 Model B+.

Software Setup: Install necessary libraries for sensor, camera

Sensor Calibration: Calibrate the ultrasonic sensors to accurately detect distances.

Image and Data Capture: Record environment images and sensor data.

Sound Detection: Process sensor readings to identify the unusual sound.

Real time Alerts : Provide real time alert message to smart phone.

Testing and Validation: Ensure system accuracy and reliability in real-world environments.

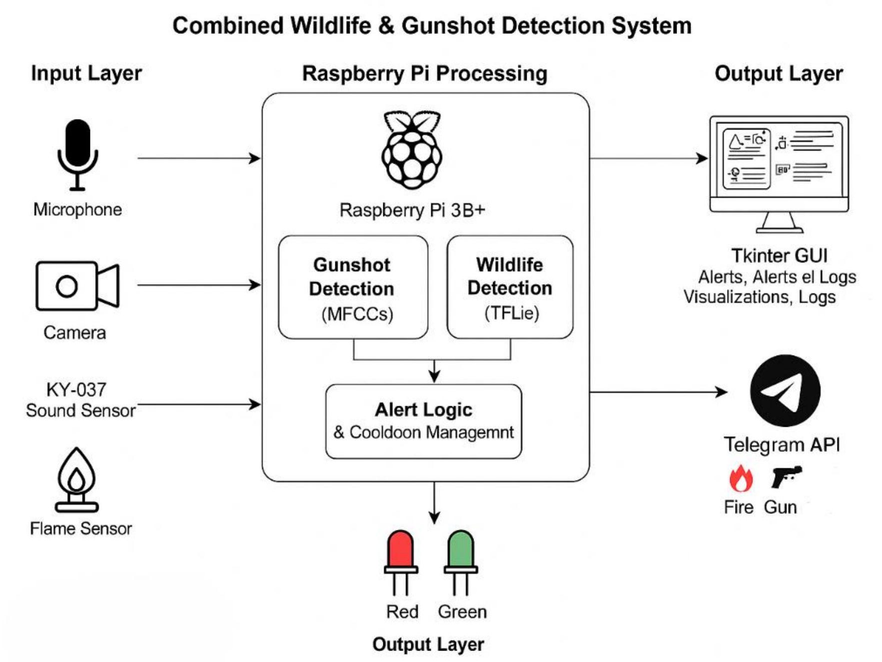
5. AI Model Design and Training

Combines computer vision and audio classification to identify wildlife, poachers, and gunshots in real-time. A YOLO object detection model trained on self-labeled datasets is used to identify animals, guns, and humans (poachers/rangers) from camera streams, while a CNN-based audio classification model analyzes audio spectrograms to identify and classify gunshots. Both models are trained on optimized datasets with data augmentation, validated on unseen data, and implemented in lightweight versions which can be run on Raspberry Pi. These AI modules provide continuous monitoring and real-time alerting for suspected poaching activity.

5.1 Model Architecture

The model design integrates a YOLO (You Only Look Once) convolutional neural network for real-time object detection and a 1D or 2D CNN-based audio classifier for gunshot noise detection. YOLO takes image frames from the camera and applies multiple layers of convolutional layers to detect and classify animals, poachers, and guns with high speed and accuracy. The audio model translates recorded audio into spectrograms, which are passed through a CNN to identify and classify gunshot noise. Both models are edge-optimized and

lightweight for deployment on a Raspberry Pi to function efficiently and react appropriately in field environments.



5.2 Dataset Preparation and Preprocessing

The AI model is trained on:

Custom Dataset: Captured using webcam in real-world environments, i.e., indoor and outdoor environments.Open Datasets: Augmented with small-scale pedestrian and obstacle detection datasets.

Preprocessing includes:

Scaling images to fit webcam inputs (e.g., 640x450 pixel).Data augmentation (rotation, flip) for better generalization.Audio recordings were transformed into mel-spectrograms to obtain sound frequencies over time.

5.3 Feature Engineering

Critical characteristics derived for improved obstacle detection:

Edge Detection: identification of prominent patterns from visual and auditory input. Object edges, shapes, and textures were automatically learned as features in image inputs using convolutional layers in the YOLO architecture. In audio detection, time-frequency features were extracted from mel-spectrograms, which possessed unique gunshot signatures.

5.4 Training and Optimization

Training: Both YOLO object detection model and sound detection model were trained separately on their own datasets. The YOLO model was trained on wildlife images with labels, whereas the sound detection model was trained on audio data with gunshot and non-gunshot samples.

Optimization: Hyperparameters like learning rate, batch size, and optimizer selection were optimized for the models.Model performance was validated with validation data and optimized by making iterative adjustments.

Early Stopping: Prevents overfitting during training.

5.5 Model Deployment and Inference

After training:

Post-optimization and training, the YOLO model is converted to NCNN and sound detection were deployed on the Raspberry Pi 3B+ with Edge Impulse to perform inference in real time with efficiency. The models were integrated into the IoT-based system for monitoring wildlife poaching and libraries and frameworks for running models locally were installed. The two models alert the monitoring system or control center in the event of suspicious activity, which triggers further action such as alerts or automated response.

5.6 Continuous Improvement:

The system is designed for ongoing improvement of performance. With fresh data collected through wildlife monitoring and environmental conditions, the models can be retrained and updated to increase accuracy and responsiveness. Regular updates to the training dataset and model parameter optimization enable the system to effectively respond to changing conditions and new threats.

5.7 Performance Benchmarking

Accuracy: 75%–85% for common indoor/outdoor obstacles.

Inference Speed: Average detection time under 200ms per frame.

Model Size: Less than 500KB, optimized for webcam and microphone

False Alerts: Maintained below 5% through threshold tuning and sensor fusion.

6. Methodology

The System was designed and developed with an iterative and systematic process emphasizing real-time performance, resource limitation, and usability by blind users. The methodology was broken down into five phases: Requirement Analysis, Design and Development, Model Training, System Integration, and Evaluation. A consideration of what can be done on a system with real-time performance, restricted hardware resources, and efficiency accompanied the activity in each phase.

6.1 Phase I: Requirement Analysis

The initial phase was to identify the particular requirements of visually impaired users and study the requirements for real-time obstacle detection and navigation guidance. Major findings were The requirement for a light system that works well on low-power devices such as the Camera,The need for real-time feedback, so the system can guide users immediately when obstacles are encountered.The system should be accurate, with clear and consistent audio cues for navigation.A requirement specification was created based on these findings, with an emphasis on Real-time obstacle detection and navigation guidance.Lightweight architecture for the Camera platform.

6.2 Phase II: Design and Development

Hardware Platform: The right IoT sensors, cameras, and microphones are selected based on the requirements of the area to be monitored. These are connected to the Raspberry Pi, and required communications protocols such as MQTT and HTTP are configured to export sensor data in real-time.

AI Model Integration: The sound classification (for gunshot detection) and object detection (YOLO) AI models are integrated on the Raspberry Pi. This entails converting the models to real-time inference and optimization to the Raspberry Pi's low computational capabilities.

6.3 Phase III: Model Training

Training of the AI model was a critical phase of ensuring accurate and efficient object recognition and sound classification. Training entailed:

Dataset Acquisition: Training of the model begins with the acquisition of a comprehensive dataset. In this project, they are images of wildlife animals, poachers, and weapons inside wildlife sanctuaries and audio recordings of gunshots or any other suspicious sound. The dataset can be augmented with existing datasets and supplemented by sensor readings (distance, angle) from IoT sensors to make the model more accurate and robust.

Data Preprocessing: Image resizing, augmentation (rotation, flipping), and normalization were applied to prepare the data for model training.

Model Selection: Model selection varies based on task and data type. For image data, the pre-trained convolutional neural network (CNN) model, e.g., YOLO (You Only Look Once), is utilized for object detection tasks like weapon, animal, and poacher detection. For sound classification, an audio-based deep learning model, e.g., convolutional neural network (CNN) or recurrent neural network (RNN), is used to classify the gunshots.

Training Strategy: Data augmentation to obtain the most diverse set of data possible by using methods like rotation, scaling, and noise injection is part of the training strategy, and transfer learning to utilize pre-trained models (e.g., YOLO for object detection or CNNs for audio classification) to hasten convergence and enhance performance. Learning rate, batch size, and optimizer are all initialized as hyperparameters to maximize the model's efficiency and cross-validation to prevent overfitting and generalization.

6.4 Phase IV: System Integration

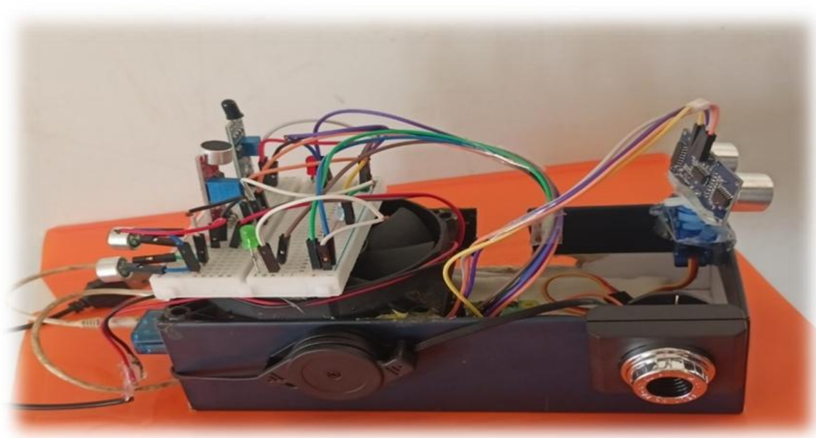
System integration is the process of integrating all the parts of the anti-poaching monitoring system as a functional unit. This is the process of integrating AI models for image and audio recognition, sensor inputs from ultrasonic sensors and cameras, and communication modules (e.g., Twilio, Telegram) for real-time alerts. The AI models run on the Raspberry Pi, which communicates with sensors and processes the incoming data. The system also incorporates a user-friendly GUI for easy monitoring and control. All the parts, including the database to store animal sightings, alerts, and sensor data, are networked together to facilitate seamless interaction between hardware, software, and communication systems to facilitate real-time monitoring and timely alerts for poaching.

6.5 Phase V: Evaluation

Evaluating its performance on major parameters like accuracy, false alarm rate, and response time. The object detection and sound classification machine learning models are tested on how well they can detect animals, poachers, and gunshots correctly with a minimum accuracy of 75-85%. The system's capability to reduce false alarms is of paramount importance for field deployment, with the objective of keeping the false alarm rate low as well as providing timely and correct alerts. The system's responsiveness, environmental robustness, and sensor integration are also tested in real-time environments to ensure field reliability.

7. Applications and Future Work

Safe Guard Wild Anti-Poaching Monitoring System are far-reaching and encompass wildlife conservation, environmental protection, and law enforcement, as well as enhancing safety in national parks and wildlife reserves. Using IoT, AI, and real-time monitoring, the system presents a viable solution for the detection of poaching activity, enabling rapid intervention. Future work entails refining the accuracy of the models, creating more capabilities in the sensors, and incorporating more advanced AI algorithms for enhanced object detection and sound classification.



7.1 Application

7.1.1 Wildlife Poaching Detection and Prevention

The first application of this system is the detection and prevention of poaching in forests and wildlife sanctuaries. The system is supported by motion sensors, sound sensors, and cameras in detecting abnormal movement or sound like gunfire, footsteps, or engine revving. Machine learning algorithms process this data in real time to recognize it as possible poaching activity. Officials are notified in real time, enabling rapid response and minimal risk of damage to wildlife.

7.1.2 Real-Time Monitoring of Protected Areas

This system allows for the surveillance of forest areas under coverage 24/7 without relying on round-the-clock human labor. IoT sensors sweep the area in real time and feed it to the central server or cloud platform. Real-time dashboards deliver real-time feeds, alerts, and analytics by which authorities can track vast expanses of land and respond to threats in a timely manner.

7.1.3 Remote Surveillance in Conservation Areas

With autonomous capabilities and IoT connectivity, the system enables real-time monitoring of remote and inaccessible locations. It reduces the requirement for constant patrolling, saving human efforts and providing better coverage over large forest regions.

7.1.4 Smart Border Monitoring

In global border wildlife sanctuaries, the system not only identifies poaching but also cross-border illegal wildlife trade. Human classification using AI distinguishes human entities from animals (rangers/poachers) and from one another based on situational awareness.

7.1.5 Early Warning Systems for Villages near Forests

Villages residing close to the habitat of wildlife are usually prone to invasions by wild animals. This system will be capable of warning villagers in advance regarding animal movement in the area so that villagers will be prepared and won't encounter conflict.

7.2 Future Work

While the Safe Guard Wild Anti-Poaching Monitoring System has proven useful, there are numerous avenues for future work and enhancement to expand its capabilities, improve its accuracy, and increase its potential for real-world application.

7.2.1 Enhanced Sensor Integration and Miniaturization

Future advancements in IoT-based anti-poaching technology will include the incorporation of more sophisticated and miniaturized sensors that can be subtly integrated into animal collars, trees, or underground. The sensors will be ultra-low-power thermal imaging cameras, vibration sensors, and acoustic sensors that can distinguish between human movement and natural wildlife movement. Multi-spectral imaging will be employed to enhance species identification, with environmental sensors monitoring habitat conditions. Additionally, bio-inspired structures such as camouflage coatings and self-cleaning systems will enable long-term operation in harsh wilderness conditions without alerting poachers.

7.2.2 AI and Machine Learning Advancements

Artificial intelligence will be critical in mapping raw sensor data into actionable insights. Future systems will employ deep learning architectures to analyze wildlife and poacher behavior patterns in support of predictive threat notification. Edge AI will allow on-the-edge processing on low-power hardware, minimizing the dependency on cloud computing and allowing for faster reaction times. All of these technologies will make anti-poaching systems more intelligent, more dynamic, and capable of learning from evolving poaching tactics.

7.2.3 Autonomous Monitoring Systems

The next-generation anti-poaching technology will employ autonomous robots and drone systems for wide-area, real-time surveillance. AI-driven swarms of drones will blanket high-risk zones with optimal flight trajectories, while silent drive technology will be inaudible to poachers. IoT underwater sensors and autonomous subs will blanket oceanic zones, monitoring illegal fishing vessels and tracking threatened sea species. Renewable-powered charging stations along remote roads will supply a continuous power source, rendering the systems autonomous even in the most remote areas.

7.2.4 Advanced Communication Networks

Having a solid communication line is paramount in remote wilderness regions. Next-generation systems will integrate LoRaWAN, satellite communication, and mesh networks to make data transfer a seamless process. Delay-tolerant networking (DTN) protocols will buffer and relay data during low-connectivity situations. In the future, quantum communication might offer ultra-secure, tamper-free data transfer, whereby it would not be feasible for poachers to jam or intercept signals. Hybrid networks will offer rangers real-time alerts even in extreme environments.

7.2.5 Blockchain for Conservation

Blockchain technology will improve accountability and transparency in anti-poaching operations. Indelible records of sensor data will be used as admissible evidence during prosecution of poachers, and smart contracts will be used to automate deployment of rangers and resource allocation. Blockchain tracing of supply chains will also enable tracing of illegal wildlife products from origin to market, disrupting trafficking chains. Tokenized reward schemes could also motivate local communities to report poaching activity, with improved cooperation in conservation.

7.2.6 Human-Centric Design and Community Integration

For IoT anti-poaching solutions to succeed, they have to involve the local communities. Future innovation will be in user-friendly mobile apps that will enable villagers to report suspicious activity with ease. Training procedures will train rangers to fix and maintain IoT devices, and culturally adapted alert systems will enable ease of use in various areas. Blending local tradition and indigenous knowledge, the systems will build trust and long-term collaboration among conservationists and communities.

7.2.7 Energy Harvesting and Sustainability

Since the majority of wildlife locations do not have a reliable power source, next-generation IoT devices will need to be self-sustaining. Solar, kinetic, and bio-energy harvesting technologies will energize sensors for years without battery replacement. Self-healing materials and energy-efficient networking protocols will also enhance longevity. Experimental concepts such as plant-powered bio-batteries could even allow sensors to capture energy from their surroundings, making them completely self-sustain in.

8. CONCLUSION

The Safe Guard anti-poaching monitoring system proposed is a revolutionary wildlife conservation solution, combining the strengths of IoT, AI, and real-time monitoring to tackle the daunting challenge of poaching. With the integration of sound detection and image identification through machine learning models, the system can accurately detect poaching activity with minimal false alarms and send timely notifications to the authorities to respond effectively. With the utilization of a well-structured system architecture, effective model training, and deployment of a variety of sensors, the solution tackles both environmental and operational challenges in the field. The deployment of the system not only guarantees increased monitoring capability but also minimizing the risks in wildlife to illegal activities. Moreover, its flexibility to tackle diverse terrains, coupled with ongoing AI accuracy improvements and system optimization, guarantees long-term system sustainability. In the future, the scalability of the system, the ability to add more sensor technologies, and integration with larger conservation and law enforcement systems will be crucial to further expanding its coverage. Finally, the anti-poaching monitoring system is an innovative solution that can be easily replicated globally to guarantee biodiversity conservation, protection of endangered species, and overall ecosystem health globally.

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