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AI – POWERED WILD LIFE MONITORING AND ANTI POACHING SYSTEM

A LoRa-Enabled Encroachment Detection System for Remote Forest Areas

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Abstract: The growing threat of poaching and habitat destruction has placed immense pressure on wildlife conservation efforts, underscoring the necessity for innovative and real-time surveillance systems. The AI-Powered LoRa Based Wildlife Monitoring and Anti-Poaching System presents an integrated system that uses AI models YOLOv8, for accurate detection of weapons and human intrusion. The system incorporates a Webcam for live image capture, a LoRa communication for long-range, low-power data transmission. Poaching activities are identified using advanced object detection and alerts are triggered for immediate response. Performance testing was carried out to confirm the accuracy of object detection, reliable data transmission, and low energy consumption, achieving real-time performance suitable for remote environments. Advantages include scalability, cost-effectiveness, and continuous monitoring for conservation. Disadvantages include dependency on camera visibility and limited frame rate, which may affect fast-motion detection. Overall, the system offers a practical approach to wildlife protection and proactive anti-poaching measures.

Index Terms - LoRa, YOLOv8, Edge AI, Anti-Poaching, Raspberry Pi, IoT, Wildlife Monitoring

I. INTRODUCTION

In the era of the Internet of Things (IoT), the need for efficient, low-power, and long-range communication technologies has become increasingly significant. Conventional wireless systems such as Wi-Fi and Bluetooth often fail to meet the requirements of large-scale or remote IoT deployments due to their limited range and high-power consumption. To address these limitations, LoRa (Long Range) technology has emerged as a leading solution, providing robust communication over several kilometers with minimal energy usage. It has the ability to operate effectively in low-signal and high-interference environments makes it ideal for smart city, environmental, and industrial applications. This project focuses on the design and simulation of a LoRa-based data communication system for remote sensing and monitoring. The proposed system consists of two primary units a transmitter node based on the Raspberry Pi 5, camera, and LoRa transmitter and a receiver node implemented using the Raspberry Pi Pico W connected to a LoRa receiver, buzzer and an LCD display. The transmitter captures location and sensor data, which is then modulated and transmitted via LoRa to the receiver unit, where the data is displayed in real time. This architecture demonstrates a low-cost, energy-efficient, and scalable IoT communication network [1].

The Web camera module introduces image-based monitoring, making the system highly effective for real-world field applications. In contexts like wildlife and forest surveillance, the camera can automatically capture visual data upon detecting movement. This enhance the system's intelligent sensing functionality, enabling real-time transmission of visual and positional data over long distances through the LoRa communication network. Overall, the project demonstrates the feasibility and advantages of integrating LoRa technology with embedded systems for long-range communication. This work can serve as a foundation for advanced IoT applications such as wildlife monitoring, smart agriculture, and environmental surveillance, where reliable and power-efficient data transmission is essential [13].

1.1 Motivation

Wildlife conservation continues to face serious challenges due to rising illegal poaching activities, habitat fragmentation, and increasing human–wildlife conflicts. Protected forest areas are often vast, remote, and difficult to access, making continuous human monitoring both impractical and expensive. Traditional anti-poaching methods, such as manual patrolling, camera traps, and shortrange sensor systems, often result in delayed threat detection, limited coverage, and high energy consumption. In addition, the absence of reliable communication infrastructure in dense forest regions further reduces the effectiveness of real-time monitoring solutions. Although recent advancements in artificial intelligence and Internet of Things (IoT) technologies offer new possibilities for smart surveillance, many existing systems depend heavily on cloud connectivity or high-power communication networks, which are not suitable for long-term deployment in remote environments.

Furthermore, several wildlife monitoring systems primarily focus on animal tracking while overlooking essential anti-poaching features such as human intrusion detection, precise location tracking, and immediate alert generation. These practical limitations highlight the need for an integrated, autonomous, and energy-efficient monitoring framework that can operate reliably in connectivity-constrained areas. The motivation behind this work is to design a system that combines edge-based AI detection, long range low-power communication, and accurate location tracking to enable proactive and real-time anti-poaching surveillance. By minimizing dependence on constant human supervision and costly infrastructure, the proposed solution aims to support stronger conservation efforts and enhance the protection of vulnerable wildlife habitats.

1.2 Novelty and Contributions

The novelty of the proposed system lies in its complete integration of artificial intelligence and long-range IoT communication into a single, practical anti-poaching framework. Unlike many existing wildlife monitoring solutions that mainly focus on animal tracking or environmental sensing, this work shifts the focus toward proactive poaching prevention by enabling real-time detection of humans and potential weapons directly at the edge device. By processing data locally and transmitting only essential alerts, the system ensures both efficiency and reliability in remote forest environments.

The key highlights of the proposed system are presented as follows:

1. **Edge-Based AI Detection**

A lightweight deep learning model is deployed on an embedded platform to perform real-time detection of animals, humans, and weapons. By executing inference directly on the device, the system reduces latency and eliminates dependence on cloud infrastructure.

2. **LoRa-Enabled Long-Range Communication**

The system utilizes low-power LoRa communication to transmit detection alerts over extended distances. This ensures reliable operation in dense forest regions where conventional network connectivity is unavailable.

3. **Location Awareness**

Each camera is assigned by a unique ID and stored its fixed location which contains the latitude and longitude of the location, enabling precise localization of wildlife movement and suspected poaching activity by using the camera ID. This location-aware approach supports faster and more targeted response from forest authorities.

4. **Energy-Efficient and Scalable Architecture**

The overall system is designed with energy efficiency and cost-effectiveness in mind. Its low-power operation and modular design make it suitable for large-scale deployment and long-term monitoring across extensive conservation areas.

1.3 YOLOv8 model

YOLOv8 (You Only Look Once version 8) is a deep learning-based object detection algorithm designed for real-time and high accuracy detection. It follows a single stage detection approach, where object identification and localization are performed simultaneously in one forward pass of the network, enabling fast and efficient inference. YOLOv8 uses an advanced backbone architecture derived from CSPDarknet, which improves feature extraction while reducing computational complexity. This makes it highly suitable for deployment on embedded platforms such as Raspberry Pi [2]. In wildlife monitoring and anti-poaching applications, YOLOv8 plays a crucial role by accurately detecting and classifying animals, humans, and potential threats such as weapons from live camera feeds. Its ability to operate with high precision under varying environmental conditions such as low lighting, dense vegetation, and motion makes it ideal for forest surveillance systems. By performing edge-based detection, YOLOv8 minimizes latency and eliminates the need for continuous cloud connectivity, enabling real-time response in remote and connectivity constrained regions. Thus, YOLOv8 forms the core intelligence of the proposed anti-poaching system, ensuring timely detection and effective wildlife protection.

1.4 LoRa transceiver

LoRa (Long Range) is a low-power, wide-area wireless communication technology specifically designed for long-distance data transmission with minimal energy consumption. It operates using chirp spread spectrum modulation (CSS), which enables reliable communication over several kilometers even in environments with high interference and weak signal conditions. Due to its low power requirements and long-range capability, LoRa is well suited for Internet of Things (IoT) applications deployed in remote and largescale areas. In wildlife monitoring and anti-poaching systems, LoRa plays a vital role by enabling real-time transmission of detection alerts where conventional communication networks such as Wi-Fi or cellular services are unavailable [12].

The technology ensures continuous connectivity between the transmitter node and the central monitoring unit while maintaining energy efficiency for long-term field deployment. By integrating LoRa with AI-based detection, the proposed system achieves reliable, scalable, and cost-effective communication, making it an ideal solution for real-time anti-poaching surveillance and wildlife conservation.

II. RESEARCH METHODOLOGY

The AI-powered LoRa-based wildlife monitoring and anti-poaching system follows a five-step process that starts with detecting and localizing threats in real-time. The first step focuses on detecting humans, animals, or weapons using an AI model, such as YOLOv8. The YOLOv8 model is important because it allows for high accuracy in detecting objects and provides real-time inference, enabling the system to identify multiple objects at once. This detection process involves data collection, where the system's camera is instructed to capture images. Once a threat is identified alert is generated and transmitted using LoRa. Here the location of the event is found using camera ID to record the exact position of animals or poachers, securing the essential data needed for intervention. The next stages of the methodology focus on making sure this important information reaches conservation authorities quickly and effectively [10].

The local data moves into Data Transmission, where the system is set up to send the data over long distances using LoRa. LoRa communication is key for this step because it works as a low-power, wide-area network. It provides a long data rate and higher energy efficiency, making it ideal for monitoring remote forests. The final step in the process is Monitoring and Alerts, where the goal is to process the received data on a central system to monitor wildlife and poaching. By combining AI detection with strong IoT communication, this method ensures the delivery of real-time alerts for conservation and safety, which improves anti-poaching surveillance [3].

2.1 Dataset collection and preparation

The effectiveness of any deep learning-based detection system largely depends on the quality and diversity of the dataset used for training. In this project, a custom dataset was created specifically for the anti-poaching surveillance application. Since publicly available datasets do not accurately represent real forest intrusion scenarios, real-time images were captured using a USB webcam connected to a Raspberry Pi 5 [4]. Data collection was carried out in environments that simulate forest-like conditions, including varying lighting levels, backgrounds, distances, and human poses. The dataset includes images of humans (representing potential poachers), and animals. Capturing diverse conditions such as partial occlusion, different camera angles, and motion blur ensured that the model would perform reliably in real-world scenarios. After image acquisition, the dataset was manually annotated using an image labelling tool. Bounding boxes were drawn around relevant objects, and class labels such as “human” and “animal” were assigned. The annotations were saved in YOLO format, which contains normalized coordinates of the bounding boxes along with corresponding class identifiers [5].

2.2 YOLOv8 Model Training

After preparing and organizing the dataset, the next step involved training the YOLOv8 model to accurately detect humans and animals in forest environments. YOLOv8 (You Only Look Once version 8) is a real-time object detection algorithm, which is suitable for edge-based applications such as wildlife surveillance. For this project, a lightweight version of the YOLOv8 model was selected to ensure compatibility with the Raspberry Pi 5 hardware. The training process was carried out using the Ultralytics YOLOv8 framework in a Python environment. The annotated dataset, formatted in YOLO structure, was supplied to the model along with a configuration file specifying class names and data paths. During training, the model learns to identify patterns in images by adjusting its internal parameters (weights) through multiple iterations called epochs. In each epoch, the model processes the training images, predicts bounding boxes and class labels, and compares them with the ground truth annotations. The difference between predicted and actual values is measured using a loss function, and this error is minimized through backpropagation and optimization algorithms [8].

2.3 Edge Deployment on Raspberry Pi

After successfully training the YOLOv8 model, the next phase involved deploying the trained model onto the Raspberry Pi 5 for real-time edge inference. Edge deployment refers to running the artificial intelligence model directly on a local device rather than relying on cloud-based processing. This approach significantly reduces latency, improves reliability, and ensures system functionality even in remote forest environments where internet connectivity is limited or unavailable. The trained model, saved in .pt format, was transferred to the Raspberry Pi 5 running Raspberry Pi OS. The required software dependencies, including Python, OpenCV, and the Ultralytics YOLOv8 framework, were installed and configured on the device. The USB webcam was interfaced with the Raspberry Pi to capture continuous video frames, which were then fed directly into the YOLOv8 model for inference. To ensure smooth performance on the embedded platform, the lightweight YOLOv8 variant was selected. Input images were resized to 640×640 pixels to balance detection accuracy and computational efficiency [7].

The system processes each frame sequentially, performs object detection, and generates bounding boxes along with class labels and confidence scores in real time. Deploying the model at the edge offers several practical advantages. First, it eliminates the need to transmit high-resolution images to a remote server, thereby conserving bandwidth. Second, it enhances privacy and security since all image processing occurs locally. Third, it enables faster decision-making, which is critical for detecting unauthorized human presence in restricted forest areas. The Raspberry Pi continuously monitors incoming frames, and upon detecting a human with confidence above a predefined threshold, it triggers the alert transmission mechanism. This real-time edge intelligence ensures immediate response while maintaining low power consumption and system autonomy. Overall, edge deployment transforms the Raspberry Pi into an intelligent surveillance node capable of performing on-device deep learning inference, making the system efficient, scalable, and suitable for remote wildlife protection applications [15].

2.4 LoRa Communication Implementation

To enable long-range and reliable communication between the detection node and the monitoring unit, LoRa (Long Range) technology was integrated into the system. Since forest environments often lack cellular coverage and stable internet connectivity, LoRa (SX1278) provides a low-power and wide-area communication solution suitable for remote deployments. In this project, the LoRa transceiver module was interfaced with the Raspberry Pi 5 using the SPI (Serial Peripheral Interface) protocol. The SPI interface allows fast and synchronized data exchange between the Raspberry Pi (master device) and the LoRa module (slave device). Proper voltage regulation was ensured using a buck converter to provide a stable 3.3 V supply required by the LoRa module. When the YOLOv8 model detects a human in a restricted area, the Raspberry Pi generates a compact alert message. Instead of transmitting images, which require high bandwidth, only essential data such as node ID and detection class are formatted into a small data packet. This lightweight packet structure ensures efficient use of LoRa's low data rate communication [14].

The LoRa module modulates the alert data using Chirp Spread Spectrum (CSS) modulation and transmits it wirelessly over long distances. At the receiving end Fig.2, another LoRa module captures the transmitted signal, demodulates the data, and forwards it to the receiver unit for further processing. Communication parameters such as frequency band, spreading factor, bandwidth, and transmission power were configured to optimize range and reliability. A higher spreading factor was selected to improve noise immunity and ensure stable communication in dense forest environments. This implementation ensures that the system remains operational even in areas without internet infrastructure. By combining edge intelligence with LoRa-based long-range communication, the proposed system achieves energy-efficient, reliable, and scalable alert transmission suitable for wildlife protection applications.

2.5 Wi-Fi based Email alert system

To ensure that detected threats are immediately communicated to responsible authorities, a Wi-Fi-based email alert system was integrated into the receiving unit. While LoRa enables long-range communication between field nodes and the control station, WiFi provides internet connectivity that allows alerts to be delivered directly to mobile devices in real time. Once the receiver obtains the alert message from the detection node, the Raspberry Pi processes and verifies the received data. If the message indicates the presence of a human in a restricted forest zone, the system automatically triggers an email notification [9].

A Python-based script utilizing the Simple Mail Transfer Protocol (SMTP) is used to compose and send the alert email securely over the internet. By keeping the alert message concise and informative, the system ensures quick understanding and rapid response. Secure authentication methods, such as encrypted connections and application-specific passwords, are employed to maintain the security of the email transmission process. This approach eliminates the need for a dedicated mobile application, as email notifications can be received on any smartphone. It also ensures scalability, allowing multiple recipients to be notified simultaneously. The integration of Wi-Fi-based email alerts enhances the practical usability of the system by bridging the gap between remote detection and immediate human intervention. Overall, the Wi-Fi-based email alert mechanism transforms the system from a standalone detection unit into a connected surveillance solution capable of delivering timely and actionable information to forest officials [11].

2.6 Power management

Efficient power management is a critical aspect of the proposed anti-poaching surveillance system, especially since it is designed for deployment in remote forest environments where continuous and reliable power supply cannot always be guaranteed. The system must operate for extended periods with minimal maintenance, making energy efficiency and voltage stability essential design considerations. The primary components of the system, including the Raspberry Pi 5, LoRa module, and peripheral devices, operate at specific voltage levels. To ensure safe and stable operation, a DC–DC buck converter is incorporated into the power supply unit. The buck converter steps down the higher input voltage (such as from a battery or adapter) to the regulated 5 V and 3.3 V levels required by the system components. Compared to linear voltage regulators, the buck converter offers higher efficiency and reduced heat dissipation, making it more suitable for battery-powered applications.

Proper voltage regulation is particularly important for the LoRa module, as fluctuations or ripple in the power supply can degrade communication reliability. By maintaining a stable output voltage, the power management system enhances overall system stability and reduces the risk of transmission errors. Additionally, the edge-based processing approach contributes to energy efficiency by eliminating the need for continuous high-bandwidth data transmission to cloud servers. Since only lightweight alert messages are transmitted, overall power consumption is minimized. The proposed power management design ensures reliable, low-power, and long-duration operation of the surveillance system, thereby making it suitable for real-world deployment in remote and environmentally challenging conditions.

III. HARDWARE IMPLEMENTATION

The hardware implementation of the proposed anti-poaching surveillance system was carefully designed to ensure reliability, efficiency, and suitability for remote forest environments. The system is centered around the Raspberry Pi 5, which serves as the main processing unit responsible for running the YOLOv8 object detection model and managing communication modules. A USB webcam is connected to the Raspberry Pi to continuously capture real-time image frames for analysis. This setup allows the system to function as an intelligent edge device capable of performing on-site detection without relying on external servers. For long-range communication, a LoRa transceiver module is interfaced with the Raspberry Pi using the SPI protocol. This enables the transmission of compact alert messages to the receiving unit over several kilometers, even in areas without cellular connectivity.

To ensure stable operation, proper voltage regulation is achieved through a DC–DC buck converter, which steps down the input power supply to the regulated voltage levels required by the Raspberry Pi and LoRa module. This approach enhances energy efficiency and protects sensitive components from voltage fluctuations. At the receiving end, another LoRa module and Raspberry Pi unit are used to process incoming alerts. The receiver is connected to a Wi-Fi network to enable automated email notifications to mobile devices. Additional components such as antennas, power adapters or batteries, and LED indicators are integrated to improve communication range, portability, and system status visibility.

Figure 1. Transmission Part

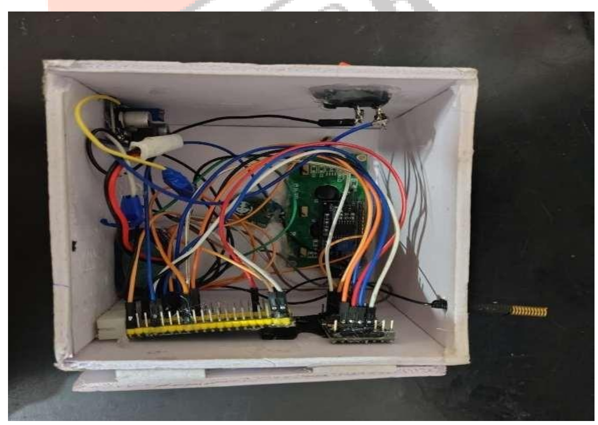


Figure 2. Receiving Part

IV. RESULTS AND PERFORMANCE ANALYSIS

The proposed AI-enabled anti-poaching system system was evaluated in terms of detection accuracy, communication reliability, and responsiveness. The trained YOLOv8 model demonstrated strong performance in accurately identifying human presence minimizing false detections caused by animals or environmental variations. When deployed on the Raspberry Pi 5, the model achieved stable real-time inference with acceptable frame rates, confirming the effectiveness of edge-based processing reducing latency. The LoRa communication module successfully transmitted compact alert messages over long distances minimal packet loss, ensuring reliable operation in remote forest environments. Additionally, the Wi-Fi-based email alert delivered notifications to mobile devices within a short response time, enabling timely intervention. The integration of efficient management further enhanced system stability and long-duration operation. Overall, the results confirm that the proposed provides a practical, reliable, and energy-efficient solution for real-time wildlife surveillance and anti-poaching. At the receiving end, an LCD display is used to provide clear and immediate status updates of the system. When the device is powered on and ready to operate, the message " SYSTEM READY " is displayed to indicate proper initialization Fig 3. As in Figure 4 and Figure 5, Upon receiving alert data from the detection unit, the display updates dynamically to show messages such as " HUMAN WITH WEAPON DETECTED " or " WEAPON DETECTED ", depending on the identified threat.

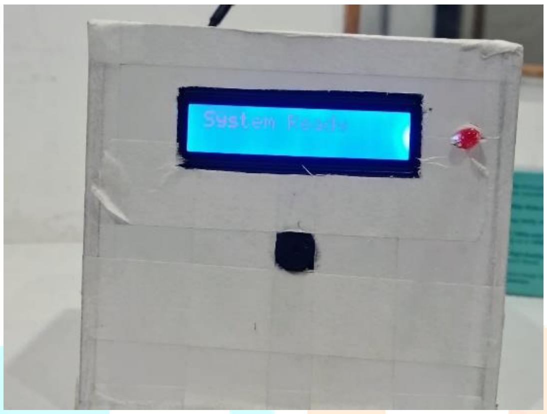
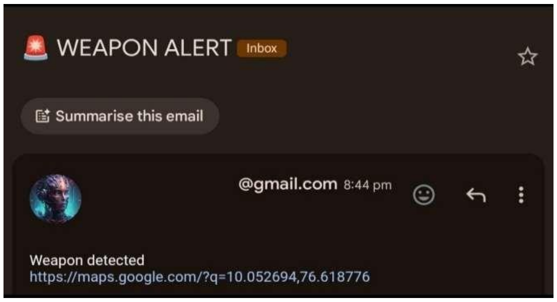


Figure 3. System is ready

Figure 4. Alert when weapon detected

Figure 5. Alert produced when human is detected

This simple visual feedback mechanism allows authorities to quickly understand the situation without relying solely on mobile notifications, thereby enhancing on-site awareness and response efficiency. The email alert system is designed to make sure that whenever the system detects something suspicious, the information quickly reaches the right people without any delay. When the YOLOv8 model running on the Raspberry Pi 5 identifies a human or weapon in a restricted forest area, it immediately creates a small alert like what was detected. This message is first sent through the LoRa module to the receiver unit. Once the receiver gets the alert, it uses its Wi-Fi connection to send an automatic email notification to the concerned authorities. The Raspberry Pi at the receiving end runs a simple Python program that prepares the email using SMTP and securely sends it over the internet.



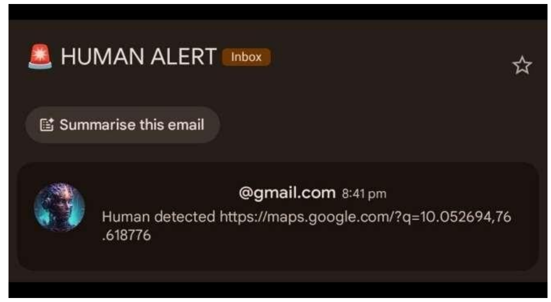


Figure 6. Weapon detection alert in gmail

Figure 7. Human detection alert in gmail

The email clearly mentions the type of threat detected along with the location details, so officials can quickly understand the situation and take action. Figure 6 and Figure 7 shows the alert messages that received in gmail. Secure login methods and encrypted connections are used to make sure the email is sent safely. One of the biggest advantages of using email alerts is convenience. Forest officers do not need to install any special application alerts can be received directly on their mobile phones or laptops through regular email. Multiple officials can be notified at the same time, ensuring faster coordination and response. By instantly converting a detection event into a clear and informative message, the email alert system makes the entire surveillance setup more practical, responsive, and effective in protecting wildlife.

V. CONCLUSION

In conclusion, the proposed AI-powered wildlife monitoring and anti-poaching system offers a practical and meaningful solution to one of the most serious challenges in wildlife conservation. By combining intelligent object detection, long-range LoRa communication and efficient power management, the system is designed to work reliably in remote forest areas where traditional monitoring methods often fail. The use of edge-based AI on the Raspberry Pi allows the system to detect threats instantly without depending on constant internet connectivity, making it both fast and dependable. The integration of LoRa ensures that alerts can travel long distances with very little power consumption, while the email notification system guarantees that responsible authorities are informed immediately. Careful attention to power management also allows the system to operate for extended periods, which is essential in forest environments where maintenance is difficult. Overall, this project demonstrates how modern technologies like AI and IoT can be thoughtfully combined to create a cost-effective, scalable, and energy-efficient surveillance solution. More importantly, it shows how technology can play a vital role in protecting wildlife, preventing illegal activities, and supporting conservation efforts in a sustainable and impactful way.

Beyond its technical strengths, the proposed system also supports broader global sustainability efforts. It aligns with the United Nations Sustainable Development Goals, particularly Goal 11 (Sustainable Cities and Communities) and Goal 15 (Life on Land), by promoting the protection of natural habitats and responsible ecosystem management. By enabling early detection of illegal activities and reducing threats to wildlife, the system contributes to the preservation of biodiversity and the long-term health of forest ecosystems. Overall, this work illustrates how advanced technologies such as artificial intelligence and IoT can be thoughtfully applied to create practical, affordable, and sustainable solutions. More importantly, it reflects how innovation can play a meaningful role in strengthening conservation initiatives and protecting natural environments for future generations.

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