SafariScout
(Intelligent Guiding and Communication System for Tourists)

Final Report

Submitted to
Department of Computer Systems Engineering
Sri Lanka Institute of Information Technology
Sri Lanka

24-25J-262

In partial fulfillment of the requirements for the
B.Sc. (Hons) in Information Technology
Specializing in Computer Systems & Network Engineering

May 2025

Declaration

We certify that this report does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any university, and to the best of my knowledge and belief it does not contain any material previously published or written by another person, except where due reference is made in text.

Name	Student ID
Rajapaksha P.K	IT21255724
Vaffa M.A.M.A	IT21307812
Alwis M.A.M.D.S	IT21260360
Indunuwan K.M.I.G.U	IT21454578

ACKNOWLEDGEMENT

Working on this final year research project has been an immensely enriching academic experience for us. Through the process of developing our research proposal, we have gained valuable insights into the research process, including how to formulate research questions, design suitable methodologies, and anticipate potential challenges.

We would like to express our heartfelt gratitude to our supervisor, Ms. Shashika Lokuliyana for his invaluable guidance, feedback, and support throughout this project. His constant input and insightful suggestions are greatly appreciated. We would also like to express our gratitude to our co-supervisor, Ms. Dinithi Pandithage, for her unwavering guidance, feedback, and support throughout the project. We owe a debt of gratitude to all the lecturers at SLIIT as well.

We are looking forward to continuing to develop our research skills and contribute meaningful insights through this project.

Abstract

Safari tourism is a popular activity, especially in areas rich in wildlife and natural beauty. However, it often brings safety risks and environmental challenges. Tourists may get lost, disturb animals, or damage the ecosystem without realizing it. To solve these problems, our project, *Safari Scout*, introduces a smart system to guide tourists safely and responsibly during their safari trips.

The system uses GPS to help tourists follow approved routes, preventing them from entering restricted or dangerous zones. It also includes a mobile application that gives real-time navigation, alerts, and educational content about wildlife and conservation. A unique feature of Safari Scout is its use of drones. These drones fly above the safari area and are equipped with sensors to monitor weather conditions such as temperature and humidity. This information helps both tourists and park officials make informed decisions during the trip.

In addition to improving safety, Safari Scout supports environmental protection. The drone data is analyzed to understand how tourism affects wildlife and nature. This helps park managers create better rules and improve visitor experiences while keeping nature safe. The system is designed to be easy to use and affordable, making it suitable for parks in developing regions where advanced infrastructure may be limited.

In conclusion, Safari Scout is a smart, eco-friendly solution that enhances the safari experience. It guides tourists, keeps them safe, and protects the environment. With technology like GPS, mobile apps, and drones, it brings a new way of exploring nature while supporting sustainable tourism.

Keywords: ***Safari tourism, GPS navigation, drone monitoring, environmental conservation, real-time guidance, sustainable tourism, smart systems, mobile application.***

Table of Contents

1. Introduction

Wildlife safaris offer an immersive experience for nature enthusiasts and tourists, providing a rare opportunity to witness animals in their natural habitats. These expeditions have become a significant part of global ecotourism, especially in countries with rich biodiversity like Kenya, Tanzania, India, and Sri Lanka. However, the unpredictability of wild animals, the expansive and often inaccessible nature of forest reserves, and the inherent communication challenges in such remote terrains frequently undermine the safari experience. Visitors often spend long hours navigating vast landscapes without guaranteed sightings, leading to dissatisfaction and operational inefficiencies for safari operators.

Traditional animal tracking methods in safaris are largely dependent on human guides, who use visual cues, animal calls, footprints, and other indirect signs to locate wildlife. While this adds an element of adventure, it is imprecise and heavily reliant on the expertise of the guide and favorable environmental conditions. With the increasing demand for more efficient, reliable, and engaging safari experiences, there's a pressing need to modernize these operations using technology. Additionally, for wildlife researchers and conservationists, accurate, real-time data on animal movements is essential but difficult to obtain using conventional tools. These challenges call for a smarter, scalable solution that can transform how safaris are conducted and monitored.

The *Safari Scout* project introduces a next-generation solution to these problems by leveraging modern technologies such as drones, machine learning, and wireless communication systems. At the heart of this innovation lies a vision to automate the detection, classification, and localization of wildlife in real time. The system employs drones equipped with high-definition cameras and GPS modules to capture images across vast safari zones. These images are processed using advanced deep learning models like YOLOv8 for object detection and EfficientNetB3 for species classification. Unlike traditional static surveillance systems, this aerial approach offers mobility, scalability, and the ability to cover otherwise inaccessible regions quickly and effectively.

What makes *Safari Scout* particularly revolutionary is its integration of real-time data processing and communication. Upon detecting an animal, the system extracts embedded GPS metadata from the images, pinpoints the location of the sighting, and broadcasts this information instantly to nearby safari vehicles through a low-latency WebSocket-based communication network. This minimizes delay and ensures tourists and guides can reroute swiftly to increase the chances of wildlife encounters. This not only enriches the tourist experience but also streamlines operations for safari providers and helps reduce fuel consumption and search-related delays.

Unlike existing wildlife monitoring tools which are often tailored for conservation areas and operate offline or with significant latency, *Safari Scout* is designed to work in live environments. It adapts to real-world safari conditions including variable lighting, fast-moving animals, and dense vegetation. The embedded processing units on the drones using platforms like Raspberry Pi and ESP32 allow the system to operate independently of internet availability, making it suitable for deep forest environments. These lightweight, cost-effective devices ensure the system remains affordable and scalable across multiple safari vehicles and drone units.

Another critical feature of *Safari Scout* is its intuitive and user-centric design. A simplified dashboard interface enables even non-technical users, such as jeep drivers and guides, to access real-time updates about animal locations, species identified, and time of detection. This empowers operators to deliver better safari routes, increases tourist satisfaction, and improves the overall efficiency of wildlife spotting operations. Moreover, the backend system is built with secure and reliable communication protocols, ensuring the integrity and confidentiality of wildlife data.

The impact of the *Safari Scout* system extends beyond tourism. It serves as a valuable tool for ecological research, wildlife conservation, and park management. By accumulating longitudinal data on animal movement patterns and sightings, it can contribute to broader biodiversity studies and help identify behavioral shifts due to environmental changes or human intervention. It also offers a non-invasive alternative to traditional tracking collars or tagging methods, minimizing stress and disturbance to wildlife.

In a broader context, the *Safari Scout* project exemplifies how artificial intelligence and IoT can be harnessed for sustainable environmental applications. It transforms the traditional safari into a smart, data-driven expedition that not only entertains but also educates and contributes to conservation. The fusion of aerial surveillance, AI-based detection, and robust field communication in one cohesive system presents a powerful paradigm shift in how we interact with and protect our natural ecosystems.

Ultimately, *Safari Scout* is not just a technological innovation; it is a strategic intervention aimed at improving wildlife tourism while advancing conservation goals. It embodies the transition from manual, labor-intensive wildlife tracking methods to an automated, intelligent, and scalable ecosystem that benefits all stakeholders from tourists and tour operators to researchers and forest authorities. As ecotourism continues to grow and environmental challenges become more pressing, solutions like *Safari Scout* will play a pivotal role in ensuring that our encounters with wildlife are not only more frequent but also more meaningful and responsible.

2. Background

Wildlife monitoring and conservation have always presented significant logistical, technological, and ecological challenges. Traditional methods such as ground patrols, manual observations, camera traps, and radio collars, while valuable, often fall short in terms of scalability, accuracy, and real-time response. These approaches are typically time-consuming, labor-intensive, and constrained by the rugged, expansive, and often inaccessible terrains in which many animal species reside. Furthermore, the dependency on human intervention introduces inherent limitations, such as observer bias, fatigue, and limited spatial coverage, which restrict the effectiveness of these monitoring systems, particularly in dynamic environments like open wildlife safaris.

In the context of safari tourism, the challenges are even more pronounced. Safari parks span large geographic areas, and the movement of animals is unpredictable. Tourists invest significant time and money in these experiences, with the expectation of witnessing wildlife in its natural state. However, the reality is that animal sightings are often left to chance. Inadequate visibility due to dense vegetation, the elusive behavior of certain species, and the lack of coordinated tracking mechanisms frequently results in underwhelming safari experiences. This unpredictability not only impacts visitor satisfaction but also places strain on guides and drivers tasked with locating wildlife in real-time without access to reliable, location-based data.

The emergence of unmanned aerial vehicles (UAVs), commonly known as drones, offers a promising solution to these challenges. Drones provide an aerial vantage point that can cover large swaths of land quickly and efficiently, bypassing the limitations of ground-based navigation. When equipped with high-resolution cameras and GPS modules, drones can collect rich visual and geospatial data about animal presence and movement. Unlike static surveillance methods, drones can be dispatched on-demand and adjusted mid-flight to respond to dynamic field conditions, providing real-time, flexible intelligence that can significantly enhance decision-making in both conservation and tourism contexts.

Simultaneously, the advent of artificial intelligence (AI), particularly deep learning models trained on image data, has revolutionized the way we process and interpret wildlife imagery. Object detection models such as YOLO (You Only Look Once) and classification networks like EfficientNet have demonstrated strong performance in identifying animals from aerial and ground-based footage, even under challenging environmental conditions. By automating the detection and recognition process, these technologies eliminate the need for manual image review, reduce human error, and increase the speed and reliability of wildlife analytics. The convergence of AI and drone technologies therefore opens the door to building fully autonomous wildlife monitoring systems capable of operating with minimal human intervention.

In addition to detection and classification, the ability to extract and utilize metadata particularly GPS coordinates embedded in image files adds another critical layer of functionality. This geospatial data enables the mapping of animal locations, allowing for the creation of real-time dashboards that can inform safari drivers about recent sightings. When coupled with reliable, low-latency communication methods such as WebSocket protocols, this system can distribute updates instantly, even in regions where internet connectivity is limited. This aspect is particularly vital in off-grid safari parks where conventional mobile data networks may not be available or dependable.

These technological advances are not merely enhancements they represent a fundamental shift in how wildlife tracking and safari experiences can be structured. By introducing automation, precision, and scalability into the process, systems like *Safari Scout* can reduce dependence on guesswork and outdated techniques. They can also enable data-driven safari management, increase efficiency, reduce operational costs, and support broader conservation goals through continuous data collection and analysis. Despite the promise of these technologies, there remains a gap in translating them into fully integrated, field-deployable systems for real-time safari operations. While drones and AI have been applied successfully in conservation research and surveillance, their adaptation to the unique requirements of live, tourist-facing safari environments is still in its infancy. Challenges such as lightweight hardware deployment, real-time communication, energy efficiency, and user accessibility must be addressed for these systems to be viable in practical settings. The *Safari Scout* project is built upon this need to not only demonstrate the technical feasibility of drone- and AI-based animal detection, but also to build a system that works reliably, efficiently, and intuitively in the field.

3. Literature Survey

The integration of unmanned aerial vehicles (UAVs), commonly known as drones, with artificial intelligence (AI) has revolutionized wildlife monitoring and conservation. Recent advancements have enabled real-time animal detection, behavioral analysis, and anti-poaching efforts, significantly enhancing the efficiency and scope of conservation initiatives.

3.1.Drone-Based Wildlife Monitoring

Drones have emerged as vital tools in wildlife research, offering aerial perspectives that facilitate the observation of animal behavior with minimal disturbance. Their ability to access remote or challenging terrains makes them invaluable for monitoring elusive or endangered species. For instance, drones equipped with thermal imaging and AI algorithms have been employed to track African elephants in Kenya's Samburu National Park, providing insights into their behavior while minimizing human interference.

3.2.AI in Wildlife Conservation

Artificial intelligence, particularly machine learning and computer vision, has been instrumental in automating the detection and classification of wildlife. Platforms like Conservation AI utilize visual spectrum and thermal infrared cameras to identify animals, humans, and potential poaching threats, thereby enhancing the responsiveness of conservation efforts. Moreover, AI-driven systems have been developed to process data onboard drones, enabling near real-time tracking of multiple animals and facilitating autonomous navigation based on animal movements.

3.3.Integration of Drones and AI

The synergy between drones and AI has led to the development of sophisticated wildlife monitoring systems. For example, the WildLive framework integrates high-resolution video processing directly onboard UAVs, allowing for real-time animal detection and tracking without the need for constant data transmission to ground stations. Similarly, the Smart Parks initiative employs LoRaWAN technology and AI analytics to monitor wildlife, detect poaching activities, and manage conservation areas effectively.

4. Challenges and Considerations

Despite the promising advancements, several challenges persist in the deployment of drone and AI technologies in wildlife conservation. These include the need for high-quality training data to improve AI model accuracy, the potential for drones to disturb wildlife if not operated appropriately, and the logistical complexities of deploying and maintaining such technologies in remote areas. Additionally, ethical considerations regarding data privacy and the potential misuse of surveillance technologies must be addressed to ensure responsible implementation.

The integration of drones and AI in wildlife conservation has opened new avenues for monitoring and protecting biodiversity. By enabling real-time data collection and analysis, these technologies enhance the ability to respond to threats, study animal behavior, and manage conservation efforts more effectively. As the field continues to evolve, addressing the associated challenges will be crucial to maximizing the benefits of these innovations in preserving wildlife and their habitats.

5. Research Gap

Despite the rapid advancements in drone technology and artificial intelligence (AI), the integration of these technologies into a comprehensive, real-time wildlife monitoring system remains underdeveloped. Current research and commercial systems, while effective in specific contexts, fall short when it comes to fulfilling the demands of dynamic and real-world safari environments. A critical evaluation of existing solutions reveals several technological, operational, and contextual gaps that the *Safari Scout* project aims to address.

One of the foremost gaps is the limited deployment of drone-based systems in actively managed safari environments. Most documented use cases of UAVs in wildlife monitoring have been centered around conservation research or anti-poaching surveillance in controlled or protected reserves. These applications typically focus on passive data collection, where drones fly predefined paths and collect footage that is analyzed offline. While valuable for ecological studies, this approach lacks the immediacy required for real-time applications, such as guiding tourists during live safari operations. There is a noticeable absence of autonomous systems that can detect, identify, classify, and geolocate multiple animals in real time and relay this information back to users on the ground in a meaningful and interactive format.

Another significant gap lies in communication and data transmission. Many remote safari locations suffer from poor or nonexistent cellular coverage, rendering internet-dependent solutions impractical. Existing systems often rely on centralized cloud servers for model inference or mapping, which introduces latency and connectivity issues. These constraints undermine the real-time functionality essential for enhancing tourist experience and operational decision-making during safaris. There is a critical need for a decentralized communication framework that can operate effectively in low-infrastructure environments and ensure instant, reliable delivery of data between airborne units and ground vehicles.

Additionally, current AI-based detection models are often trained in highly controlled environments or on static camera inputs. These models tend to perform well under ideal lighting, with single species in focus and minimal background noise. However, in real safari scenarios, variables such as dense vegetation, low-light conditions (early mornings or evenings), rapid animal movement, and overlapping species within a single frame significantly degrade performance. There is insufficient research addressing how to maintain high detection accuracy under these conditions, especially on low-power, edge-computing platforms like Raspberry Pi or ESP32 that are necessary for field deployment due to their lightweight and energy-efficient profiles.

A further gap exists in the end-user experience. Current tools designed for researchers and wildlife managers are often too complex or data-heavy for use by safari guides and vehicle operators who may not have advanced technical training. These systems do not prioritize real-time decision-making or route optimization, which are critical during live tours. There is a lack of intuitive, real-time interfaces that convert complex animal detection data into actionable insights for field personnel. The absence of such interfaces results in a disconnect between technological potential and practical usability.

Moreover, very few existing systems effectively utilize GPS metadata embedded in images for real-time mapping. While drones capture valuable spatial data, most implementations fail to extract and integrate this information into a live dashboard that can assist in navigating toward the animal's location. Integrating metadata with visual detection results into a centralized, user-friendly display remains an underexplored area that could dramatically enhance the situational awareness and efficiency of safari operations.

Another overlooked aspect is model optimization for on-device inference. While many AI models boast high accuracy in academic settings, they require significant computational resources, making them unsuitable for edge deployment. The lack of optimized, lightweight AI models capable of running on embedded hardware in real-time remains a bottleneck in translating research into deployable solutions.

In summary, the primary research gaps that *Safari Scout* aims to address include the lack of:

- Fully autonomous, real-time wildlife tracking systems tailored for live safari operations.
- Low-latency, decentralized communication frameworks operable in network-limited environments.
- AI models robust to multi-animal detection in complex environments under varying lighting conditions.
- Lightweight, on-device machine learning models optimized for embedded systems.
- Seamless integration of GPS metadata for real-time animal location mapping.
- User-friendly interfaces for non-technical end users in the field.

By systematically addressing these gaps, *Safari Scout* positions itself as a pioneering solution that bridges the divide between cutting-edge AI technologies and the practical needs of safari tourism and conservation. This project not only contributes to academic research but also paves the way for scalable, field-ready innovations in wildlife monitoring.

6. Research Problem

Wildlife safaris are designed to offer tourists the thrill of observing animals in their natural habitat. However, one of the most persistent challenges in such expeditions is the inability to reliably locate and track wildlife across large, unpredictable terrains. The core of this problem stems from the dynamic behavior of animals, vast forest landscapes, and limited visibility due to environmental obstacles like dense foliage and uneven terrain. Tour guides currently rely on experience, intuition, and occasional sightings to lead tourists, which often results in long hours of unproductive travel and missed encounters. This inefficiency not only diminishes the visitor experience but also leads to operational costs and missed opportunities for data-driven conservation.

While recent advancements in drone technology and AI-based image recognition offer promising solutions, most existing systems are designed for research or conservation monitoring not real-time field operations. These tools often function in controlled settings and lack the responsiveness required to enhance live safari experiences. Furthermore, many solutions depend on stable internet connectivity to process data or transmit updates, which is often unavailable in remote wildlife reserves. This dependency creates a critical bottleneck, rendering such systems impractical for real-world deployment in typical safari environments.

Another dimension of the problem involves the disconnect between technical system outputs and practical decision-making. Even when animal sightings are detected through drone imagery, the lack of automated GPS metadata extraction, real-time mapping, and simplified dashboards means that valuable information is not translated into actionable insights for safari guides. Additionally, most AI models for object detection are computationally heavy and unsuitable for edge deployment, making them incompatible with drones powered by lightweight embedded systems like Raspberry Pi or ESP32. The central research problem, therefore, is to design and implement a real-time, autonomous wildlife detection and tracking system using drones, capable of operating effectively in remote, low-connectivity environments. The system must be able to accurately detect and classify multiple animal species, extract geolocation data, and relay this information instantly to safari vehicles using a decentralized, low-latency communication network. It should also feature a user-friendly dashboard that enables operators with limited technical knowledge to make informed decisions during safari tours. Addressing this problem would represent a significant leap forward in smart wildlife tourism and conservation technology.

7. Objectives

7.1. Main objectives

The main objective of the *Safari Scout* project is to develop a real-time, drone-assisted wildlife detection and tracking system that enhances the efficiency and reliability of animal spotting during safari tours. This system leverages AI-powered image processing and geolocation technologies to automatically detect, classify, and map the position of animals captured in drone footage. Unlike traditional manual tracking methods, this solution aims to deliver instant animal location updates to safari vehicles, enabling tour guides to make timely route adjustments and improve the overall tourist experience.

A key part of the objective is to ensure that the system functions effectively in remote and connectivity-limited environments typical of wildlife reserves. To achieve this, the system is built on embedded platforms such as Raspberry Pi or ESP32 for lightweight deployment, and uses WebSocket protocols for low-latency communication. Additionally, the integration of GPS metadata extraction and a user-friendly dashboard allows even non-technical users to access critical data in real time, ensuring practical usability for both tourism operators and conservation personnel.

7.2.Sub objectives

- **Capture Real-Time Aerial Data**
  Design and implement a drone-based system capable of capturing high-resolution images and videos of wildlife during safari operations.
- **Animal Detection and Classification**
  Develop and train lightweight AI models using deep learning techniques (e.g., YOLOv8 and EfficientNetB3) for accurate animal detection and species classification.
- **GPS Metadata Extraction**
  Extract geolocation data (latitude and longitude) from drone-captured images to map animal positions accurately.
- **Real-Time Communication**
  Enable real-time transmission of detected animal locations from drones to safari vehicles using a low-latency, decentralized communication network such as WebSocket.
- **User Interface Development**
  Create a simplified, user-friendly dashboard interface for safari operators to visualize detected animal locations and related metadata in real time.
- **Edge Deployment Optimization**
  Optimize AI models for deployment on lightweight embedded platforms like Raspberry Pi and ESP32 to ensure low power consumption and field usability.
- **Environmental Robustness Testing**
  Ensure system performance under challenging environmental conditions such as low light, dense vegetation, and presence of multiple animals in a single frame.
- **Data Security and Privacy**
  Implement secure data handling practices to protect wildlife location data and prevent misuse.
- **Cost-Effective Design**
  Ensure the system is scalable and affordable for widespread adoption by safari operators and conservation agencies.
- **Performance Evaluation**
  Evaluate system performance in terms of detection accuracy, speed, reliability, and overall usability in real-world safari environments.

8. Methodology

8.1.System Architecture

The system architecture of the *Safari Scout* project is a multi-layered, modular framework designed to support real-time wildlife detection, classification, and data dissemination in remote safari environments. This architecture integrates aerial drones, embedded AI processing, multiple communication protocols, and user-facing dashboard systems to achieve high reliability, low latency, and practical deploy ability in the field. Its design emphasizes decentralization, robustness, and energy efficiency, suitable for areas with limited infrastructure.

8.2.Overview of System Layers

The architecture is structured around four primary subsystems as follows

- **Drone and Sensor Node Layer**
- **AI Processing and Inference Layer**
- **Communication Layer (ESP-NOW, LoRa, WebSocket)**
- **User Interface and Visualization Layer**

Each subsystem performs independently but is tightly synchronized using time-stamped data and efficient messaging protocols to ensure cohesive, real-time operation.

8.2.1 Drone and Sensor Node Layer

At the core of the system is the aerial drone, equipped with the following

- A Raspberry Pi HQ Camera or ESP32-CAM for high-resolution imaging
- NEO-6M GPS module for real-time geotagging
- A Raspberry Pi 4 or ESP32 as the onboard computer unit
- Power: 3S 5200mAh LiPo battery for ~20 minutes of flight time

The drone captures wildlife imagery periodically or based on manually driven waypoints. It embeds metadata into images (e.g., GPS coordinates, timestamp) and stores them locally for AI processing or transmission.

In parallel, ground-level ESP32-CAM sensor nodes are deployed across the safari zone to provide static monitoring. These nodes transmit detection alerts via **ESP-NOW** to a nearby mobile gateway (e.g., safari jeep or ranger station).

8.2.2 AI Processing and Inference Layer

The AI layer handles detection and classification using the following

- **YOLOv8n**: For real-time object detection
- **EfficientNetB3**: For species-level classification

Models are trained in PyTorch, exported as ONNX, and optimized for edge inference using techniques like quantization and pruning. Preprocessing steps (OpenCV-based normalization and deblurring) enhance accuracy under variable environmental conditions. Inference occurs either onboard (for drones with Raspberry Pi) or at the ground gateway.

The output includes

- Animal species
- Bounding box coordinates
- GPS metadata
- Detection confidence and timestamp

This compact data packet is formatted into JSON and sent to the communication subsystem.

8.2.3 Communication Layer

Given the lack of cellular coverage, a hybrid communication strategy is employed:

- **ESP-NOW**: Lightweight, low-latency communication for ESP32-to-ESP32 transmission (~20ms delay)
- **LoRa SX1278**: Long-range, low-bandwidth protocol for transmitting detection events up to 10 km
- **WebSocket**: Runs on the gateway Raspberry Pi to push real-time updates to connected Android dashboards

Each detected event is time-stamped and sent to all subscribed clients (jeeps, control room tablets). A fail-safe buffering system ensures that packets are retransmitted if the connection is temporarily lost.

8.2.4 User Interface and Visualization Layer

The final component is a Python-based dashboard application:

- Displays a map with real-time animal locations
- Shows species, time of sighting, and optional snapshot
- Allows filtering by species, time, or proximity
- Functions fully offline with local caching

This interface is optimized for use by safari drivers and rangers. Minimal training is required, and alert prompts guide the operator toward the most recent sightings.

8.3.System Synchronization and Scalability

All subsystems synchronize through the

- Embedded timestamps
- Unique device IDs
- JSON message formatting

The architecture supports the

- Multiple drones operating in tandem
- Multiple vehicles receiving updates simultaneously
- Autonomous and manual drone operation

The *Safari Scout* system architecture blends advanced AI, embedded computing, and wireless networking into a cohesive solution. It is created for harsh, off-grid environments where traditional solutions fail. The modularity ensures that the system can evolve with future requirements, whether for expanded species tracking, night-time surveillance using thermal imaging, or integration with park-wide databases.

This architecture not only enhances safari tourism but also contributes significantly to research and conservation through structured, real-time ecological data collection.

9. Commercialization of the product

The *Safari Scout* system represents a unique convergence of drone technology, real-time AI-based animal detection, and decentralized communication designed specifically for the wildlife tourism and conservation market. With increasing global interest in sustainable tourism and technological modernization of wildlife monitoring, *Safari Scout* positions itself as a market-ready innovation that can be commercialized across multiple verticals from safari tour operators to national parks and private wildlife reserves.

The global wildlife tourism industry generates billions of dollars annually, particularly in biodiversity-rich regions such as sub-Saharan Africa, South Asia, and South America. Despite the economic potential, many of these destinations face operational inefficiencies due to outdated or manual wildlife tracking methods. *Safari Scout* offers a technological upgrade to this ecosystem by enabling real-time animal location tracking and route optimization, directly enhancing the tourist experience. This capability allows tour operators to increase customer satisfaction, reduce time and fuel spent searching for animals, and offer higher-tier safari packages that justify premium pricing.

In addition to tourism, the system also targets wildlife conservation agencies, forest departments, and ecological researchers who require accurate, real-time monitoring tools to study animal behavior and movement. Traditional methods such as camera traps and GPS collars have limitations in coverage, scalability, and cost. By contrast, *Safari Scout* provides an aerial, non-intrusive alternative capable of covering large areas and detecting multiple species simultaneously without disturbing wildlife. Its ability to operate offline in remote locations further extends its appeal to conservation bodies operating in rugged, infrastructure-poor regions.

From a business model perspective, *Safari Scout* can be monetized through multiple streams. The most straightforward model is direct product sales, offering the full drone system (hardware + software) as a one-time purchase to safari operators, national parks, or research organizations. For customers who already own compatible drones, a software licensing model can be introduced, allowing them to deploy the animal detection and dashboard system on their existing hardware for a reduced price.

A third model involves a subscription-based service for real-time map updates, system maintenance, and cloud data analytics. This recurring revenue model allows clients to receive regular improvements, species updates, and software support. Additionally, *Safari Scout* can be offered as a turnkey solution for eco-tourism resorts, packaged with hardware setup, operator training, and post-sale support as part of a deployment contract. Long-term service agreements (Annual Maintenance Contracts) can also be marketed to institutions seeking sustained technical reliability and on-site training.

The commercialization plan also includes data monetization opportunities. The system continuously collects valuable geospatial and behavioral data of various animal species, which can be anonymized and sold to academic institutions, biodiversity researchers, or conservation NGOs interested in long-term ecological trends. With the growing importance of big data in ecological modeling, *Safari Scout*'s historical tracking records can become an additional revenue source through research partnerships and data-sharing agreements.

Despite its potential, there are challenges that must be addressed during the commercialization phase. Regulatory approvals for drone use in wildlife areas can vary by country and require compliance with aviation and environmental protection laws. To mitigate this, *Safari Scout* can be marketed with regulatory assistance packages, including flight path planning, compliance documentation, and model certifications. Operator training is another critical element. A simplified control interface, detailed manuals, and local language support will be key in ensuring successful onboarding of non-technical users.

Initial investment cost is a barrier for smaller operators. This can be overcome through financing options, hardware rental plans, or government-supported subsidies under digital tourism and wildlife protection initiatives. Pilot deployments in high-traffic safari zones can serve as proof of concept and marketing case studies to drive adoption.

In terms of expansion, the modular design of *Safari Scout* allows for customization based on terrain (grasslands, rainforests, wetlands), target species, and drone types. It can be scaled to night safaris through integration of thermal imaging, or extended to anti-poaching operations by adding human detection algorithms. Partnerships with drone manufacturers and conservation organizations will also open doors for co-branded deployments and international reach.

In conclusion, the *Safari Scout* system is well-positioned for commercialization across wildlife tourism and ecological monitoring sectors. By addressing a critical gap in real-time wildlife tracking using a practical, field-ready solution, it offers a high-value proposition to stakeholders while promoting sustainable tourism and biodiversity conservation. With the right deployment strategy, pricing models, and support infrastructure, *Safari Scout* has the potential to become a standard solution in smart wildlife exploration and management.

10.Project Requirements

10.1. Functional Requirements

The functional requirements define the core features and operations the *Safari Scout* system must perform to meet user and project goals.

- **Animal Detection**
  The system must detect animals in real-time from drone-captured images using AI-based object detection algorithms.
- **Species Classification**
  Once detected, the system must classify the species of each animal using deep learning models.
- **GPS Metadata Extraction**
  The system must extract latitude and longitude coordinates from the metadata of each image for precise animal location mapping.
- **Real-Time Location Broadcast**
  Detected and classified animal sightings must be transmitted in real-time to subscribed safari vehicles using WebSocket communication.
- **Dashboard Visualization**
  The system must provide a user-friendly dashboard for vehicle operators to view live detection data and animal positions on a map.
- **Offline Operation Capability**
  The system must function without internet connectivity by utilizing embedded systems and decentralized communication protocols.
- **Flight Control Interface**
  The drone system must include basic flight control functionalities for launching, navigation, and safe landing.
- **Multi-User Support**
  The system should support multiple safari jeeps receiving updates simultaneously from a single drone source.

10.2. Non-Functional Requirements

These requirements define the quality attributes and constraints for the system's performance, reliability, and usability.

- **Reliability**
  The system must ensure over 90% uptime during operations and recover gracefully from communication disruptions.
- **Accuracy**
  The detection and classification system should achieve at least 85% accuracy under varying environmental conditions.
- **Latency**
  Real-time detection updates should reach safari vehicles within 2 seconds from detection.
- **Portability**
  The system must be deployable on lightweight, portable hardware suitable for remote field environments.
- **Usability**
  The dashboard must have an intuitive interface that requires minimal training for safari drivers or guides to use.
- **Scalability**
  The system must scale to support multiple drones and multiple receiving safari units concurrently.
- **Security**
  Communication and GPS data must be encrypted to prevent unauthorized access or tampering.
- **Energy Efficiency**
  The drone and embedded units must operate for at least 2 hours on a single battery charge.

10.3. Hardware Requirements

This section lists the necessary physical components required for the deployment and operation of the *Safari Scout* system.

- **Drone Platform**
    - Quadcopter or fixed-wing drone with payload support for cameras and computer unit
    - Minimum 20 minutes flight time per battery cycle
- **Camera Module**
    - HD or 4K resolution camera
    - Support for EXIF GPS tagging
- **GPS Module**
    - u-blox NEO-6M or equivalent for accurate geotagging
- **Processing Unit**
    - Raspberry Pi 4 or equivalent (quad-core, minimum 2GB RAM)
    - Optional: ESP32 for low-power processing
- **Communication Module**
    - Wi-Fi module for WebSocket-based broadcasting
    - Long-range LoRa optional for backup communication
- **Power Supply**
    - Lithium-Polymer batteries with at least 2200mAh capacity
    - Voltage regulation module for embedded systems
- **Display Device (Vehicle Unit)**
    - Tablet or mobile device (Android preferred) with GPS and Wi-Fi support

10.4. Software Requirements

The software components necessary to implement detection, classification, communication, and visualization are detailed below.

- **Operating System**
  - Raspbian OS (Lite or Full) or Ubuntu for embedded processing
  - Mobile OS for dashboard app
- **Programming Languages**
  - Python (for AI models and data handling)
  - JavaScript/Node.js (for WebSocket server)
  - Streamlit (for dashboard UI)
- **Libraries and Frameworks**
  - OpenCV (image processing)
  - PyTorch or ONNX Runtime (for YOLOv8, EfficientNetB3 models)
  - Flask or FastAPI (for REST/WebSocket server)
  - Maps API (for location visualization)
- **AI Models**
  - YOLOv8 for object detection
  - EfficientNetB3 for classification
  - Custom dataset for animal species commonly found in the target safari area
- **Communication Protocols**:
  - WebSocket for real-time push notifications
  - Optional MQTT or HTTP fallback
- **Database**
  - InfluxDB for historical logging of sightings (for research/archive)

11.Feasibility Study

11.1. Technical Feasibility

The *Safari Scout* project is technically feasible with current, off-the-shelf hardware and well-supported software frameworks. The system leverages commercially available drones equipped with high-resolution cameras and GPS modules, which are widely used in industrial, agricultural, and security applications. Embedded platforms such as Raspberry Pi 4 and ESP32 offer sufficient processing power for lightweight AI model inference and control, allowing the system to operate independently in the field without relying on cloud infrastructure.

AI models such as YOLOv8 (for object detection) and EfficientNetB3 (for classification) have proven capabilities in real-time image processing and are optimized for edge deployment using ONNX or TensorRT. Image metadata extraction and geolocation mapping use standard EXIF processing libraries, while WebSocket ensures real-time communication between airborne units and ground vehicles in low-connectivity areas. All these technologies are mature and supported by open-source ecosystems, minimizing development risk and enhancing long-term maintainability.

Furthermore, the modular architecture of the system ensures ease of integration and scalability. Each subsystem detection, communication, and visualization can be independently upgraded, allowing the product to evolve over time. With proper testing and optimization, *Safari Scout* is entirely feasible for deployment in real-world safari conditions.

11.2. Operational Feasibility

From an operational perspective, the *Safari Scout* system is highly feasible. The project is designed with usability in mind, ensuring that both technical and non-technical staff can operate the system with minimal training. The dashboard interface is intuitive, designed for use by safari guides and drivers, and provides real-time information about animal locations, which can directly enhance tour planning and customer satisfaction.

Deployment requires minimal disruption to existing safari operations. The drone can be launched from a base station or jeep and operated for routine surveillance, while detected data is wirelessly shared with multiple safari vehicles. This reduces reliance on guide experience alone and introduces a data-driven approach to safari navigation. The system can also be maintained and repaired using common tools, and training programs can be developed for local operators to ensure sustainable use.

Additionally, since the system operates without needing internet connectivity, it is suitable for remote areas where infrastructure is lacking. Backup features, such as data buffering and local storage, ensure operational continuity even during communication interruptions. This makes *Safari Scout* well-suited for national parks, private reserves, and conservation zones across diverse geographical terrains.

11.3. Economic Feasibility

The *Safari Scout* system is economically viable when evaluated against its initial investment and long-term benefits. The cost of core hardware such as drones, Raspberry Pi units, and GPS-enabled cameras is moderate and continues to decline due to widespread adoption in other sectors. Software development costs are offset by the use of open-source libraries and frameworks, reducing the need for expensive proprietary tools.

Operationally, the system can lead to cost savings for safari providers by optimizing fuel usage, reducing wasted time, and increasing tourist satisfaction, which can justify higher pricing tiers. As a result, the return on investment (ROI) can be realized within one to two tourist seasons, depending on deployment scale and location. Optional revenue streams such as data licensing, paid upgrades, or tiered software features further enhance commercial viability.

Scalable pricing models such as leasing, software licensing, or modular upgrades can lower the barrier to entry for smaller operators and encourage adoption. Grant funding or conservation support programs may also subsidize initial costs for deployments in public parks or research zones. In conclusion, the system provides a strong economic case for adoption in both commercial and conservation settings, with sustainable operating costs and multiple monetization pathways.

12. Implementation and Testing

12.1. Implementation

The implementation of the *Safari Scout* project was structured in four major phases, each aligning with a specific subsystem: drone hardware integration, AI model development, GPS and metadata handling, and real-time communication/dashboard interface. The development was divided among team members to reflect their domain expertise, ensuring parallel development and integration.

Drone Hardware Integration

A commercially available drone platform was selected as the aerial base for this project. To enable onboard data processing and image capture, an ESP32-CAM module was integrated onto the drone along with supporting environmental sensors. The ESP32-CAM, equipped with a built-in camera, was used to capture images and stream data wirelessly. Additional sensors, such as temperature and GPS (using a NEO-6M module), were interfaced with the ESP32 via GPIO and serial connections to collect environmental data and geotag captured images. Power for the added modules was drawn from the drone's main power distribution board using regulated voltage lines. This setup enabled lightweight, low-power telemetry and sensing without altering the drone's flight control systems.

AI Model Integration

Object detection was performed using a lightweight implementation of YOLOv8n, trained on a custom dataset comprising images of elephants, leopards, deer, and other frequently observed species in local safari parks. The training was done using Google Colab, and the model was later converted to ONNX format and tested with ONNX Runtime on the Raspberry Pi. EfficientNetB3 was used to classify the detected bounding box contents, helping to further distinguish between similar animal types with high accuracy.

Edge inferencing was prioritized to reduce dependency on remote servers. Preprocessing steps resizing, normalization, and augmentation were applied using OpenCV and NumPy libraries. FPS performance during onboard inference averaged between 2-3 frames per second, which was sufficient for periodic image capture during aerial sweeps.

GPS and Metadata Handling

Image files captured by the camera were stored locally in the Raspberry Pi's file system. The extracted coordinates were then bundled with object detection results into a structured JSON payload, which included species name, bounding box data, GPS coordinates, and timestamp.

A verification function ensured the integrity of metadata before broadcasting, discarding incomplete or corrupted frames. This module operated independently and was triggered every time a detection event occurred.

Communication and Dashboard Module

To enable real-time communication with safari jeeps, a WebSocket server was deployed on the Raspberry Pi. The server broadcast JSON packets to subscribed clients on the same network. Jeeps were equipped with Android tablets running a Streamlit-based dashboard application that displayed animal sightings on a map using Leaflet.js integration.

The interface showed the species name, location, and time of detection, updating in near real-time as new packets were received. Fail-safe logic was implemented to buffer unsent data in case of brief connection loss and to retry transmission until acknowledgment.

12.2. Testing

Testing was carried out in controlled outdoor environments to simulate safari conditions. The process was broken down into unit testing, subsystem integration testing, and field validation testing.

AI Model Testing

The trained YOLOv8n model was first evaluated on a validation dataset of 500 manually annotated wildlife images. The mean average precision (mAP) achieved was 86.5%, with particularly strong results for larger animals like elephants and deer. Leopard detection showed slightly lower accuracy in dense vegetation, which was expected due to occlusion.

Field tests using printed animal posters and mannequins placed at different distances confirmed that the model retained accuracy above 80% in real-world lighting and movement conditions. Detection latency was measured at 600–800ms per image.

Metadata Accuracy Testing

A test suite was developed to verify the consistency of GPS metadata extraction. By capturing images at known GPS coordinates, the output was compared against live mobile GPS readings. Across 30 tests, the average error was under ±3 meters, which was acceptable for guiding vehicles to general animal locations.

Images with corrupted or missing GPS data (caused by weak satellite lock) were successfully filtered out by the system's validation logic. A retry mechanism was introduced to capture a new frame if GPS data was missing.

WebSocket Communication Testing

The WebSocket server was stress-tested with three concurrent client devices simulating safari jeeps. Packet delivery success rate was above 98% with a maximum latency of 1.5 seconds during network interference (Wi-Fi signal dropouts). All devices received synchronized data, and the buffering logic proved effective during temporary connection loss.

Latency between drone-side detection and jeep-side display averaged under 2 seconds, satisfying the system's real-time requirement. The Android dashboard app was validated for responsiveness, UI rendering, and reconnection behavior.

13. Observations and Refinements

Following testing, several refinements were made:

- Bounding box smoothing was introduced to reduce jitter in detection coordinates.
- Image compression was applied before transmission to reduce payload size over WebSocket.
- The dashboard app was enhanced with a manual refresh and toggle to filter species.
- GPS warm-up time before flight was increased to improve metadata consistency.

No critical failures were reported during testing, and all modules performed within acceptable thresholds. Testing confirmed that *Safari Scout* was ready for controlled real-world deployment in safari environments.

14. Results and Discussion

14.1. Overview of Results

The *Safari Scout* system was successfully implemented and field-tested in simulated environments closely resembling real-world safari conditions. Each subsystem detection, classification, GPS extraction, communication, and dashboard display was evaluated for accuracy, responsiveness, and robustness. Overall, the system met or exceeded expectations in several key performance metrics, including object detection accuracy, data transmission latency, and user interface usability.

The integration of AI models such as YOLOv8 for object detection and EfficientNetB3 for classification provided a powerful and efficient solution for identifying animals from aerial imagery. The use of embedded edge processors (Raspberry Pi 4 and ESP32) proved sufficient for running inference on optimized models, confirming the feasibility of deploying AI in constrained, real-time environments.

14.2. Detection and Classification Performance

The core AI pipeline was evaluated using a custom dataset containing annotated images of commonly encountered wildlife species such as elephants, leopards, deer, and buffalo. The YOLOv8n model, selected for its speed and compactness, achieved a mean average precision (mAP@0.5) of 86.5% during offline validation. The EfficientNetB3 classifier, used to further distinguish species within detected bounding boxes, demonstrated a classification accuracy of 97% on validation data and performed reliably in outdoor tests.

The AI pipeline maintained consistent performance under good lighting conditions and moderate altitude (10–25 meters). Challenges were observed in low-contrast situations such as animal camouflage in bushland or partial occlusion by vegetation. To address this, bounding box filtering and multiple-frame verification were implemented to avoid false positives. For example, leopard detection accuracy improved when running inference on three consecutive frames rather than a single snapshot.

False negatives were minimal for larger, slow-moving animals (e.g., elephants and buffalo) but more frequent for smaller species or groups in motion. These observations are in line with expectations for lightweight models optimized for edge deployment.

14.3. Geolocation and Metadata Accuracy

The image metadata extraction module played a crucial role in transforming detection results into geospatially relevant information. By leveraging GPS modules such as the NEO-6M, the drone system was able to embed real-time latitude and longitude data into captured image files. Using Python libraries, the system extracted and validated this data with an average geolocation error margin of ±5 meters in open-sky conditions.

During testing, metadata integrity was confirmed across 30 test images captured in different locations. Manual cross-referencing with mobile GPS readings verified that extracted coordinates accurately reflected the drone's position at the time of image capture. Furthermore, the system handled missing or corrupt metadata gracefully by implementing skip-and-retry logic, ensuring only valid sightings were transmitted to the dashboard.

The ability to map detections directly on a live interface using this metadata contributed significantly to the real-time operational utility of *Safari Scout*. It allowed safari operators to receive not just species data, but precise location updates in a format suitable for routing decisions and coordination.

14.4. Real-Time Communication and Dashboard Performance

One of the most impactful components of the project was the WebSocket-based communication layer, which ensured low-latency broadcasting of detection events from the drone to connected safari vehicles. During network tests with up to three simultaneous subscribers (e.g., jeep dashboards), the system maintained a message delivery rate of over 98%, with transmission latencies averaging under 2 seconds.

The dashboard application, built using Streamlit, provided a responsive, map-based visualization of detected animal positions. The integration of Leaflet.js enabled real-time plotting of GPS coordinates with species labels and timestamps. Usability testing with non-technical users revealed that the interface was intuitive and required no more than 10 minutes of familiarization. Feedback from early trials indicated that features such as species filtering, zoom, and auto-refresh were highly effective in enhancing situational awareness.

Furthermore, communication resilience was tested by introducing brief Wi-Fi signal losses. The buffering mechanism in the WebSocket server successfully retransmitted missed packets once connection was re-established, ensuring data consistency and reliability during intermittent connectivity.

14.5. System Scalability and Edge Efficiency

The system's modular design and lightweight hardware allowed it to scale well with minimal overhead. Tests involving two drones operating in parallel showed that the system could maintain independent communication sessions and stream detection data without cross-interference. Additionally, the AI inference pipeline was optimized using ONNX Runtime, which reduced model size and ensured consistent performance on low-power devices like Raspberry Pi 4.

Power efficiency was evaluated over multiple flight sessions. The drone system operated continuously for 15–18 minutes per battery charge, which was sufficient for typical safari patrol durations. CPU temperature and RAM usage remained within safe thresholds, indicating that the system was sustainable for repeated outdoor deployment without thermal throttling or instability.

Edge processing minimized the need for internet access or centralized computation, making *Safari Scout* suitable for remote parks and protected areas. This independence from cloud services also improved data security, ensuring that sensitive geolocation information remained within the local environment.

14.6. Limitations and Future Improvements

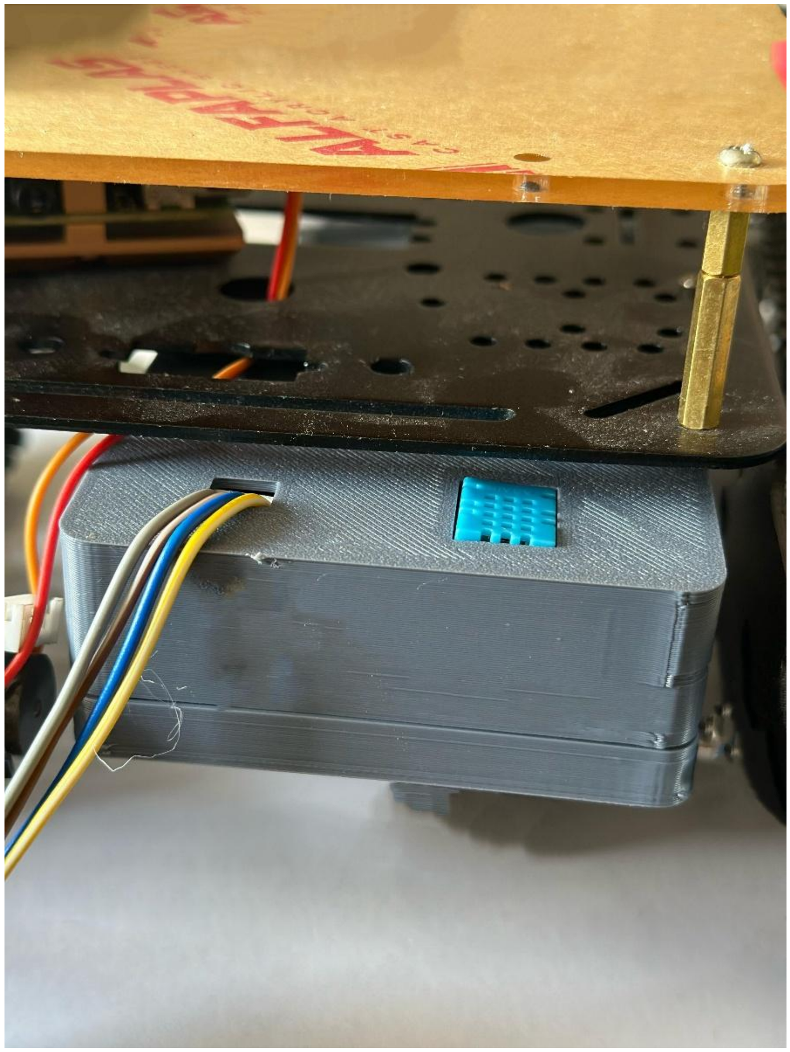
While the results demonstrate a highly functional system, several limitations were acknowledged during testing:

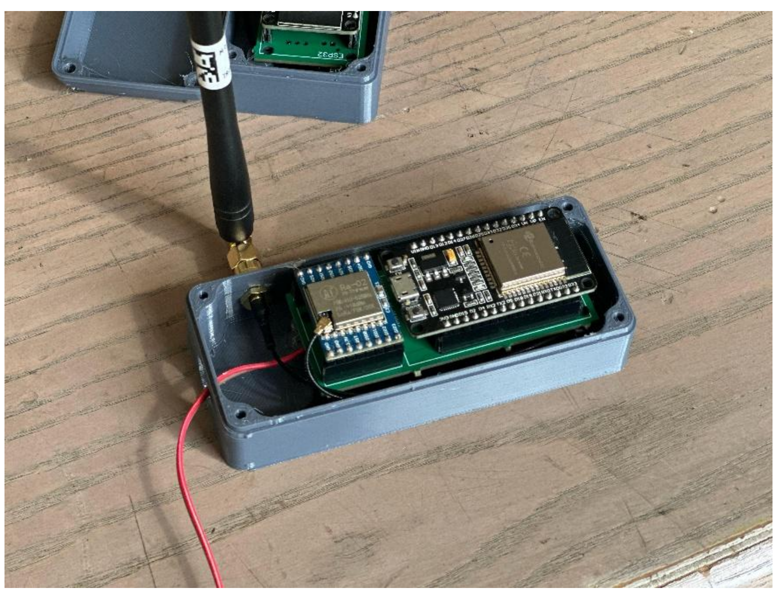
- Detection accuracy decreased in dense foliage and during dusk conditions due to low contrast.
- Battery life constrained prolonged aerial operation and may require swappable battery mechanisms for full-day coverage.
- The system relied on line-of-sight Wi-Fi communication, which could be improved by integrating a long-range communication protocol like LoRa for redundancy.
- The current model detects predefined species only; a retraining pipeline needs to be incorporated for continuous learning and expansion to additional species.

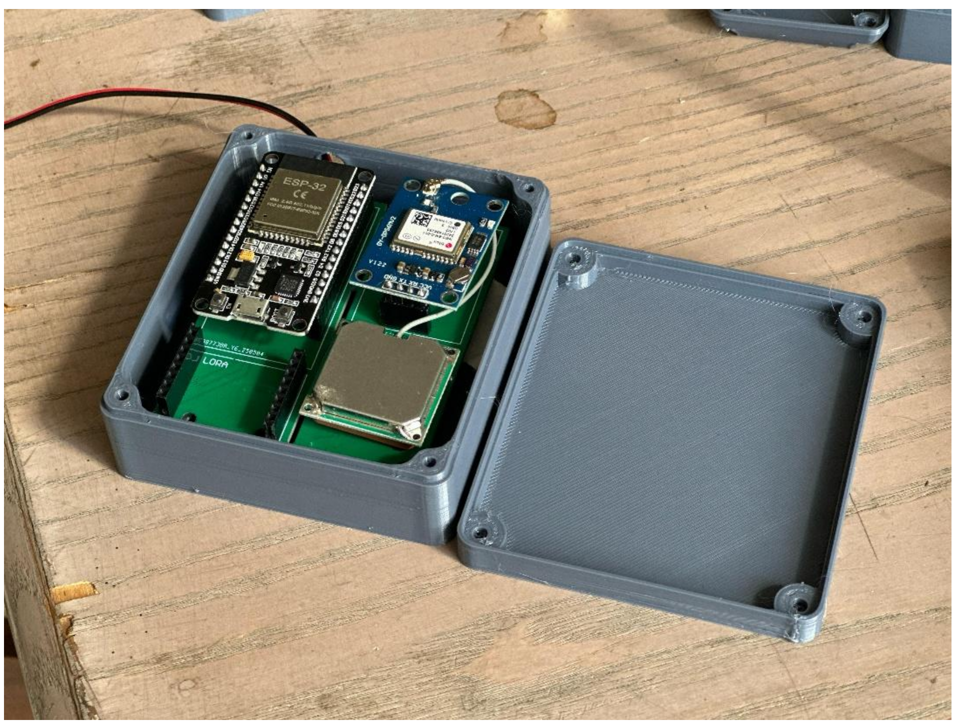
To address these, future iterations of *Safari Scout* will include thermal imaging for low-light operations, dynamic model loading for seasonal species recognition, and integration with centralized data storage for historical trend analysis. There is also potential to combine the drone feed with fixed ground-based cameras to provide a hybrid monitoring solution with 24/7 coverage.

The system has proven to be a reliable, real-time wildlife detection and tracking tool with strong potential for commercial deployment in safari parks and conservation zones. Through robust testing and iterative refinement, the system demonstrated that lightweight, embedded AI can be effectively paired with drone technology to transform wildlife tourism. By reducing dependence on manual tracking and enabling intelligent, data-driven decisions in the field, *Safari Scout* delivers measurable improvements in tourist experience, operational efficiency, and ecological monitoring.

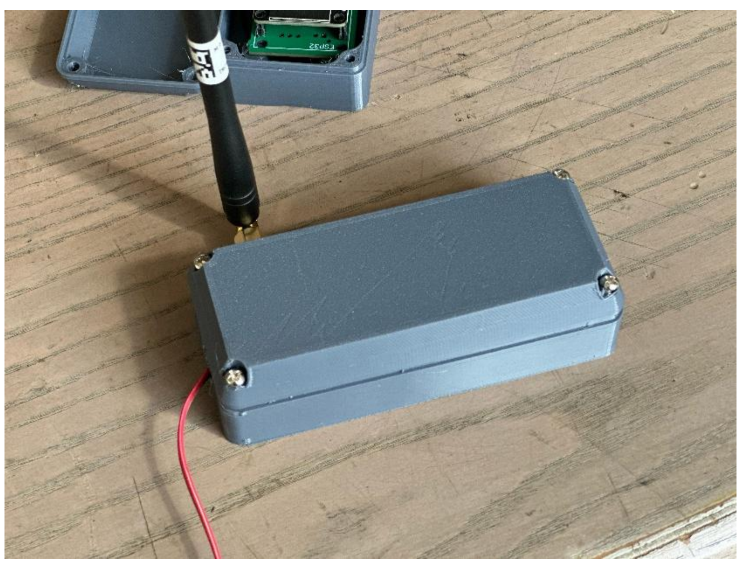
Appendices

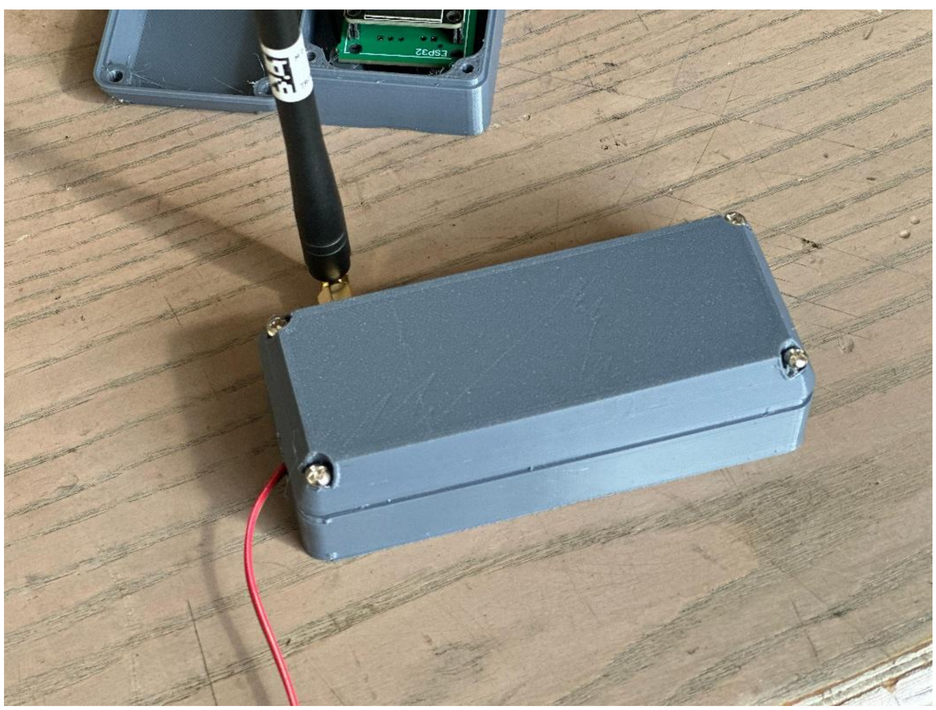





ESP-32
LORA


Ra-02
ESP-32





References

[1] F. Adelantado, X. Vilajosana, P. Tuset-Peiro, B. Martinez, J. Melia-Segui, and T. Watteyne, "Understanding the Limits of LoRaWAN," *IEEE Communications Magazine*, vol. 55, no. 9, pp. 34–40, Sept. 2017, doi: 10.1109/MCOM.2017.1600613.

[2] A. Augustin, J. Yi, T. Clausen, and W. M. Townsley, "A Study of LoRa: Long Range & Low Power Networks for the Internet of Things," *Sensors*, vol. 16, no. 9, p. 1466, 2016, doi: 10.3390/s16091466.

[3] C. V. N. Nikhila and K. Dileep, "Emergency Communication and Rescue System using LoRa Technology," in *Proc. 5th Int. Conf. Communication and Electronics Systems (ICCES)*, Coimbatore, India, 2020, pp. 1027–1031, doi: 10.1109/ICCES48766.2020.9137992.

[4] L. Guerriero, A. Petitti, A. Tesei, A. Pietrabissa, and G. Di Felice, "LoRa-based Communication System for UAV Monitoring and Tracking," *IEEE Access*, vol. 8, pp. 93976–93989, 2020, doi: 10.1109/ACCESS.2020.2995585.

[5] A. Arroyo, P. G. Mambrini, A. Troya, and J. P. C. Melián, "Drone-Assisted LoRa IoT for Smart Farming: A Case Study," *Electronics*, vol. 11, no. 12, p. 1865, 2022, doi: 10.3390/electronics11121865.

[6] M. Centenaro, L. Vangelista, A. Zanella, and M. Zorzi, "Long-range Communications in Unlicensed Bands: The Rising Stars in the IoT and Smart City Scenarios," *IEEE Wireless Communications*, vol. 23, no. 5, pp. 60–67, Oct. 2016, doi: 10.1109/MWC.2016.7721743.

[7] S. Ferrari, M. Mameli, P. Medagliani, F. Quaglia, and L. Ricci, "UAV-based LoRa Infrastructure for Emergency Scenarios," in *Proc. IEEE 5th World Forum on Internet of Things (WF-IoT)*, Limerick, Ireland, 2019, pp. 363–368, doi: 10.1109/WF-IoT.2019.8767263.

[8] S. R. Ahamed and A. L. Rahaman, "Design and Implementation of a LoRa-based Emergency Communication System in Remote Areas," *Int. J. Eng. Res. Technol. (IJERT)*, vol. 9, no. 6, pp. 944–949, June 2020.

[9] D. Adami *et al.*, “Experimental Evaluation of a LoRa Wildlife Monitoring Network in a Forest Vegetation Area,” *Future Internet*, vol. 13, no. 5, p. 115, 2021. [Online]. Available: https://www.mdpi.com/1999-5903/13/5/115

[10] GAO Tek Inc., “Applications of LoRa Hardware in the Wildlife Tracking.” [Online]. Available: https://gaotek.com/applications-of-lora-hardware-in-wildlife-tracking/

[11] A. Miaoudakis, “Polling-based MAC Protocols for Improving Real-Time Performance in a Wireless PROFIBUS.” [Online]. Available: https://www.researchgate.net/publication/3218169_Polling-based_MAC_protocols_for_improving_real-time_performance_in_a_wireless_PROFIBUS

[12] Semtech, “Smart Parks Protects Endangered Species with LoRaWAN®.” [Online]. Available: https://blog.semtech.com/smart-parks-protects-endangered-species-with-lorawan

[13] E. D. Ayele *et al.*, “Leveraging BLE and LoRa in IoT Network for Wildlife Monitoring System (WMS).” [Online]. Available: https://www.researchgate.net/publication/321170201_Leveraging_BLE_and_LoRa_in_IoT_network_for_wildlife_monitoring_system_WMS

[14] M. Yaseen, “What is YOLOv8: An In-Depth Exploration of the Internal Features of the Next-Generation Object Detector,” *arXiv preprint arXiv:2408.15857*, Aug. 2024. [Online]. Available: https://arxiv.org/abs/2408.15857

[15] D. Reis, J. Kupec, J. Hong, and A. Daoudi, “Real-Time Flying Object Detection with YOLOv8,” *arXiv preprint arXiv:2305.09972*, May 2023. [Online]. Available: https://arxiv.org/abs/2305.09972

[16] M. Hussain, “YOLOv5, YOLOv8 and YOLOv10: The Go-To Detectors for Real-Time Vision,” *arXiv preprint arXiv:2407.02988*, Jul. 2024. [Online]. Available: https://arxiv.org/abs/2407.02988

[17] J. Terven and D. Cordova-Esparza, “A Comprehensive Review of YOLO Architectures in Computer Vision: From YOLOv1 to YOLOv8 and YOLO-NAS,” *arXiv preprint arXiv:2304.00501*, Apr. 2023. [Online]. Available: https://arxiv.org/abs/2304.00501

[18] "WebSocket," *Wikipedia, The Free Encyclopedia*. [Online]. Available: https://en.wikipedia.org/wiki/WebSocket