# User-Centric Wildlife Monitoring: AI-Powered Animal Detection and Tracking with Drone-Based Thermal Imaging

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The integration of AI-powered drones with thermal imaging technology presents significant potential for enhancing wildlife conservation efforts. Traditionally, wildlife monitoring requires two operators—one to control the drone and another to analyze the data. This paper introduces an autonomous system based on YOLOv8, designed to streamline both tasks by enabling automated animal detection and classification using thermal imagery. Developed through a human-centered approach informed by the specific needs of wildlife conservation and hunting experts, this system supports single-operator use and reduces on-site labor demands. Our findings emphasize the importance of real-time data processing and user-friendly interfaces, which are embedded into a smartphone application designed to accommodate varied roles within wildlife management. This application offers flexible support, enabling users to identify, track, and monitor species in real-time based on their specific needs. This study contributes to existing literature by providing insights into the practical application of AI and drone technology, driven by user requirements, in wildlife conservation.

CCS Concepts: • **Information systems** → **Geographic information systems**; • **Computing methodologies** → **Object detection**; • **Applied computing** → **Environmental sciences**; *Cartography*; *Computers in other domains*; *Decision support systems*; • **Computer systems organization** → *Sensor networks.*

Additional Key Words and Phrases: Wildlife Monitoring, Thermal Imaging, Drone Technology, Artificial Intelligence, Object Detection, Conservation

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## 1 INTRODUCTION

The ongoing expansion of human populations into natural habitats intensifies the need for innovative approaches to wildlife monitoring and conservation. This encroachment, combined with the impacts of climate change, poses a growing threat to biodiversity, underscoring the urgency for effective monitoring solutions. Technological advancements, particularly the use of thermal imaging cameras on drones, offer promising tools for this purpose, enabling the tracking and observation of wildlife from a distance [9, 13]. However, current systems often require two operators: one to pilot the drone and another to analyze the video footage for animal identification, which can be labor-intensive and challenging in adverse weather conditions [4]. Additionally, traditional video-based identification is limited by environmental factors such as low lighting and animal camouflage, highlighting the need for alternative, automated solutions [15].

To address these operational limitations, this paper proposes an autonomous system that integrates artificial intelligence (AI) for the detection and classification of animals using thermal imagery. By leveraging advanced AI algorithms to identify species accurately, the system eliminates the need for manual video analysis by a dedicated operator. This advancement not only simplifies the monitoring process but also enhances efficiency, allowing a single operator to manage both drone control and data analysis autonomously. A mobile application has been developed based on specific requirements gathered from conservation professionals, providing a user-friendly interface for real-time visualization and data analysis. This application supports field personnel in making informed wildlife management decisions tailored to their respective roles.

In addition to streamlining the monitoring process, the application aims to establish a comprehensive database of wildlife sightings, incorporating critical data such as weather conditions and geographical locations. This data is expected to contribute to the creation of detailed wildlife maps, a feature emphasized in prior studies as beneficial for conservation efforts [10].

The central research question guiding this study is:

> *RQ: To what extent is it feasible to develop a user-centered mobile application that, through an AI-driven thermal imaging system, can autonomously detect and classify animals with high accuracy to support diverse wildlife management needs?*

## 2 RELATED WORK

Several studies have explored the potential of thermal imaging and AI for wildlife monitoring. Uchiyama et al. [22] developed a system using thermal images to detect the presence, type, and posture of animals, optimizing power usage by activating sensors in stages. Tuia et al. [21] emphasize the impact of machine learning (ML) and deep learning (DL) in ecology, showcasing examples where these methods have scaled local wildlife studies to global insights. They underline the necessity of collaboration between ecologists and ML specialists to ensure methodological robustness and data quality. In reviewing advancements in AI-driven wildlife monitoring, Gonzalez et al. [6] highlighted the integration of deep learning with UAVs and thermal imaging to improve detection accuracy. Hoecke et al. [23] similarly demonstrate how thermal imaging-based navigation enhances the efficiency of field robots.

In the domain of autonomous UAVs, Ward et al. [24] present a cost-effective system using UAVs with thermal imaging and predictive navigation for animal detection. This system, which integrates GPS and computer vision, demonstrates the versatility of UAVs in various applications, including agriculture and search and rescue. Rey et al. [17] developed a semi-automated approach for animal detection in aerial images of the African Savanna. Their system combines UAVs and object recognition models, showcasing effective collaboration between human operators and automated systems in conservation. Applications of thermography in monitoring physiological states, such as stress responses in animals, are explored by Gonzalez et al. [7], revealing another avenue for AI-assisted conservation. Kelling et al. [11] discuss the role of semantic data and mobile technology in citizen science, showing the potential of engaging the public in data collection for species mapping.

Wildlife monitoring with drones faces challenges from environmental factors such as vegetation occlusion, lighting variations, and atmospheric interference. Burke et al. [3] examine these factors, noting the importance of thermal contrast and visibility conditions for effective detection, particularly in dense vegetative areas. Betke et al. [2] utilized thermal imaging to revise bat colony population estimates, revealing the reliability of thermal data in refining wildlife population assessments. This work underscores the precision offered by advanced imaging technologies for monitoring.

Recent research has highlighted the importance of ethical frameworks in conservation technologies. Sandbrook et al. [18] discuss privacy and security concerns in the deployment of drones for biodiversity conservation, underscoring the need for data management practices that respect privacy and mitigate potential disturbances to wildlife. Similarly, Hodgson and Koh [8] discuss the ethical responsibilities of minimizing disturbances to wildlife during drone use in conservation.

Integrating user needs into wildlife monitoring systems is critical for adoption in the field. Bele et al. [1] emphasize that user-centered design, grounded in interdisciplinary and community dialogue, supports ethical practices in conservation technology and enhances system relevance for local needs. Kuhn et al. [12] stress the need for collaborative decision-making systems, integrating human expertise with automated technologies to improve conservation outcomes. This underscores the importance of intuitive interfaces that facilitate seamless interaction between human operators and AI-driven systems.

Recent advances in wildlife monitoring showcase an increased focus on efficiency and innovation. Researchers are leveraging machine learning for species identification [21, 22] and employing autonomous UAVs for aerial surveys [24]. Thermal imaging has become an essential tool for enhancing population estimates and monitoring behavior [2]. Additionally, the real-time detection capabilities of AI models, such as the YOLO framework [16], have proven valuable in conservation efforts, as shown by Redmon et al. and further explored in wildlife-specific studies by Norouzzadeh et al. [14] and Tabak et al. [20].

Our work builds on this foundation by integrating AI for autonomous detection and classification in wildlife monitoring. Driven by real-world requirements from conservation professionals, our approach emphasizes the importance of user-centered mobile applications, aligning with recommendations from prior studies on intuitive, accessible technology in fieldwork environments [11, 12].

## 3 REQUIREMENT ANALYSIS

To determine the requirements for our project, we conducted interviews with eight experts and professionals in wildlife conservation. Each interview consisted of 22 questions covering demographic data, wildlife-related activities, and personal views. Our aim was to gather detailed insights into the potential application of a drone equipped with a thermal imaging camera combined with artificial intelligence (AI) for wildlife monitoring. Interviews were conducted both online and in person, and previous conversations were referenced when needed to deepen insights.

The interviewees represented a diverse age range from 37 to 61 years and various professions (Table 1), including zoology, species conservation, wildlife research, and hunting. Their backgrounds provided a broad perspective on practical challenges and priorities in wildlife monitoring. To ensure anonymity, each participant was assigned a numerical ID.

Analysis of the interview data involved categorizing responses into key themes relevant to wildlife monitoring, such as species identification, animal counting, and data storage. This thematic approach enabled the extraction of core requirements from the qualitative data provided by the interviewees.

Many interviewees were familiar with thermal imaging technology, even if not all had direct experience. For instance, a conservation officer had used thermal cameras once, while a researcher had frequently utilized infrared imaging with

Table 1. Profession of Interviewees

| ID | Field of Work |
|---|---|
| 1 | Professor of Zoology, Wildlife Ecology, and Entomology |
| 2 | Species Conservation Officer |
| 3 | Director of Wildlife Biological Research for the Environment |
| 4 | Director of Nature and Species Conservation |
| 5 | Hunter |
| 6 | Biologist and Species Conservation Officer |
| 7 | Scientific Associate for Wildlife Monitoring |
| 8 | Wildlife Researcher |

an ultralight aircraft. A hunter noted their use in tracking wildlife, and a biologist employed them to monitor bird interactions with wind turbines.

**Key Requirements Identified**:

- **Animal Recognition**: A central requirement was automated animal recognition to reduce reliance on manual analysis. This capability was seen as beneficial for identifying concealed animals in fields or forests (Person 4) and for applications such as identifying bird nests prior to harvesting (Person 1). The potential for AI to replace a second person on-site was also highlighted (Person 8).
- **Species Distinction**: Differentiating between species was crucial for conservation management. Distinct species identification would aid in monitoring specific populations, such as packs or herds, as noted by several interviewees (e.g., Person 2). It was also emphasized that current methods of individual identification are often time-consuming (Person 7).
- **Animal Counting**: Accurate counting of animals was identified as essential, particularly for tracking the impacts of certain species on ecosystems. For instance, concerns were raised regarding the effects of lynx populations on deer (Person 1).
- **Data Storage and Retrieval**: Efficient data storage and retrieval were prioritized to support long-term monitoring and data-driven management decisions. Interviewees highlighted the value of an organized database with information on each sighting, including metadata such as weather conditions and geographical location.
- **Cost-Effectiveness**: The need for affordable solutions was underlined, as funding for such technology is often limited.
- **Minimizing Disturbance to Animals**: Ethical considerations were raised regarding drone usage, with concerns about potential disturbance to wildlife. This points to the importance of low-impact drone operation strategies.

Based on these findings, we developed an Android application focused on automated animal recognition, data storage, and intuitive data retrieval features, including map view, calendar view, and search functions. We selected an AI model compatible with these needs and conducted preliminary tests to evaluate its performance in recognizing common species. Future improvements will focus on refining species distinction capabilities and expanding the dataset for training to increase detection accuracy.

## 4 TECHNOLOGIES AND SYSTEM OVERVIEW

Our wildlife detection system combines advanced AI models, a commercially available UAV, and open-source mapping tools to create an effective and user-friendly solution for wildlife monitoring.

**Key Technologies**:

- **YOLOv8 for Object Detection**: For real-time object detection, we use YOLOv8, a state-of-the-art deep learning model known for high speed and accuracy in detecting objects. YOLOv8's real-time capabilities are crucial for tracking wildlife in dynamic settings, enabling accurate identification and classification of animals directly in the field.[1]
- **DJI Mavic 3T UAV Platform**: The DJI Mavic 3T is a commercially available UAV equipped with an RGB camera, multispectral sensor, and thermal imaging capabilities, making it ideal for wildlife monitoring. With a 46-minute flight time and integrated GNSS for geotagging, the Mavic 3T facilitates accurate, efficient data collection across remote areas. Its ease of deployment and robust sensor suite make it a practical choice for conservation fieldwork.[2]
- **Mapping and Visualization with OpenStreetMap**: To display animal sightings, we use OpenStreetMap (OSM), an open-source mapping tool that provides extensive geographical data, including terrain and vegetation. Using the osmdroid library on Android, animal sightings are visualized with intuitive map-based interaction, making the data accessible and easy to manage for field personnel.[3]

## 5 IMAGE PROCESSING AND TRACKING

Our system processes live video from the UAV to detect and track animals in real-time. The image processing pipeline consists of three main steps: detection, tracking, and data storage. In the detection phase, frames from the UAV's video feed are analyzed by YOLOv8 to identify animals based on pre-trained classifications. Detected animals are then tracked across frames using a robust tracking algorithm, which maintains consistent identification of individuals as they move through the environment. This allows for real-time updates on a map-based interface, where sightings are recorded and visualized for users. The system's efficient management of detection and tracking ensures data consistency and supports accurate monitoring of wildlife across field sessions.

## 6 PROTOTYPE IMPLEMENTATION

Our wildlife monitoring application is designed for the Android[4] platform using Kotlin[5], and leverages a combination of technologies to provide a seamless user experience for conservation professionals.

**Core Technologies**:

- **DJI Drone Integration**: The application interfaces with the DJI Mavic 3T through DJI's Mobile SDK V5[6], enabling control of the camera stream and flight path to optimize data collection during field operations.
- **Real-Time Detection**: For animal detection, we use a pre-trained YOLOv8 model, which is converted to TFLite[7] for mobile compatibility. This setup ensures efficient, real-time processing directly on the Android device.[8]
- **Data Management**: Sightings are stored in a SQLite[9] database, allowing easy access and retrieval of species data, location, and timestamps.

[1] https://github.com/ultralytics/ultralytics
[2] https://developer.dji.com/mobile-sdk/downloads/
[3] https://github.com/osmdroid/osmdroid
[4] https://developer.android.com
[5] https://kotlinlang.org
[6] https://developer.dji.com/mobile-sdk/downloads
[7] https://www.tensorflow.org/lite
[8] https://github.com/ultralytics/ultralytics
[9] https://www.sqlite.org/

- **Mapping and Visualization**: OpenStreetMap[10] and osmdroid[11] enable intuitive visualization of sightings on a map interface, supporting spatial analysis of animal movements.

**User Interface Design**: The application interface, designed with the Material 3[12] framework, prioritizes clarity and ease of use for field applications. Key views include:

- **Map View**: Displays animal sightings as pins, filterable by species and date (Figure 1). Pins are summarized at certain zoom levels to keep the display clear.
- **Live View**: Shows the live camera feed with bounding boxes for detected animals, enabling real-time monitoring (Figure 2).
- **Search View**: Allows users to filter sightings by species, date, and location, with auto-complete functionality for species names (Figure 3).
- **Settings View**: Provides customization options for notifications, allowing users to set sound alerts or vibration for animal sightings.

**Tracking and Identification**: A tracking module, based on linear tracking algorithms, consistently identifies individual animals across frames. This feature enables longitudinal data collection, which is essential for studying animal behavior and patterns in conservation work.

**Data Storage and Retrieval**: Each sighting is recorded with relevant metadata, including species, time, location, and an initial image of the animal, facilitating later retrieval and analysis. This structured data management supports effective tracking and reporting over extended periods.

Figures 1 to 3 illustrate core functionalities, emphasizing the intuitive layout and accessibility for field operators.


Fig. 1. Screenshot of the map view with sample locations. The red pins symbolize sighted cows, and the orange pins symbolize sighted deer. Close pins are summarized as a blue marker with the number of sightings.

[10]https://www.openstreetmap.org
[11]https://github.com/osmdroid/osmdroid
[12]https://m3.material.io


Fig. 2. Screenshot of the live view with two detected cows. The red bounding boxes mark the animal sightings. Additional information about the detected animals is displayed on the right side. The number in each entry corresponds to the number on top of the boxes, identifying the animal.

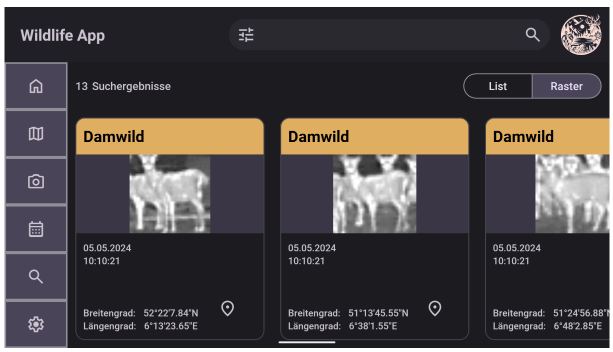


Fig. 3. Screenshot of the search view with deer as search results. The list of deer has horizontal scrolling.

## 7 EVALUATION

To assess the usability and perceived value of the wildlife monitoring application, we conducted a two-step evaluation, focusing on usability, functionality, and user satisfaction—core requirements identified in the initial analysis. The evaluation involved a combination of interactive prototype testing and post-interaction feedback, aligning with the requirements for ease of use, data accessibility, and field applicability.

### 7.1 Evaluation Methodology

Due to logistical constraints, participants interacted with a Figma prototype[13] that simulated the main functions of the application. Seven participants engaged in tasks using a think-aloud protocol to assess key aspects such as navigation, data filtering, and interaction with map and live views. Feedback was collected in two forms: qualitative insights from think-aloud commentary and quantitative ratings on a 7-point scale, focusing on task realism, difficulty, and satisfaction.

Following the prototype interaction, participants reviewed a video demonstration of the actual app and completed surveys based on the Technology Acceptance Model (TAM) [5] and the User Experience Questionnaire (UEQ) [19]. These instruments gauged perceived usefulness, ease of use, and overall user experience.

[13]https://www.figma.com/

### 7.2 Results

Participants spanned an age range of 37 to 61 years, representing various roles in wildlife conservation. Overall, feedback highlighted moderate to high satisfaction with the app's usability and functionality.

**Perceived Usefulness (TAM)**: As shown in Table 2, participants rated the application as useful for field tasks, with average scores between 5 and 6 on the 7-point scale. The primary benefits mentioned included the simplification of data collection and real-time animal tracking. However, some variability was noted, as indicated by standard deviations in the responses. The Cronbach's alpha ($\alpha = 0.54$) suggests moderate reliability, potentially reflecting diverse user expectations regarding functionality.

**Perceived Ease of Use (TAM)**: Table 3 summarizes responses on ease of use, with participants rating this aspect similarly between 5 and 6. Positive feedback emphasized the intuitive interface, though some participants noted initial difficulty in navigating the map and live views. The Cronbach's alpha for ease of use ($\alpha = 0.73$) reflects a relatively high consistency in responses, aligning with the application's goal of being user-friendly and accessible for non-technical users.

**User Experience (UEQ)**: Participants rated overall user experience favorably, particularly in terms of engagement and simplicity. These results underscore the application's potential to meet field users' needs, supporting its practical utility in wildlife monitoring.

Table 2. Summary of TAM Ratings for Perceived Usefulness

| Question | Avg Score | Std Dev | Cronbach's Alpha |
|---|---|---|---|
| Perceived Usefulness | 5.71 | 0.75 | 0.54 |

Table 3. Summary of TAM Ratings for Perceived Ease of Use

| Question | Avg Score | Std Dev | Cronbach's Alpha |
|---|---|---|---|
| Perceived Ease of Use | 5.57 | 1.27 | 0.73 |

**Qualitative Feedback**: The think-aloud protocol provided additional insights, highlighting that participants valued real-time tracking and found the data filtering and search features useful. However, suggestions were made for clearer map icons and more customization options for notifications. These insights align with initial requirements for intuitive interfaces and real-time data accessibility, indicating that the application meets core user needs but may benefit from additional user interface refinements.

In summary, the evaluation demonstrates that the application meets the primary requirements of usability, usefulness, and ease of use, as identified in the initial requirement analysis. Feedback supports the application's practical potential for field use, with further opportunities for iterative improvement.

## 8 DISCUSSION

The primary objective of this study was to develop a mobile application for wildlife monitoring that combines real-time animal detection with a user-centered design suitable for field conditions. By integrating thermal imaging with AI on a mobile Android platform, our work addresses specific usability needs for conservation professionals, especially in dynamic, remote environments. Prior research has demonstrated the potential of thermal imaging and machine learning in conservation [2, 21]; our approach builds on these findings by providing a portable, field-ready solution optimized for practical, real-time applications.

The evaluation results offer insights into both the application's performance and user experience. The YOLOv8 model achieved a moderate mean average precision (mAP50) of 0.635, which, while effective, was impacted by dataset imbalance and challenges with fast-moving animals. This accuracy is notable given the mobile platform constraints and aligns with user expectations for reliable detection under typical field conditions. However, the variability in perceived usefulness (Cronbach's alpha $\alpha = 0.54$) suggests that improvements in detection precision could enhance the perceived utility across diverse user roles. This aligns with the emphasis by Tuia et al. [21] on the need for collaborative refinement of conservation tools to ensure they meet real-world requirements.

User feedback further highlighted the strengths of a mobile, adaptable platform that allows offline functionality and easy deployment in the field. The familiar Android interface and Material UI design contributed to high user satisfaction and minimized learning curves for non-technical users, addressing critical usability needs identified in our requirements analysis. This feedback supports findings by Burke et al. [3], who recommend accessible, portable monitoring tools for effective conservation.

A unique feature of our system is its modularity, allowing the application to adapt to both mobile and stationary monitoring setups. While this flexibility broadens its applicability, it also introduces challenges in data integration and consistency across diverse contexts, as noted in previous studies on wildlife monitoring with drones [17]. Addressing these complexities could enhance data precision and ensure consistent user experience in varied environments.

### 8.1 Limitations and Future Work

While the application meets key requirements for ease of use and adaptability, several limitations provide directions for future research:

- **Dataset Balance and Model Accuracy**: The dataset's class imbalance affected detection performance, particularly for less common species. Expanding the dataset and exploring methods to balance class representation could improve detection accuracy and user confidence in the application's utility [21].
- **Adaptive Tracking for Dynamic Conditions**: Real-time tracking of fast-moving animals remains a challenge. Future work could focus on adaptive tracking algorithms to support responsive detection in dynamic field conditions, enhancing practical usability for wildlife monitoring [16].
- **Modular Flexibility vs. Data Precision**: While modularity supports flexibility, improvements in data integration and spatial accuracy are needed to ensure precise location tracking. This refinement could improve usability across diverse monitoring environments [17].
- **Ethics and Privacy in Conservation Technology**: With increased adoption of drones and AI in conservation, ethical data practices and privacy considerations are crucial. Addressing these through best practices in data handling and collaboration with regulatory bodies will be essential for user trust [8, 18].

In summary, this study demonstrates the feasibility of combining a user-centered design with real-time animal detection in a mobile application tailored to conservation needs. By meeting core user requirements while highlighting areas for iterative improvement, this application offers a promising step toward accessible, field-ready conservation technology that balances technical performance with practical usability.

## 9 CONCLUSION AND OUTLOOK

This study developed a mobile application for real-time wildlife monitoring, focusing on user-centered design principles to create a tool that conservation professionals can easily use in the field. By integrating thermal imaging with AI on a familiar Android platform, we aimed to address practical needs for ease of use, adaptability, and effective field functionality. Our evaluation results, particularly the positive user experience ratings, demonstrate that the application effectively supports usability and accessibility, essential components for HCI-oriented conservation tools.

The feedback from conservation professionals confirms that our system meets core user requirements, such as intuitive navigation, reliable data access, and offline functionality. These aspects contribute to a positive user experience, reinforcing the application's potential as a practical and field-ready solution. The design choices, such as the use of Material UI, align well with user expectations for a simple and familiar interface, supporting ease of learning and minimizing cognitive load during use.

### 9.1 Future Work

Future research should continue to refine the user experience and broaden the system's applicability in diverse conservation contexts:

- **Enhanced Species Recognition**: Expanding the range of recognized species would make the tool more versatile for conservationists working in various ecological regions, aligning with the user need for a broader application scope [21].
- **User-Centered Tracking Improvements**: Further refining the tracking algorithms with feedback from field testing could enhance the reliability of animal tracking in dynamic environments. This refinement would support the user experience by improving the accuracy of real-time animal detection.
- **Integration of Environmental Contexts**: Adding contextual environmental data, such as vegetation and terrain information, could provide richer insights into animal behavior, aligning with user needs for comprehensive monitoring tools that go beyond detection alone [17].
- **Accessibility and Inclusivity Enhancements**: Addressing accessibility considerations, such as accommodating colorblind users and including customizable settings, would improve inclusivity and broaden the system's utility for diverse conservation stakeholders.
- **Comparison with Ground-Based Monitoring**: Exploring how drone-based monitoring compares with traditional methods, like camera traps, could offer insights into the most effective combination of tools for comprehensive wildlife monitoring strategies.

These directions emphasize the importance of a holistic approach to HCI in wildlife monitoring, integrating user feedback and ecological considerations to support more inclusive, accessible, and effective conservation practices. By further refining these aspects, future research can contribute to sustainable conservation efforts that are both technologically advanced and user-centered.

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