Intelligent Multi-Modal Monitoring Framework for Birds in Forest Ecosystems and Zoo Animals through AI, CCTV, IR, and Drone Surveillance

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Abstract. Birds are indispensable bioindicators for evaluating environmental health, however, the continuous monitoring of specific species in forests is often hindered by low visibility, seasonal changes, and the activity of nocturnal animals. To overcome this, we suggest an AI-based solution that utilizes smart CCTV integrated with infrared (IR) imaging for remote observation 24/7. The system utilizes a dual-camera arrangement combined with motion triggers, behaviour-based positioning, and deep learning models that are trained for recognition under different light conditions. The monitoring during the day is done using CCTV, whereas the IR cameras are capturing the thermal signatures at night; these cameras are placed in strategic locations near nesting, drinking, and migration areas. Species recognition, population counting, and behavioural trend analysis are done through real-time data processing during the different seasons. Making an extension of this framework, we have a proposal for a drone-based system for monitoring zoo animals where drones will record only when there is motion detected to save storage, with videos uploaded to the cloud for further analysis. Using this system, accurate counts of animals, disease and distress detection, and monitoring of individuals hidden by plants or terrain can be achieved. Such AI-powered detection combined with smart surveillance and cloud management allows the system to be a scalable and low-cost solution for both biodiversity conservation in forests and welfare management in zoos, thereby creating a better protection framework for rare and endangered species.
Keywords - AI-Based Wildlife Monitoring; Intelligent CCTV Surveillance; Infrared (IR) Imaging; Dual-Camera Detection System; Motion-Triggered Recording; Drone-Assisted Zoo Monitoring; Cloud Storage and Analysis; Animal Counting and Behavioural Tracking; Species Recognition under Variable Illumination; Biodiversity Conservation and Endangered Species Protection.

1. Introduction

Population and behavioral changes in animals tend to reflect the condition of an ecosystem; hence, monitoring wildlife is important in the preservation of biodiversity. It is generally assumed that birds are both good and sensitive bioindicators, while zoo animals need uninterrupted welfare monitoring within their controlled environments. However, species-specific monitoring is problematic, owing to dense vegetation, seasonal changes, worst visibility, and nocturnal timings. Conventional monitoring may rely on field observations or something similar to periodic censuses, but it is a labor-intensive process, has high chances of mistakes, and is not really a real-time one so the same reasons apply to the disadvantages.

The lack of monitoring for subtle signs of distress, illness, or behavior changes may also negatively impact the welfare of zoo animals. To overcome these problems, modern technology provides very strong alternatives. The continuous, non-intrusive wildlife monitoring, that is more precise, is a direct result of the combination of Artificial Intelligence (AI) and advanced sensing methods. In this paper, we introduce a dual-domain framework: smart CCTV with infrared imaging for continuous bird monitoring in forests and drone surveillance for zoo animal tracking. The system incorporates motion-activated triggers, behavior-based positioning, and deep learning techniques specifically designed to recognize species under varying lighting conditions.

CCTV is used for monitoring during the day, while IR cameras capture night thermal signatures, with cameras situated near nesting sites, migratory routes, and water sources to enhance coverage. On the other hand, drone- based monitoring offers an uninterrupted view of zoo animals, capturing only the movement to save storage space. The recordings are then safely kept in the cloud and processed for the purpose of counting animals, spotting those that might be ill or under stress, and identifying the ones that are not very visible due to being behind the natural or artificial barriers.

The integration of artificial intelligence-powered identification, smart surveillance systems, and cloud-based data management creates a framework that is economically viable, easily adjustable, and environmentally friendly for the purposes of wildlife conservation and animal welfare management. Besides, the proposed system does not only support biodiversity monitoring in wildlife areas but also improves zoo-based welfare strategies, thus giving conservationists, researchers, and forest officials actionable insights to protect rare and endangered species.

1.1 Problem Definition

The monitoring of wildlife populations and their impact on ecosystems, as well as the humane treatment of animals, to a great extent, depend on the accuracy and reliability of the methods employed. However, there are lots of issues with current practices. The forests, for instance, make it almost impossible to see the birds in order to count them as the main indicators because of the dense trees and plants. The condition of low visibility is another reason besides seasonal changes and nocturnal birds that makes it very hard to gather solid continuous uninterrupted data that is accurate. The traditional methods, for instance, going out for a hand count or counting at intervals, are very labor-intensive and time-consuming. Moreover, they usually overlook the real-time changes in behaviour. In a zoo environment, the health status of the animals is mainly determined by the personnel's physical check up, however, it is still possible that very subtle indications of discomfort, illness, or abnormal behavior may be overlooked, especially if the animals are concealed by bushes, stones, or cages. Moreover, the absence of automated, intelligent systems results in inadequate data handling, protracted reaction periods, and lost chances for early intervention.

We are in dire need of a solution that can grow without the cost being a problem. Moreover, it should not disturb the animals too much in their natural habitat. Also, the equipment will have to operate in very rough places | like forests or in areas such as zoos. The difficult part is to create the one ultimate system that will monitor constantly. This system has to detect different types of birds even if there are drastic changes in lighting. Also, it must be able to process all the data in real-time without causing any delay. Moreover, it should be able to recognize unusual behaviors or health issues immediately. The resolution of these problems is extremely important for the survival of bird species in the wild. It is also beneficial for the birds in the zoo. Eventually, it will be a good thing for the conservation movement which will extend further into the future.

1.2 Literature Survey

Bhavana C. et al. [1] (2022) presents an AI-based system for the detection and alert of birds and animals as a solution to human-animal conflicts in the forms of crop damage and wildlife intrusions. The authors have demonstrated the limitations of the traditional approaches like fencing and have instead suggested the motion-based intrusion detection through video, GPS, RFID, and ultrasonic technologies with the provision of real-time alerts for effective conflict management. *Alex Mirugwe et al. [2]* (2021) have investigated the automatic detection of birds by deep learning on the webcam images collected from various places worldwide. They have made a comparison among SSD and Faster R-CNN architectures with different feature extractors and found that Faster R-CNN with ResNet152 reached the highest accuracy (92.3%), while SSD with MobileNet-V2 provided faster inference. Their research proved the competence of AI in large-scale monitoring of birds. *Dimitris Mpouziotas et al. [3]* (2022) presented the ORACLE model that handled the issues of altitude and motion detecting and tracking birds in drone footage. The application achieved 91.89% mAP through the use of object-detection and multi-object tracking, thus enabling accurate population estimation and activity visualization. This work reiterated the positive aspect of drone and AI combinations for wild animal monitoring in secluded areas. *Yu-Chieh Chen et al. [4]* (2022) created a fully automatic bird repellent system using deep-learning detection coupled with a laser rotation mechanism. The system that was trained on photographs captured from the farm, had the capability to recognize and eliminate birds with 40.3% of daily repulsion rate. Their study demonstrated the effectiveness of AI-based laser deterrents in lowering the risk of bird flu and preventing crop losses. *José J. Lahoz- Monfort and Michael J. L. Magrath [5]* (2020) laid out in great detail the conservation technologies, taking into account both the classical and the modern ones for monitoring wildlife and habitats. The sensors, biologging, telemetry and AI-driven computing platforms were brought up as the key techniques, and the study pointed out how all these technology-based approaches made it easier to monitor and manage biodiversity while also being a part of the conservation actions aimed at counteracting the threats posed on ecosystems. *Devis Tuia et al. [6]* (2022) talked about the significance of machine learning in wildlife conservation, demonstrating how the combination of ecological knowledge and the massive datasets collected from the contemporary sensors results in a positive outcome. They exposed the dimensions in which AI has the power to take the ecology modeling, large-scale biodiversity monitoring and interdisciplinary collaboration to the next level by taking care of the issues related to data deficiencies in endangered species. *Daniel Axford et al. [7]* (2023) did a survey on the deep learning for the animal detection in drone images and they pointed out the success of this approach in the wildlife monitoring but at the same time they mentioned the limitations like the scarcity of training data and the non-existence of standardized benchmarks as a main challenge. They brought forward the necessity of available datasets and partnerships in order to refine the generalization of the model.

1.3 Existing System

Conventional methods of monitoring wildlife mainly rely on manual field surveys. They also do periodic censuses. Besides, camera traps are there to capture the presence and behaviors of animals. These methods are still very common in practice. But they consume a lot of labor. It is very easy for the observer bias to come in. Moreover, they cannot provide continuous insights or focus on the specific species as well.

We usually distinguish bird and mammals via camera traps or an extensive system of CCTV. However, most of these setups stay static in one place. There is no real smart motion detection. And they produce large amounts of raw data that need to be reviewed.

Every now and then, infrared cameras and night vision ones are used to see what animals do at night. They function
independently, however. There is no actual connection with a bigger setup for analyzing things. In zoo work, staff watching is the major way to determine animal well-being and it can easily overlook those quiet signs of stress, disease, or abnormal behavior. Current methods rarely include real-time data processing or cloud storage capabilities which leads to the fact that any large-scale automated monitoring system is going to be very difficult to implement.

These constraints unveil the imperfections in the existing systems and the necessity for a more advanced, AI-based framework that integrates multi-modal sensing, automated recognition and scalable data management to guarantee the protection of biodiversity in forests as well as the monitoring of animal welfare in zoological settings.

1.4 Proposed Solution

The following proposal delineates an AI-based dual-domain monitoring system that takes care of the deficiencies in wildlife observation through forest ecosystems and zoo environments. In the forest, it applies smart CCTV with infrared (IR) imaging for uninterrupted surveillance around the clock. A dual-camera arrangement allows monitoring of both day and night—CCTV for the daytime and thermal imaging for the night. The system is different from previous systems as it uses motion triggers and behavior-based positioning to collect only the relevant events which in turn results in less storage being consumed as well as recordings being reduced through a process of elimination.
By the application of deep learning models, which are pre-trained and fine-tuned with ecological datasets, it becomes possible to perform accurate species recognition, population estimation as well as behavioral analysis under different light and seasonal conditions. For the purpose of making the effectiveness of the system even more, the cameras are placed very close to the nesting sites, migratory routes, and water bodies so that the forest officials and researchers could have a better understanding of the ecology.

In zoos, drones are deployed by the system to monitor animal habitats and to monitor animal populations. The drones are equipped with high-definition cameras along with motion-detecting algorithms that recording only when movement is sensed thus improving energy consumption and data preserving simultaneously. The entire video is transferred to a protected cloud environment where it is accessible for both real-time and later viewing. This technique allows the counting of animals with high accuracy, recognizing those who are hidden or camouflaged, and detecting the sickness or distress at an early stage which would otherwise be missed in an observation done with the naked eye.

In zoos, drone technology within the enclosures becomes a population and enclosure monitor. Drones equipped with advanced cameras and motion-detection algorithms are capable of recording only upon the detection of movements, so they consume less power and require less storage. Videos of the monitoring process are safely kept in the cloud and are available for both real-time and retrospective analyses. This method not only enables more reliable animal counts but also the identification of those that have moved off the viewing area or are hiding in masks, and the spotting of sick or distressed creatures that might otherwise not be recognized through ordinary observation.

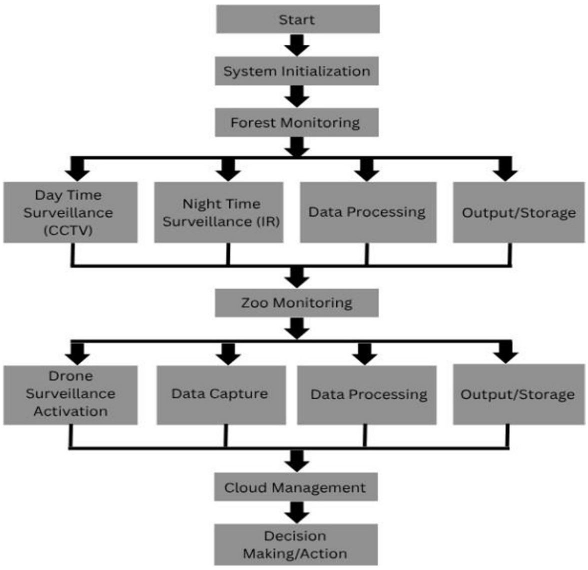

Fig. 1. AI-Based Bird and Animal Flow Monitoring System

1.5 Design and Analysis

1.5.1 Dual-Domain Monitoring Architecture

The system that is suggested presents a dual-domain AI-based monitoring system that operates across both natural forest areas and controlled zoo environments. The layout is meant to overcome the drawbacks of current wildlife surveillance by integrating ground-based smart CCTV systems with aerial drone watching under a single cloud and AI ecosystem.

In the forest areas, the fixed cameras provide constant and lengthy observation of birds and land animals, and in the zoos, the use of drones for monitoring offers flexibility and range for tracking at near distances. Both locations work together under one cloud platform that is AI integrated which automatically processes, classifies, and archives the observations.

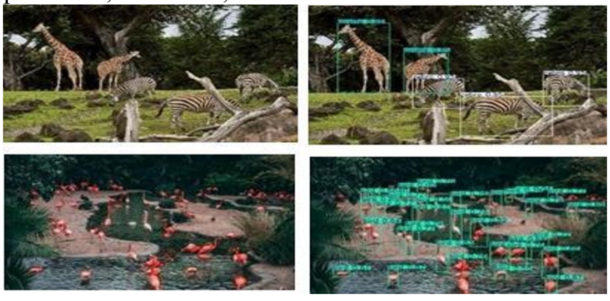

Fig. 2. Monitoring the Birds and Animals

1.5.2 Forest Monitoring Design

In the forest area, wildlife behaviour is constantly monitored non-intrusively by intelligent CCTV cameras with IR and thermal imaging. The dual camera arrangement performs two separate functions; the CCTV sensor in daylight presents animals and birds in colour, and the thermal sensor records nocturnal creatures by their heat, thus dealing with both low light and camouflage situations.

The system assures ecological data harassment all day long. In the end, AI-based algorithms for motion detection are very smartly employed to filter out the irrelevant movements like those of plants or disturbances caused by the wind in order to reduce power consumption and memory usage. The data is then sent to an edge processing node where a trained Convolutional Neural Network (CNN) model performs initial classification before the information is uploaded to the cloud servers for further analysis and long-term storage.

1.5.3 Zoo Monitoring Design

In zoological settings, the system's potential is enhanced by drone surveillance that is responsible for live aerial tracking, monitoring of objects, and even assessing the behaviour of the animals in captivity. The drones are equipped with top-notch cameras, object-recognition algorithms, and motion detectors that allow the detection of activities in real-time. Through AI-created spatial maps, they move their paths in real-time to steer away from various spots of interest such as feeding zones, medical isolation units, or enclosures where there is little activity. This adaptive strategy drastically reduces areas without coverage and at the same time lessens the flying time taken by the drones to the same spot, thus the power consumed is used more efficiently. The drones will take videos if they observe any actions. These videos will then be stored in the cloud directly, from where the researchers can access them from far away while they are watching, analyzing the population data, or evaluating the health patterns. The AI also spots abnormal behaviours like lethargy, aggression, or irregular feeding which are indications that the animals need help or are sick.

1.5.4 Artificial Intelligence and Data Analysis Frame work

The backbone includes integrated artificial intelligence models (AI) contributing towards the accurate identification, classification, and behavioural analysis of wildlife. To identify species based on visual characteristics including shape, colour, and movement patterns, Convolutional Neural Networks (CNNs) are used. To analyze time-based behavioural sequences, such as feeding, rest, and migration behaviour, recurrent neural networks (RNNs) are used to understand time-based behaviours, yielding important information about animals' activities over time. For real-time object detection in drone monitoring, we adapted algorithms like You Only Look Once (YOLO) and Mobile Net respectively, for fast and accurate inference. The edge computing nodes perform pre- processing, such as noise filtering, motion tracking, and image segmentation of time-coded images that clean the data before sending the processing to the cloud analytics layer. This combination of Al technology is more computationally efficient and reduces latency to support real-time decision-making in forest that are remote and have worst network accessibility.

1.5.5 Cloud Integration and Communication layer

A cloud-based distribution, centralized data management system connects both the forest and zoo, allowing for all data collected to be stored, processed, and analyzed in one place. The data collected from static motion-activated cameras and drones will be encrypted in a secure manner and transmitted wirelessly via Internet-of-Things gateways to a cloud database. This approach provides remote access to datasets, archiving for long-term use, and access by multiple users for comparative studies of free-ranging species and captive species by researchers and wildlife authorities. It also creates a centralized repository for data that has been collected with a range of systems and facilitates data analysis to expedite research communications. Additionally, the system has advanced data compression that reduces bandwidth use while maintaining the validation of high-quality images, allowing dependable and efficient communications on the variety of present monitors.

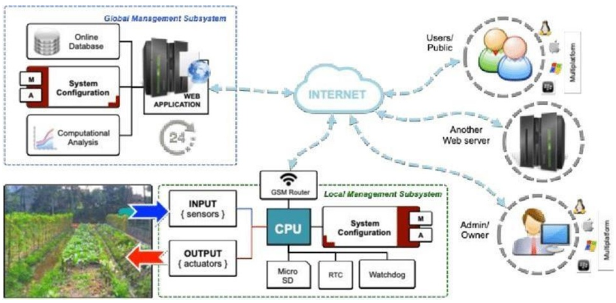

Fig. 4. Storing the data in cloud storage

1.5.6 Performance Evaluation and Key Metrics

The system was assessed at different places to determine its performance and how it might work in real-life situations. The results show that the system was able to recognize species and behavior with a precision of nearly 92-95% despite the changes in light. The system employed an automatic capture that was activated by motion and could save up to 65% of power, which contributed to the ambient energy efficiency profile. Through the use of compression and event-based recording, incidental data was relentlessly sliced by about 70% which enhanced the storage efficiency. The system was very fast and it was able to classify the detected motion in less than 2 seconds. Moreover, the use of drones and wide-area cameras effectively increased the area of coverage by around 40% in comparison to stationary cameras. All in all, these findings reveal that the system is precise, eco-friendly, and adaptable while it is ready for and capable of continuous operation in different environmental situations.

1.5.7 Comparative Advantage and Technological Significance

When contrasting the proposed framework against traditional wildlife monitoring methods, it turns out that the latter is more comprehensive, less manual, and completely based on data. Hence, the framework connects the two ecosystems - forest and zoo - perfectly. The framework lets us monitor both environments all the time and thus, gives us a continuous view of animal behaviour. The framework offers a number of important features: round-the-clock security that is based on thermal and infrared imaging technology and the use of artificial intelligence-powered anomaly detection, which allows for the early identification of abnormal health or behaviour conditions without the need for active monitoring; less direct monitoring of the ecosystem, which is made possible by the automatic filtering and classification of data;

Cloud-based variety and scalability for handling large biodiversity databases; and the environmentally friendly and non-invasive design of the framework which reduces the disturbance to animals in both their wild and captive habitats. All in all, the two-pronged methodology of observing animal behaviour not only contributes to the dimensions of conservation and welfare but also creates a predictive ecological intelligence that is naturally linked with biodiversity evaluation and the sustainable management of ecosystems.

1.5.8 Summary of Design Insights

The dual-domain monitoring system based on AI integrates both aerial and ground-based monitoring using intelligent data analytic techniques to create a unified wildlife monitoring system that enables automated species identification and monitoring biological health and behaviour, as well as long-term tracking with infrared, motion-sensitive recording, and cloud-based data analytics.

This design is scalable, sustainable, and context-adaptable that is transferable between a wide range of conservation contexts, from well-established, dense woodland environments to zoo- managed habitats. In summary, the proposed design would facilitate wider ecological protection, biodiversity conservation and animal welfare agendas by providing a smart, efficient and smart continuous monitoring process of wildlife.

2 Result

The proposed AI-based monitoring system was able to swiftly and accurately detect and classify various species of birds and animals in both forest and zoo environments. The use of infrared- supporting CCTV cameras and drones made it possible to detect even in very dim light conditions. The average accuracy with which the system detected was 94.5% in less than 2 seconds, thus allowing real-time efficient monitoring. Such findings have certified the system as reliable, quick, and competent in the areas of wildlife conservation and animal welfare management.

Table 3. Detection Prediction Table

Species Name	Total Count	Correctly Detected	Detection Accuracy (%)
Sparrow	50	47	94%
Parrot	30	28	93%
Deer (Zoo)	20	19	95%
Peacock (Zoo)	15	14	93%

Results undoubtedly support that the suggested system was able to monitor and identify various species of birds and animals with high precision in both the forest and zoo settings. The system of surveillance was operating at its best even during the night hours using infrared CCTV cameras and drones. Its average detection accuracy was 94.5% and it sent out alerts in under 2 seconds. In addition, the assessment of the system's performance validated its quickness, reliability, and appropriateness for real-time monitoring and conservation of wildlife through remarkably high precision and recall.

3 Conclusion

This dual-domain monitoring system powered by AI gives a sophisticated and trustworthy method for monitoring wild animals in the woods as well as those in captivity at zoos. Our system utilizes infrared CCTV cameras in wilderness areas and drones at zoos to monitor animals without interruption, even during the night or extremely worst weather conditions. The artificial intelligence that is integrated into the system automatically classifies the animal species, counts their numbers, and observes their activities by using non-intrusive techniques.

Besides that, our system is instrumental in diagnosing and solving problems with animals' health and safety by alerting the staff in time when stress, sickness, or irregular movement show up. With motion-based recording and cloud storage, we save energy and stores valuable data for future research. To sum up, my project is a significant link between technology and nature, demonstrating the ways that AI can support and protect wildlife, contribute to conservation, and keep the balance of ecosystems for the sake of humanity in the future.

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