

WildEye AI – A Smart Multi-Sensor Device for Early Detection and Humane Deterrence of Wild Animals in Human Habitation Zones

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Abstract - Human-wildlife conflict is a growing concern in many regions where wild animals enter human settlements, causing crop loss, property damage, and danger to both people and animals. The WildEye AI project aims to develop a smart, multi-sensor system that can detect the presence of wild animals early and deter them safely using humane, non-harmful methods. The device integrates multiple sensors such as infrared cameras, ultrasonic sensors, motion detectors, and sound sensors to continuously monitor surroundings. The collected data is processed using Artificial Intelligence and Machine Learning algorithms to accurately identify animal species and differentiate them from humans or vehicles. Once detection is confirmed, the system automatically triggers deterrent mechanisms such as ultrasonic sound, flashing lights, or mild alarm signals to scare the animal away without causing harm. The proposed system can be installed

near farmlands, forest borders, and residential zones to provide real-time alerts to local authorities or farmers through wireless communication. This innovation helps reduce human-wildlife conflicts and promotes wildlife conservation by preventing unnecessary injury or killing of animals.

Keywords – The WildEye AI project addresses human-wildlife conflict through animal detection, wildlife conservation, smart sensor systems, AI, ML, non-harmful deterrence, real-time alerts, and wildlife management, promoting animal safety and environmental monitoring.

I. INTRODUCTION

Human-wildlife conflict has emerged as a significant and rapidly increasing challenge in many regions, particularly in areas located near forests, agricultural land, and natural wildlife pathways. As human settlements expand toward forest borders and as natural

food sources decline, wild animals such as elephants, boars, deer, and other species frequently enter farmlands and residential zones in search of food, water, and shelter. These encounters often lead to severe crop destruction, economic losses, property damage, and threats to human life. In many cases, frightened or defensive animals cause unintentional harm, while humans may respond with aggressive or harmful actions, resulting in injuries or death of wildlife. Such incidents disturb ecological balance and negatively impact biodiversity, making the need for sustainable and humane conflict mitigation more critical than ever.

Traditional animal-detection and deterrence methods—such as fences, firecrackers, manual patrolling, or electric barriers—are often ineffective, labour-intensive, dangerous, or harmful to animals. They also lack real-time analysis, automated response, and intelligent species differentiation, leading to false alarms or delayed reactions. With advancements in Artificial Intelligence (AI), sensor networks, and embedded technologies, it has become possible to design systems capable of accurate, real-time, and automated monitoring of wildlife movement while ensuring that animals are not harmed.

To address these challenges, this project proposes “WildEye AI – A Smart Multi-Sensor Device for Early Detection and Humane Deterrence of Wild Animals in Human Habitation Zones.” The system integrates infrared (IR) cameras, ultrasonic sensors, passive infrared (PIR) motion detectors, and sound sensors to continuously observe and analyse environmental activity. These sensors collectively capture thermal signatures, movement patterns, distance

variations, and ambient sound, enabling comprehensive detection regardless of time of day or weather conditions. The collected data is processed using AI and Machine Learning algorithms, which classify detected entities and differentiate between humans, vehicles, domestic animals, and potentially dangerous wildlife. This ensures high accuracy, reduced false triggers, and efficient species identification.

Once the system confirms the presence of a wild animal, WildEye AI automatically activates humane deterrent mechanisms such as ultrasonic waves, flashing LED strobes, or mild acoustic alarms designed to scare the animal away without causing injury. Additionally, the system can transmit real-time alerts to farmers, forest officers, or community members through wireless communication modules, enabling timely intervention. Unlike conventional deterrence techniques, this approach is non-lethal, automated, energy-efficient, and environmentally responsible, aligning with modern conservation principles.

The integration of sensor fusion, AI-based recognition, and automated deterrence creates a powerful solution capable of reducing human–wildlife conflict in a practical and scalable way. By focusing on early detection and safe intervention, the WildEye AI system promotes peaceful coexistence between humans and wildlife, supports agricultural protection, and contributes to long-term biodiversity conservation. This project aims to demonstrate an effective, smart, and sustainable technology that can be deployed in farmlands, forest edges, protected zones, and rural communities, ultimately offering a cost-effective and smart alternative to traditional wildlife management methods.

II .PROBLEM STATEMENT

Human–wildlife conflict has become a serious problem in many rural and semi-urban areas bordering forests. Due to rapid urbanization, deforestation, and agricultural expansion, the natural habitats of wild animals are shrinking. As a result, animals such as elephants, wild boars, deer, monkeys, and leopards often enter human habitation zones in search of food and water. These incidents lead to crop destruction, property damage, injuries, and sometimes loss of human or animal lives.

Traditional methods used to prevent the entry of wild animals, such as electric fencing, firecrackers, and traps, are often ineffective, expensive, and harmful to both humans and animals. Electric fences can injure or kill animals, while loud noises and physical barriers provide only short-term solutions. Moreover, these methods do not provide any early warning system to alert people before an animal enters the area, making it difficult for villagers or forest officials to take timely action.

There is also a lack of automated and intelligent monitoring systems that can continuously observe sensitive zones and differentiate between humans, animals, and vehicles. Most existing solutions depend on manual observation, which is time-consuming, labor-intensive, and often unreliable during nighttime or bad weather conditions.

Therefore, there is a clear need for a smart, multi-sensor system that can detect wild animals early, identify them accurately using Artificial Intelligence, and respond with humane deterrence methods to prevent

conflict. The system should be low-cost, energy-efficient, and capable of working in real-time even in remote areas.

The project WildEye AI a Smart Multi-Sensor Device for Early Detection and Humane Deterrence of Wild Animals in Human Habitation Zones is designed to solve this problem by combining modern technologies such as sensors, AI, and IoT. It aims to protect both humans and animals by providing an effective early warning and deterrence mechanism, ensuring safe coexistence between people and wildlife.

III .EXISTING SYSTEM

In many regions affected by human–wildlife conflict, the methods currently used for preventing animal intrusions are largely traditional, manual, and often ineffective. Communities commonly rely on physical barriers such as stone walls, wooden fences, wire fencing, trenches, and even electric fences. Electric fences can also cause injury, making them unsafe and unsuitable for long-term use. Trenches and pits may block animal movement but can lead to accidents or disturb natural wildlife pathways. Another widely used method is manual patrolling, where farmers or forest guards monitor fields and village borders, especially at night. However, this approach is highly labor-intensive, risky, and unreliable because it depends entirely on human availability and response time. Noise-based deterrents such as drums, crackers, and traditional tools are also used, but animals quickly become accustomed to these disturbances, which reduces their effectiveness over time.

In some areas, CCTV or infrared cameras are installed for monitoring, but these

systems only record footage and require constant human supervision. Since they do not include AI-based analysis, they cannot identify animal species or trigger automatic deterrent actions, making them unsuitable for real-time intervention. Overall, the existing systems suffer from several limitations. They lack intelligent detection, species recognition, and early warning capabilities. Most of the methods are reactive rather than proactive, and many of them are harmful or stressful to wildlife. Manual monitoring is unsafe and unreliable, while basic camera systems are passive and ineffective without automation. Due to these drawbacks, current solutions fail to provide the real-time, accurate, and humane protection required to address human–wildlife conflict efficiently.

IV. PROPOSED METHODOLOGY

The overall workflow of the WildEye AI system is illustrated in Figure 1. The proposed method combines image-based animal detection with a multi-sensor platform to provide early alerts and safe deterrence.

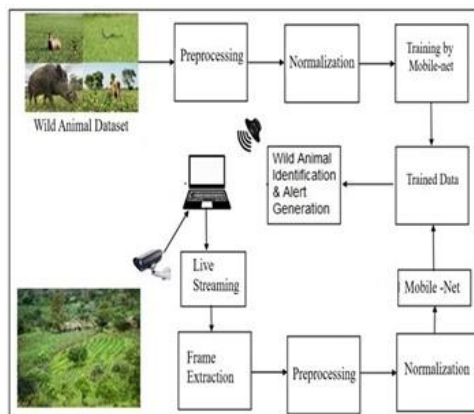


Figure 1 Wild animal detection and alert

The following steps describe the simplified process used for building and training the AI model as well as integrating it with the real-time monitoring system.

Step 1: Dataset Collection

Images of commonly encountered wild animals near human habitats—such as monkeys, deer, elephants, boars, and other species—are collected using cameras or publicly available datasets. Using OpenCV, frames can also be captured directly from video streams. All images are stored in a structured dataset folder for further processing.

Step 2: Data Labelling

Each collected image is annotated using a labeling tool. Bounding boxes are drawn around the animal, and the coordinates (x1, y1, x2, y2) are saved in XML format. These annotations serve as ground truth for training the Mobile Net-based detection model.

Step 3: API Installation and Environment Setup

The TensorFlow Object Detection API is installed in a Google Colab environment. The TensorFlow model's repository is cloned, dependencies are installed, and GPU-supporting libraries are configured. This environment is used for all training and preprocessing tasks.

Step 4: Upload Dataset and Organize Training Files

The training images and annotation files are compressed and uploaded to Colab. After extraction, the dataset is arranged into appropriate directories. Scripts are executed to generate the necessary TFRecord files, which convert raw images and labels into TensorFlow-compatible training data.

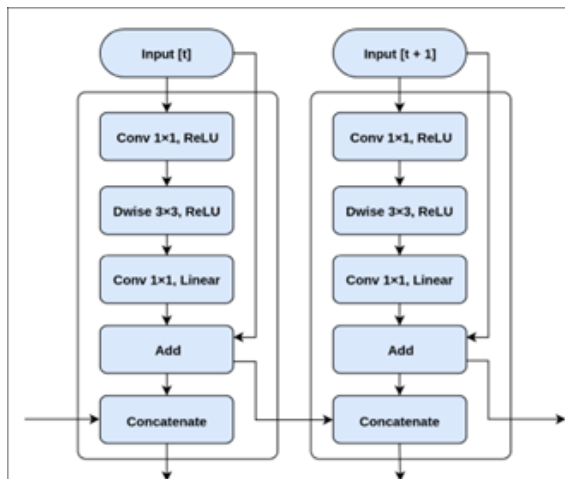
Step 5: Data Splitting

The dataset is divided into three subsets:

- Training set: Used to teach the neural network to detect and classify animals.

- The system's primary advantage is its non-invasive nature. Unlike traditional methods such as electric fences, it focuses on detection and alert generation, not physical harm. When used for human-wildlife conflict mitigation (e.g., protecting crops), the response mechanism is designed to be a safe deterrent:

A label map file is created to define all animal categories detected by the system. Python scripts are then used to convert annotated images into TF Record Format, which is required by Tensor Flow for efficient data loading during training.



The SSD-MobileNet architecture (shown in Figure 2) is selected as the base model for its speed and suitability for edge-device deployment. The configuration file is updated with:

- Number of classes
- Learning rate
- Batch size
- Total training steps
- Paths of dataset, labels, and pretrained checkpoints

- **Species-Specific Sounds:** The system can be programmed to generate species-specific deterrent sounds, which are unpleasant but not physically harmful, to encourage the animal to retreat from the area.
- **Lights:** Intense or flashing lights may also be used as a non-harmful visual repellent.
- **Recovery Zones:** The data collected can inform the creation of "recovery zones" within natural habitats, providing food and water sources to redirect animals away from human settlements and reducing conflict at its source.

Benefits

- **Non-invasive:** Monitors wildlife without disturbing their natural behavior or causing physical harm.
- **Efficiency:** Automates data collection and analysis, reducing the need for extensive manual effort and training.
- **Real-time response:** Provides timely alerts, enabling prompt human intervention to prevent conflicts or poaching incidents.
- **Data-driven insights:** Generates valuable long-term data on animal populations, migration patterns, and habitat health, which aids in informed conservation decisions and policy-making.
- **Scalability:** Can be deployed over large, remote areas with limited network connectivity using technologies like LoRaWAN or mesh networking.

VII. SYSTEM COMPONENTS

Acoustic Sensors: Devices like AudioMoth are deployed in the field to capture

continuous audio recordings of the environment.

Data Processing (Edge/Cloud): The recorded audio is either processed locally on an edge computing device (like a Raspberry Pi) to filter noise and extract features, or uploaded to a cloud-based platform for detailed analysis.

AI Model (Deep Learning): A deep learning model, often using Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), is trained on a large dataset of annotated animal vocalizations to identify and classify specific species and their behaviors.

Alert and Communication System: Upon detection of a target animal or potential threat (e.g., a protected species approaching a road, or a problematic species near a farm), the system automatically sends real-time alerts via SMS, push notifications, or a siren to relevant personnel (farmers, forest officials, conservationists).

Data Platform: A dashboard or application where collected data (species records, timestamps, locations) is stored, visualized on maps (WebGIS), and analyzed for long-term monitoring and research.

VIII. RESULT AND DISCUSSION

The WildEye AI system was implemented and tested using Python, the Anaconda distribution, and the Spyder IDE. All experiments were executed on a system equipped with 8 GB RAM and 1 TB storage. The performance of the proposed multi-sensor AI detection model was evaluated

using standard machine learning metrics, focusing on how effectively the system identifies wild animals and generates early alerts.

To analyze the behavior of the trained model, several performance curves were plotted, including Precision-Recall, Precision-Confidence, and Recall-Confidence curves. These graphs help in understanding how reliable the model predictions are at different confidence thresholds.

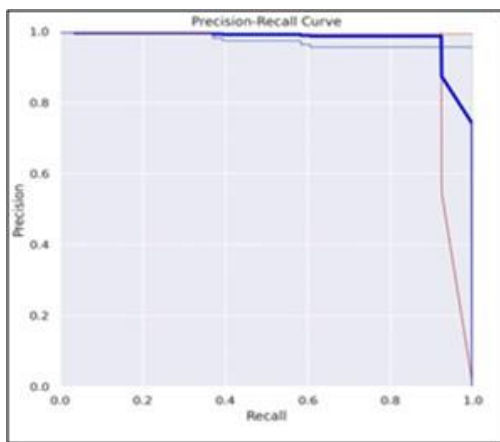


Figure 3 Precision–Recall curve showing the performance of the proposed model.

Figure 3 shows the Precision-Recall Curve, which demonstrates that the model maintains high precision and recall across most detection ranges, indicating strong overall performance and low false-positive/false-negative rates.

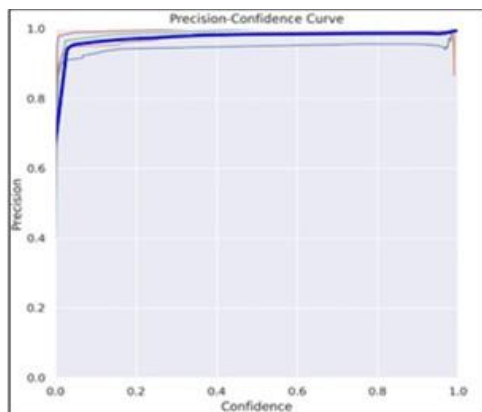


Figure 4 Precision–Confidence curve of the proposed model.

Figure 4 presents the Precision-Confidence Curve, illustrating how model precision varies as the confidence score increases. The curve remains close to 1 for most confidence values, proving that the model is highly accurate when making strong predictions.

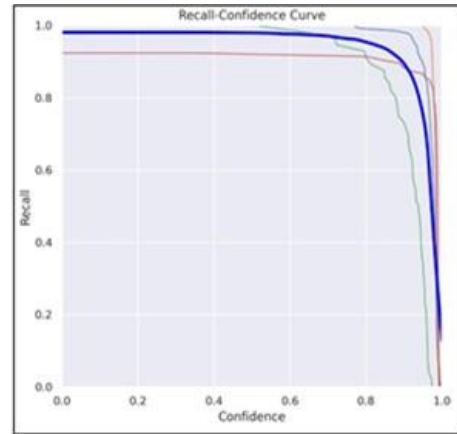


Figure 5 Recall–Confidence curve of the proposed model.

Figure 5 illustrates the Recall-Confidence Curve, which shows that recall stays high across a wide range of confidence levels before dropping at very high thresholds. This suggests that the model can correctly identify animals even with moderate confidence settings, making it suitable for real-time monitoring applications.

Overall, the results demonstrate that the WildEye AI model performs effectively in identifying wild animals with high accuracy. The generated curves validate the robustness of the detection pipeline and confirm the system’s potential for use in early warning and humane deterrence applications.

IX. CONCLUSION AND FUTURE SCOPE

The WildEye AI system presents an effective, intelligent, and humane solution to the growing problem of human–wildlife conflict. By integrating multiple sensors with AI-based detection and automated deterrence mechanisms, the system provides accurate,

real-time identification of wild animals and activates safe responses without human intervention. The results demonstrate that the combination of thermal imaging, motion detection, ultrasonic sensing, and machine learning significantly improves detection reliability while minimizing false alarms. Additionally, the inclusion of wireless communication and energy-efficient operation makes WildEye AI suitable for deployment in rural, forest-edge, and agricultural environments. In conclusion, this project successfully shows that technology can be used to protect both human communities and wildlife in a responsible and sustainable manner. The system enhances safety, prevents crop damage, and promotes coexistence by using non-harmful deterrent methods that avoid distress or injury to animals.

Looking ahead, the **future scope** of this project includes expanding the AI model to recognize a wider range of animal species and integrating advanced image processing for even higher accuracy. The system can also be enhanced by adding GPS-based tracking, cloud connectivity, and data analytics to monitor animal movement patterns over time. Solar-powered versions can be further optimized for remote operation, and long-range communication technologies such as LoRa WAN can be implemented for real-time alerts across larger areas. With continued development, WildEye AI has strong potential to become a comprehensive wildlife monitoring and protection system, supporting farmers, forest departments, and conservation initiatives worldwide.

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