

# Wild Animal Alert System using Deep Learning

Barath Vikram R<sup>1</sup>, NarasimhaK.L<sup>2</sup>, Prof. Mrs. Jeyanthi A<sup>3</sup>, Dr. Saravanan N<sup>4</sup>

<sup>1,2</sup>Dept of Artificial Intelligence and Data Science

<sup>3,4</sup>Guide, Dept of Artificial Intelligence and Data Science

<sup>1, 2, 3, 4</sup>Misrimal Navajee Munoth Jain Engineering College, Chennai, Tamil Nadu – 600097

**Abstract-** Monitoring wild animals in their natural habitat are critical. In this project, an algorithm is created to identify animals in the outdoors. Since there are so many different kinds of animals, manually recognizing them might be challenging. In order to better effectively monitor animals, these system categories them based on their photographs. Animal tracing, theft prevention, and animal-vehicle accident prevention can all be aided by animal detection and classification. Applying efficient deep learning techniques will enable this. In our country, the density of highways is constantly growing and increasing, and many of them are close to a wood, which raise the risk of human-animal collision and heightens the likelihood of tragic incidents. The application suggested in this study employs an algorithm to quickly identify and categorize the animals present in the photographs that are sent to it as input, alerting the user through GSM to provide the position, and then displays the results. Animal identification and categorization in this case employ the Deep Learning approach. An alert and detection system is suggested that uses deep learning.

**Keywords-** Artificial Intelligence (AI), Deep Learning, Global positioning system(GPS), Convolution Neural Network (CNN), Global System for Mobile Communications(GSM), Internet of Things (IoT)

## I. INTRODUCTION

Wildlife alert systems with deep learning are cutting-edge technological solutions aimed at addressing the critical problem of human-wildlife conflict and improving wildlife conservation efforts. Harness the power of deep learning, a subset of artificial intelligence, to create sophisticated proactive systems that protect both humans and wildlife. This innovative system represents a major advance in wildlife management and environmental protection.

Wildlife conservation has become increasingly important in recent years due to habitat destruction, climate change, and encroachment of human settlements on natural habitats. Human-wildlife conflicts, including situations where wild animals pose a threat to human life and livelihoods, are becoming increasingly common and pose significant challenges around the world. These conflicts often result in

loss of human and animal life, damage to crops, and economic hardship for local communities.

Wildlife warning systems aim to quell these conflicts and promote human-animal coexistence. This is achieved through a combination of cutting-edge technology and real-time monitoring capabilities. Here are some important features and components of the system.

1. Deep learning algorithms: The core of the system is based on deep learning algorithms, which can process and analyze large amounts of data quickly and accurately. Deep learning models such as convolution neural networks (CNNs) are used to identify and classify wildlife species, their behavior, and potential threats.
2. Surveillance cameras and sensors: The system is equipped with a network of surveillance cameras and sensors strategically placed in wildlife habitats and areas where human-animal conflict may occur. These cameras capture images and videos of animals and their activities.
3. Real-time data processing: Once data is collected from cameras and sensors, it is processed in real-time by deep learning algorithms. This allows you to instantly identify wild animals, their behavior, and any unusual or potentially dangerous activity.
4. Generate alerts: Generate real-time alerts when the system detects potential threats or unusual behavior patterns. These alerts can be sent to wildlife authorities, communities, and individuals through various communication channels such as mobile apps, SMS.
5. Remote monitoring: Conservationists and authorities can remotely monitor system alarms and access live camera feeds from a central dashboard. This allows for faster response and decision-making.
6. Geospatial Mapping: The system also integrates geospatial mapping technology to track wildlife movement and proximity to human settlements. This helps predict potential conflicts and take preventive measures.
7. Community Engagement: To promote coexistence, the system fosters community engagement by providing educational resources and guidelines on safe behavior when encountering wild animals. It also provides resources for reporting wildlife sightings and incidents.

Wildlife alert systems using deep learning represent a major advance in wildlife conservation and human-wildlife conflict resolution. By harnessing the power of deep learning and real-time data analysis, we provide a proactive approach to protecting both humans and endangered wildlife. This innovative system not only saves lives, but also contributes to the long-term sustainability of ecosystems and biodiversity

## II. EXISTING SYSTEM

Existing study on background subtraction was done with the assumption of static background. Many models for background segmentation use a base frame that consists of only background explicitly. The challenge of dynamic background is handled by considering the local segmentation sensitivity using feedback loops.

## III. LITERATURE SURVEY

Alka Agrawal [1] Object recognition is an important task in image processing and computer vision. This paper aims to include suitable segmentation, feature extraction and classification methods for elephant recognition. Mean-shift filtering is used for image segmentation and k-nn classifier is used for the object recognition based on the shape features of the segmented image. This approach of object recognition detects elephants that are single as well as in group of different sizes and poses performing different activities. The infrared elephant images are considered for experimentation. The database created by us for this type of object recognition includes elephant, bear, horse, pig, tiger, and cow and lion images. The recognition rate is calculated for performance evaluation. The results indicate that our approach is successful in elephant recognition.

Chandana H C [2] The state-of-the-art technique for animal detection and alerting for crop protection with the goal of achieving high precision with a real-time performance in addition to overcome the disadvantages of the traditional system this computer vision-based system will add more efficiency. In earlier, traditional system consist sensors and registers to identify the movement of object. Some human interventions are required to handle the traditional system, overcome that problems this Image processing based system will work efficiently. The resulting system is fast and accurate, thus aiding those applications which require animal detection.

Balch T [3] Our understanding of social insect behavior has significantly influenced A.I. and multi-robot systems' research (e.g. ant algorithms and swarm robotics). In this work, however, we focus on the opposite question, namely:

"how can multi-robot systems research contribute to the understanding of social animal behavior?." As we show, we are able to contribute at several levels: First, using algorithms that originated in the robotics community, we can track animals under observation to provide essential quantitative data for animal behavior research. Second, by developing and applying algorithms originating in speech recognition and computer vision, we can automatically label the behavior of animals under observation. Our ultimate goal, however, is to automatically create, from observation, executable models of behavior. An executable model is a control program for an agent that can run in simulation (or on a robot). The representation for these executable models is drawn from research in multi-robot systems programming. In this paper we present the algorithms we have developed for tracking, recognizing, and learning models of social animal behavior, details of their implementation, and quantitative experimental results using them to study social insects.

Wei Huang [4] Convolutional neural network (CNN) is an important way to solve the problems of image classification and recognition. It can realize effective feature representation and make continuous breakthroughs in the field of image recognition, but it needs a lot of time in the training process. At the same time, random forest (RF) has the advantages of fast training speed and high classification accuracy. Aiming at the problem of image classification and recognition, this paper proposes a hybrid model based on CNN, which inputs the features extracted by CNN into RF for classification. Since the random weight network can also obtain valid results, the gradient algorithm is not used to adjust the network parameters to avoid consuming a lot of time. Finally, experiments are conducted on MNIST dataset and rotated MNIST dataset, and the results show that the classification accuracy of the hybrid model has improved more than RF, and also, the generalization ability has been improved

Shuqiang Jiang [5] Learning similarity of two images is an important problem in computer vision and has many potential applications. Most of the previous works focus on generating image similarities in three aspects: global feature distance computing, local feature matching, and image concepts comparison. However, the task of directly detecting the class agnostic common objects from two images has not been studied before, which goes one step further to capture image similarities at the region level. In this paper, we propose an end-to-end image Common Object Detection Network (CODN) to detect class agnostic common objects from two images. The proposed method consists of two main modules: locating module and matching module. The locating module generates candidate proposals of each two images. The matching module learns the similarities of the candidate

proposal pairs from two images, and refines the bounding boxes of the candidate proposals. The learning procedure of CODN is implemented in an integrated way and a multi-task loss is designed to guarantee both region localization and common object matching. Experiments are conducted on PASCAL VOC 2007 and COCO 2014 datasets. The experimental results validate the effectiveness of the proposed method.

#### IV. PROPOSED SYSTEM DESIGN

The proposed system introduces an autonomous patrolling robot equipped with advanced technology. The robot is equipped with a camera and weapon detection algorithms, allowing it to actively monitor its surroundings. Weapon detection algorithms provide real-time identification of potential threats, significantly reducing response time. The robot uses GPS to provide precise location data.

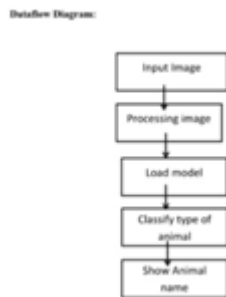


Fig 1:SYSTEM ARCHITECTURE

As illustrated in Figure 1, Image: Users can upload any animal image through a webpage interface. The uploaded image serves as the input for the identification process.

Process the Image: Upon receiving the image, the system initiates preprocessing steps to optimize it for analysis. This includes resizing the image to a standardized format to ensure compatibility with the model and reducing its size for faster processing. Additionally, the image is converted to grayscale to simplify feature extraction and decrease computational overhead, thereby accelerating the identification process.

Load Model: A pre-trained deep learning model is loaded into the system. This model has been trained on a dataset containing various animal images, enabling it to recognize and classify different species accurately. During training, parameters such as training set size and batch size are adjusted to optimize model performance, with the aim of minimizing loss and maximizing validation accuracy.

Classify Animal: The preprocessed image is passed through the loaded model for classification. The model employs sophisticated neural network algorithms to analyze the image's features and predict the type of animal depicted. As the image is processed through the model, it undergoes multiple layers of computations.

Result: Once the classification process is complete, the system generates a result displaying the identified animal. This result is superimposed onto the original image, marking the location of the animal and providing its classified name. Additionally, the classification result is presented alongside the image for user reference, ensuring clarity and ease of interpretation.

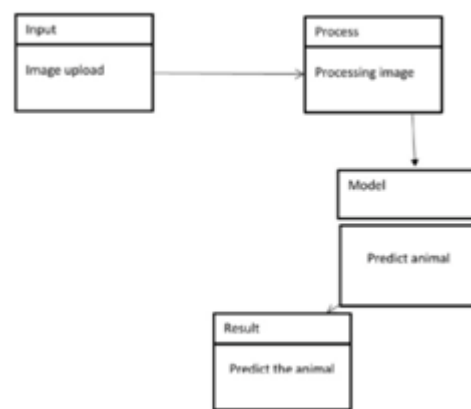


Fig2: SYSTEM FLOW DIAGRAM

The data flow architecture of the Wild Animal Alert System begins with the input image captured by the PC camera. This image undergoes processing to enhance clarity and remove noise. Subsequently, it enters the "load model" module, where a pre-trained deep learning model is loaded.

The loaded model then classifies the type of animal present in the image, employing sophisticated neural network algorithms. This classification is based on learned features extracted from the image. Upon classification, the system generates an alert if a wild animal is detected, triggering the subsequent stages of UART communication with the microcontroller and further actions, including GSM/GPS alerts and video feed transmission.

#### V. SOFTWARE DESCRIPTION

It is crucial to keep an eye on wild animals in their natural environment. This project develops an algorithm to recognize animals in the wild. It could be difficult to manually identify all the different kinds of animals because there are so many of them. These systems categorize animals based on their pictures to more efficiently monitor them.

Animal detection and categorization can help with animal tracing, theft prevention, and accident prevention involving animals and vehicles. This will be possible by applying effective deep learning algorithms. The following procedure is depicted below

The Convolutional Neural Network (CNN) model architecture employed in the Wild Animal Alert System consists of several layers designed for efficient feature extraction and classification. The initial layers perform convolution and pooling operations to extract hierarchical features from the input image. Subsequent layers utilize fully connected layers for classification, learning to distinguish between different types of animals based on the extracted features. The model is trained using a dataset of animal images, adjusting parameters such as batch size and training set size to optimize performance. Throughout training, the model aims to minimize loss and maximize validation accuracy, ensuring accurate identification of animals in real-world images. EfficientNet B2 is a convolutional neural network (CNN) model that takes an image as input and classifies it into one of multiple classes. It was introduced in the paper EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks by Mingxing Tan and Quoc

EfficientNet B2 was trained on ImageNet-1k at a resolution of 260x260. The model's architecture is the same as the above model, with the only difference being the number of feature maps (channels).

EfficientNet is based on the idea of "compound scaling", which scales three critical aspects of a neural network: breadth, depth, and resolution. This idea tackles the trade-off between model size, accuracy, and computing efficiency.

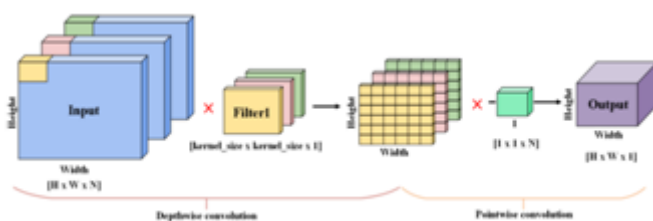


Fig3:MODEL ARCHITECTURE

**VI.HARDWAREDESCRIPTION**

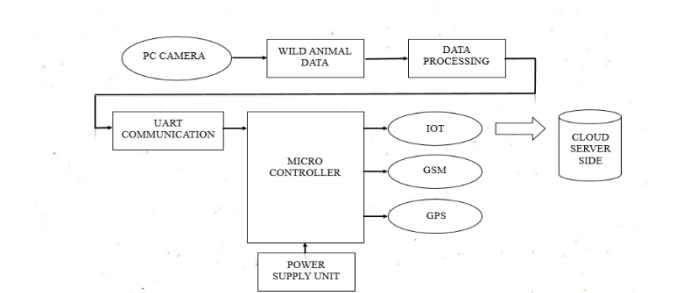


Fig. 4 HARDWARE ARCHITECTURE

The most common set of requirements defined by any operating system or software application is the physical computer resources, also known as hardware, A hardware requirements list is often accompanied by a hardware compatibility list (HCL), especially in case of operating systems. An HCL lists tested, compatible, and sometimes incompatible hardware devices for a particular operating system or application.

The hardware requirements may serve as the basis for a contract for the implementation of the system and should therefore be a complete engineer as the starting point for the system design.

- ✓ MICRO CONTROLLER (ARDUINO UNO)
- ✓ GSM
- ✓ GPS
- ✓ CP2102(UART COMMUNICATION)
- ✓ SOLDERING KIT
- ✓ CONNECTING WIRES



FIG5:ARDUINO UNO

**A. Arduino Uno**

Arduino Uno is a microcontroller board based on the ATmega328P (datasheet). It has 14 digital input/output pins (of which 6 can be used as PWM outputs), 6 analog inputs, a 16 MHz ceramic resonator (CSTCE16M0V53-R0), a USB connection, a power jack, an ICSP header and a reset button. It contains everything needed to support the microcontroller;

simply connect it to a computer with a USB cable or power it with a AC-to-DC adapter or battery to get started. You can tinker with your Uno without worrying too much about doing something wrong, worst-case scenario you can replace the chip for a few dollars and start over again. "Uno" means one in Italian and was chosen to mark the release of Arduino Software (IDE) 1.0. The Uno board and version 1.0 of Arduino Software (IDE) were the reference versions of Arduino, now evolved to newer releases. The Uno board is the first in a series of USB Arduino boards, and the reference model for the Arduino platform; for an extensive list of current, past or outdated boards see the Arduino index of boards



FIG 6: GLOBAL POSITIONING SYSTEM

### B. Global Positioning System (GPS)

The Global Positioning System (GPS), originally Navistar GPS, is a space-based radio navigation system owned by the United States government and operated by the United States Air Force. It is a global navigation satellite system that provides geo location and time information to a GPS receiver anywhere on or near the Earth where there is an unobstructed line of sight to four or more GPS satellites. The GPS system does not require the user to transmit any data, and it operates independently of any telephonic or internet reception, though these technologies can enhance the usefulness of the GPS positioning information. The GPS system provides critical positioning capabilities to military, civil, and commercial users around the world. The United States government created the system, maintains it, and makes it freely accessible to anyone with a GPS receiver.

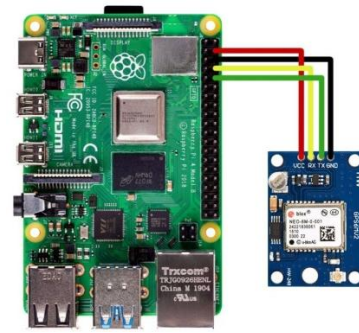


FIG 7: GSM MODULE

### C. Global System for Mobile Communications (GSM)

A Global System for Mobile Communications (GSM) modem is a specialized type of modem which accepts a SIM card, and operates over a subscription to a mobile operator, just like a mobile phone. This tutorial will explain how to interface a GSM modem with Toradex modules. This GSM Modem can accept any GSM network act as SIM card and just like a mobile phone with its own unique phone number. Advantage of using this modem will be that you can use its RS232 port to communicate and develop embedded applications. The SIM900A is a complete Dual-band GSM/GPRS solution in a SMT module featuring an industry-standard interface; the SIM800 delivers GSM/GPRS 900/1800MHz performance for voice, SMS, Data, and Fax in a small form factor and with low power consumption. With a tiny configuration of 24mm x 24mm x 3 mm, SIM800 can fit almost all the space requirements in your applications, especially for slim and compact demand of design.

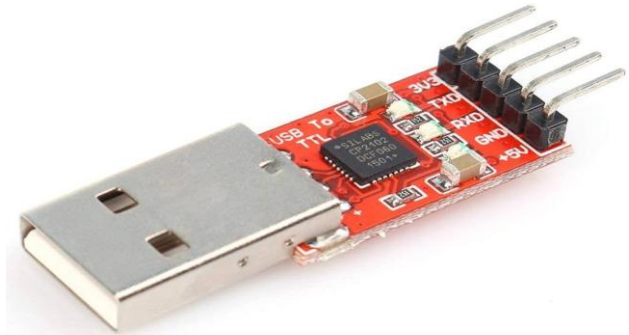


FIG 8: UART COMMUNICATION

### D. UART Communication

UART (Universal Asynchronous Receiver/Transmitter) serial communication is a widely used method for transmitting data between electronic devices. It employs two wires for communication: one for transmitting data (TX) and the other for receiving data (RX). UART operates asynchronously, meaning it does not require a shared clock signal between the sender and receiver. Instead,



data is sent in individual bytes, with start and stop bits framing each byte to indicate its beginning and end. UART is commonly utilized in embedded systems, microcontrollers, and communication interfaces, providing a simple and reliable means of data exchange between devices over short distances.

#### Features of UART Communication

0 digital I/O pins

5x5 mm QFN28 package

Standard USB type A male and TTL 6pin connector

6pins for 3.3V, RST, TXD, RXD, GND & 5V

Baud rates: 300 bps to 1.5 Mbps

Byte receive buffer; 640 byte transmit buffer

Full hardware UART has flow control for baud rates from 300bps to 921600bps

## E. SOLDERING KIT & CONNECTING WIRES

A soldering kit typically consists of a soldering iron, solder wire, flux, and other accessories for joining electronic components. The soldering iron is the primary tool used to heat and melt solder, which is a metal alloy, to create electrical connections between components. Flux is applied to clean and prepare the surfaces to be soldered, ensuring a strong and reliable bond.

When connecting wires for UART communication with an Arduino Uno, you'll need to solder the wires to appropriate connectors or pins on the Arduino board. For UART communication, you typically use pins labeled TX (transmit) and RX (receive) on the Arduino Uno. These pins facilitate bidirectional communication between the Arduino and other devices.

## VI. PHYSICAL IMPLEMENTATION



FIG 9: PHYSICAL IMPLEMENTATION OF DETECTING AN WILD ANIMAL TRAINED IN A MOEL

## IMPLEMENTATION OF SOFTWARE:

The menu bar contains all commands, and in particular the Kernel menu is for changing it if necessary.

The button row gives you a one-click access to Run the current cell (otherwise press your Shift Return keys), a way to restart the kernel (which clears the current session) and a Save button to make sure CoCalc has stored the file. The Time Travel button allows you to see previous versions of that notebook, such that you can go back in time to recover from a bad change.

**Active cell:** in the screenshot above, the blue bar on the left and a blue border around a cell indicates that this is the currently active one. Actions like Run, Delete Cell, etc. operate on the currently selected cell. It is also possible to select more than one cell.

**Execution counter:** On the left of each cell, there is an execution counter. The number increases each time a cell is being run. After the kernel stopped and restarted, that counter starts again at 1.

The output of code cells is below the input cell. For example, in the right hand corner of the input cell is some information about how long it took to calculate the result.

Text cells are slightly different. Select “Markdown” in the dropdown menu in the button bar to change a code cell to such a markdown text cell. There, you can use Markdown to format the text. Similar to code-cells, either run these text cells to see the processed Markdown code or press Shift+Return. To edit a text cell, either double click it or press your Return key.

Saving: more general, the nice things about Jupyter Notebooks is that they save all your input and output in one single file. This means you can download or publish the notebook as it is, and everyone else sees it in exactly the same way.

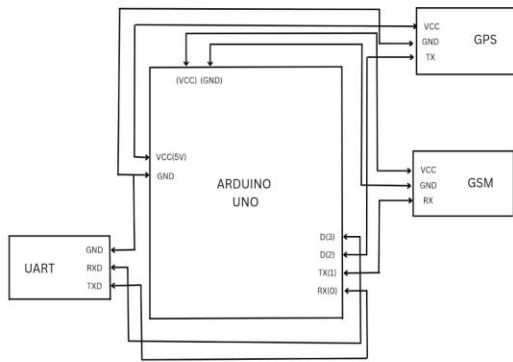


FIG 10: ARDUINO PIN DIAGRAM (MICRO CONTROLLER)

**VII. EVALUATION**

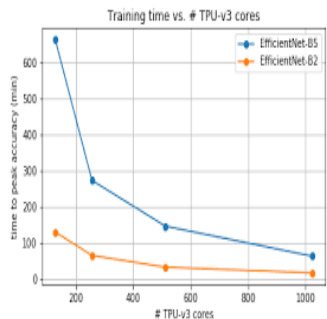


FIG 11: THE TRAINING ACCURACY AND LOSS OF THE EFFICIENT NET MODEL

Figure 11 illustrates the calculated training error and loss graphically. As shown in the figure, the mean squared error loss is decreasing over the 5 training epochs, while the accuracy increases consistently.

Evaluation is reviewing performance (accuracy) of models and deciding a best model. This is the process where the models are improved based a goal performance. Success criteria can be based on speed of algorithm, memory usage, or prediction accuracy. The sum of correct classification divided by the total number of classifications, can be used. The idea of building machine learning models works on a constructive feedback principle. You build a model, get feedback from metrics, make improvements, and continue until you achieve a desirable accuracy. Evaluation metrics explain the performance of a model. An important aspect of evaluation metrics is their capability to discriminate among model results.

Since our project uses classification, some criteria for classification are introduced

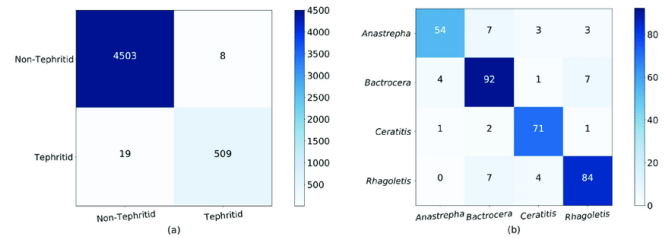


FIG 12: THE CONFUSION MATRIX FOR THE EFFICIENTNET MODEL

**VIII. CONCLUSION**

The Wild Animal Alert System, leveraging deep learning and advanced communication technologies, stands as a pivotal solution in mitigating human-wildlife conflicts and enhancing environmental monitoring. By integrating a PC camera, data processing algorithms, microcontroller, and UART communication, the system offers real-time detection and notification of wild animal presence.

Through a streamlined process, the system analyzes input images, preprocesses them for efficient processing, and classifies detected animals using a Convolutional Neural Network (CNN) with efficientnet B2 model which comes under the . This robust architecture ensures accurate identification and classification of various species, facilitating prompt responses to potential wildlife encounters.

Furthermore, the utilization of UART communication enables seamless interaction between the system components, ensuring swift transmission of alerts to designated recipients via GSM and GPS modules. This allows for timely intervention and management of wildlife-related incidents, thereby safeguarding both human safety and wildlife conservation efforts.

In conclusion, the Wild Animal Alert System represents a sophisticated yet accessible tool for wildlife monitoring and management. Its integration of cutting-edge technologies empowers stakeholders with actionable insights, promoting coexistence between humans and wildlife while fostering environmental sustainability. Through continued innovation and deployment, such systems hold promise in addressing complex challenges at the intersection of human development and biodiversity conservation.

**FUTURE DIRECTIONS**

As a future work, we are trying to modify the model with a greater number of images with some other Wild Animals.

Moreover, we are also in process to improve the same model on same dataset as testing accuracy is less

In the future, the Wild Animal Alert System can evolve to encompass several enhancements and expansions. Firstly, incorporating more advanced deep learning techniques, such as recurrent neural networks (RNNs) or attention mechanisms, could improve the system's ability to detect and classify a wider range of wildlife species with higher accuracy.

Additionally, integrating advanced sensors like infrared cameras or acoustic sensors could enhance the system's detection capabilities, especially in low-light conditions or dense vegetation.

Furthermore, enhancing the system's communication capabilities by incorporating emerging technologies like LoRa (Long Range) or NB-IoT (Narrowband Internet of Things) could enable broader coverage and more efficient transmission of alerts in remote or rugged environments. Moreover, collaborating with wildlife conservation organizations and local communities could facilitate the deployment of the system in conservation areas, contributing to broader conservation efforts and promoting coexistence between humans and wildlife.

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