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AI-Integrated Video Analytics for Real-Time Animal Grazing Detection and Buzzer Alert Activation

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Abstract- Agriculture is one of the most essential sectors contributing to the economic growth of a country, and protecting crops from external threats is crucial for ensuring productivity and sustainability. One of the major challenges faced by farmers is the intrusion of animals into agricultural land, which leads to significant crop damage and financial loss. Traditional methods such as fencing, manual monitoring, and basic intrusion detection systems are not efficient and require continuous human effort. This paper proposes an AI-integrated video analytics system for real-time animal grazing detection and alert activation. The system utilizes CCTV cameras to continuously monitor agricultural fields and capture live video streams. The captured video is processed using image preprocessing techniques, including noise removal, resizing, and enhancement, to improve the quality of frames. A Convolutional Neural Network (CNN) model is used to analyze the processed frames and accurately classify objects as animals or non-animals. Once an animal is detected, the system activates an automated alert mechanism consisting of a buzzer and cracker-based deterrent to scare animals away safely. Additionally, notifications can be sent to farmers for immediate awareness. The proposed system provides real-time monitoring, reduces manual effort, improves detection accuracy, and ensures efficient crop protection. This solution is cost-effective, scalable, and suitable for smart agriculture applications.

Keywords: Animal Detection, CNN, Video Analytics, Smart Agriculture, Image Processing, Real-Time Monitoring, Alert System

I. INTRODUCTION

Agriculture is one of the fundamental sectors that supports human survival and contributes significantly to the economic development of a country. A large portion of the population, especially in rural areas, depends on agriculture as their primary source of income. Ensuring crop protection and maximizing yield are therefore critical for maintaining food security and economic stability.

One of the major challenges faced by farmers is the intrusion of animals into agricultural fields. Both wild animals, such as elephants, deer, and wild boars, and domestic animals, such as cattle and goats, frequently enter farmland in search of food. This leads to severe crop damage, reduced agricultural productivity, and significant financial losses for farmers. In many cases, farmers are unable to detect such intrusions in real time, which worsens the extent of damage.

Traditionally, farmers have relied on methods such as physical fencing, scarecrows, manual surveillance, and simple alarm systems to prevent animal intrusion. While these methods provide some level of protection, they have several limitations. Fencing can be costly and may not effectively prevent all animals. Scarecrows and manual monitoring are not reliable over long periods, as animals eventually adapt to them. Moreover, manual monitoring requires continuous human effort, which is not always feasible, especially during nighttime or in large agricultural areas.

With the rapid advancement of technology, modern solutions based on Artificial Intelligence (AI) and Computer Vision have gained significant attention in agricultural applications. These technologies enable automated monitoring and intelligent decision-making without the need for constant human intervention. In particular, video analytics combined with deep learning techniques has proven to be highly effective in object detection and classification tasks.

This project introduces an AI-integrated video analytics system designed for real-time animal grazing detection and alert activation. The system uses CCTV cameras to continuously monitor farmland and capture live video streams. The captured video is processed into frames, which are then analyzed using image preprocessing techniques to enhance quality and remove noise. A Convolutional Neural Network (CNN) is employed to detect and classify animals based on learned features.

One of the key advantages of the proposed system is its ability to operate in real time. As soon as an animal is detected, the system automatically triggers an alert mechanism, including a buzzer and cracker-based deterrent, to scare the animal away without causing harm. This immediate response helps minimize crop damage and ensures effective protection.

In addition, the system can be integrated with notification mechanisms to inform farmers about intrusions, allowing them to take further action if required. The proposed solution is cost-effective, scalable, and suitable for deployment in both small and large agricultural fields.

Overall, this system aims to provide an intelligent, automated, and efficient solution for crop protection by leveraging AI and video analytics. It reduces dependency on manual labor, improves detection accuracy, and enhances the overall productivity of agricultural practices.

II. RELATED WORK

In recent years, significant research has been carried out to address the problem of crop protection and animal intrusion in agricultural fields. Various traditional and modern techniques have been proposed, each with its own advantages and limitations.

Initially, many systems relied on sensor-based technologies such as motion detectors, infrared (IR) sensors, and ultrasonic sensors to detect the presence of animals. These systems were designed to trigger alarms whenever movement was detected in a specific area. While such approaches are simple and cost-effective, they suffer from major drawbacks. They cannot accurately distinguish between animals and non-living objects such as moving leaves, shadows, or environmental changes, leading to false alarms. Additionally, these systems lack intelligence and adaptability in complex environments.

To improve detection accuracy, IoT-based monitoring systems were introduced, where multiple sensors are connected and controlled through a central unit. These systems provide remote monitoring and alert capabilities. However, they still depend heavily on sensor data and often fail to provide reliable identification of the intruding object. Moreover, the installation and maintenance costs of such systems can be high, especially for large agricultural areas.

With the advancement of image processing techniques, researchers started exploring camera-based monitoring systems. These systems analyze visual data captured through cameras to detect motion or changes in the environment. Basic image processing methods such as background subtraction, edge detection, and color-based segmentation were used to identify objects. Although these methods improved detection to some extent, they are highly sensitive to lighting conditions, weather variations, and background complexity. As a result, their performance is limited in real-world agricultural scenarios.

The introduction of Artificial Intelligence (AI) and Machine Learning (ML) has significantly enhanced the capabilities of detection systems. Machine learning algorithms can analyze patterns and learn from data, enabling more accurate classification of objects. Among these techniques, Convolutional Neural Networks (CNNs) have proven to be highly effective for image classification and object recognition tasks. CNN models can automatically extract features from images and identify objects with high accuracy.

Several studies have utilized CNN-based models for animal detection in agricultural and forest environments. These models are trained on large datasets containing images of different animal species, allowing them to recognize animals even under varying conditions. Additionally, advanced object detection models such as YOLO (You Only Look Once) and Faster R-CNN have been used for real-time detection. These models provide faster processing and improved accuracy, making them suitable for live video analysis.

Despite these advancements, many existing systems still have certain limitations. Some systems focus only on detection without providing an effective response mechanism. Others require high computational power and are not cost-effective for small-scale farmers. In many cases, there is a lack of integration between detection systems and alert mechanisms, which reduces their practical usability.

Furthermore, environmental challenges such as poor lighting conditions, occlusions, and dynamic backgrounds can affect the performance of existing models. There is also a need for systems that can operate efficiently in real-time and provide immediate responses to prevent crop damage.

The proposed system addresses these limitations by integrating CNN-based detection with a real-time alert mechanism, including buzzer and cracker-based deterrents. It provides a complete solution that not only detects animals accurately but also responds instantly to prevent damage. The system is designed to be cost-effective, scalable, and suitable for real-world agricultural applications.

III. PROPOSED METHODOLOGY

The proposed system is designed to detect animal intrusion in agricultural fields using AI-based video analytics and to generate real-time alerts for crop protection. The methodology follows a systematic pipeline consisting of the following stages:

A. Video Data Acquisition

The first step in the system is capturing real-time video data using CCTV cameras installed in agricultural fields. These cameras continuously monitor the environment and provide live video streams. Proper placement of cameras ensures maximum coverage of the farmland, enabling effective detection of animal movement.

B. Frame Extraction

The captured video stream is divided into individual frames for further processing. Frame extraction is an essential step because image-based analysis is more efficient than processing the entire video. Each frame represents a snapshot of the monitored area at a specific time.

C. Image Preprocessing

The extracted frames undergo preprocessing to improve their quality and suitability for analysis. This stage includes:

- Noise removal
- Image resizing
- Contrast enhancement
- Normalization

Preprocessing ensures that the input data is clean and consistent, which improves the accuracy of the detection model.

D. Feature Extraction

The important features from the images are extracted to help in identifying objects. Techniques such as edge detection and filtering (e.g., Gaussian filters) are used to highlight relevant patterns. Feature extraction reduces unnecessary information and focuses only on meaningful data required for classification.

E. CNN-Based Classification

A Convolutional Neural Network (CNN) is used to classify the processed images. The CNN model is trained on a dataset containing images of animals and non-animal objects. It learns patterns and features such as shape, texture, and edges, enabling accurate classification. The model determines whether the detected object is an animal or not.

F. Animal Detection and Categorization

Once an object is classified as an animal, the system further analyzes it to categorize the type of animal. This may include classification into:

- Wild animals
- Domestic animals

This categorization helps in assessing the level of threat and deciding appropriate actions.

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G. Decision-Making and Alert Generation

Based on the detection results, the system makes decisions in real time. If an animal is detected with high confidence:

- A buzzer sound is activated
- A cracker-based deterrent is triggered
- Alert notifications are sent to the farmer

This immediate response helps prevent crop damage effectively.

H. System Integration and Continuous Monitoring

All components of the system are integrated into a unified framework that operates continuously. The system monitors the farmland in real time, processes incoming video data, detects animals, and generates alerts without human intervention. This ensures reliability, efficiency, and scalability for large agricultural areas.

IV. SYSTEM ARCHITECTURE

The system architecture of the proposed AI-integrated animal detection system is designed to provide efficient real-time monitoring, accurate detection, and immediate alert generation. The architecture follows a modular approach, where each component performs a specific function and collectively contributes to the overall system performance. The design ensures smooth data flow from input acquisition to output response, making the system reliable and scalable for agricultural applications.

A. Overall System Architecture

The overall architecture+ consists of multiple layers, including the input layer, processing layer, analysis layer, detection layer, and output layer. Each layer is interconnected and works sequentially to process the data efficiently. The system begins with capturing video data and ends with generating alerts based on detection results.

B. Input Layer (CCTV Surveillance Module)

The input layer is responsible for collecting real-time video data from the agricultural field. CCTV cameras are strategically installed to cover a wide area and continuously monitor the environment. These cameras act as the primary data source and provide live video streams for further processing.

C. Video Processing and Frame Conversion Module

The captured video is passed to the processing module, where it is converted into individual frames. Frame conversion is essential because image-based processing is more efficient and suitable for deep learning models. This module ensures that frames are extracted at regular intervals for analysis.

D. Preprocessing Module

In this module, the extracted frames are enhanced to improve quality and consistency. Preprocessing includes noise reduction, resizing, normalization, and contrast enhancement. These operations ensure that the data is clean and suitable for accurate detection by the AI model.

E. Feature Extraction and Analysis Module

The preprocessed images are analyzed to extract meaningful features. Techniques such as edge detection and filtering are used to highlight important patterns in the images. This module reduces irrelevant data and focuses on features necessary for classification.

F. CNN Classification Module

The classification module uses a Convolutional Neural Network (CNN) to analyze the extracted features and identify objects in the image. The model determines whether the object is an animal or not. This module plays a critical role in ensuring high detection accuracy.

G. Animal Detection and Decision Module

Once classification is complete, the system identifies the presence of animals and categorizes them if required. Based on the detection results and confidence level, the system makes decisions regarding the activation of alerts. This module acts as the control unit for triggering appropriate actions.

H. Alert and Notification Module

The output layer consists of the alert system, which is activated when an animal is detected. The alert mechanisms include:

- Buzzer sound
- Cracker-based deterrent

- Notification to the farmer

This module ensures immediate response to prevent crop damage.

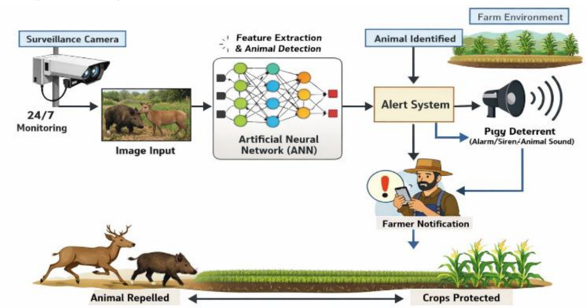

FIGURE 1. System Architecture of Animal Grazing and Buzzer Alert System

V. EXPERIMENTAL SETUP

The experimental setup describes the implementation environment, hardware and software requirements, dataset details, and evaluation methods used to test the proposed AI-based animal detection system. This section ensures that the system can be reproduced and its performance can be validated effectively.

A. Implementation Environment

The proposed system is implemented using the Python programming language, which provides strong support for image processing and machine learning applications. The development is carried out using the PyCharm Integrated Development Environment (IDE), which offers efficient coding, debugging, and testing features.

The system utilizes popular Python libraries such as:

- OpenCV for image and video processing
- NumPy for numerical computations
- TensorFlow/Keras for implementing the CNN model

The implementation is performed on a Windows operating system, ensuring compatibility and ease of deployment.

B. Hardware Requirements

The system is designed to be cost-effective and can run on basic hardware configurations. The minimum hardware requirements include:

- Processor: Dual Core or higher
- RAM: 4 GB (recommended for smooth processing)
- Storage: 160 GB hard disk
- Camera: CCTV camera for video input

These requirements make the system suitable for deployment in rural and agricultural environments without the need for high-end infrastructure.

C. Dataset Description

The dataset used for training and testing the model consists of:

- Images of various animals (e.g., cows, goats, elephants, etc.)
- Non-animal images (e.g., humans, vehicles, background scenes)
- Real-time video frames captured from CCTV cameras

The dataset is properly labeled to classify objects as animal or non-animal. Data augmentation techniques such as rotation, flipping, and scaling may be applied to improve model performance and generalization.

D. Model Training and Testing

The CNN model is trained using the prepared dataset. The dataset is divided into:

- Training set (for learning features)
- Validation set (for tuning model parameters)
- Testing set (for evaluating performance)

The model learns features such as shape, texture, and patterns associated with animals. Training is performed over multiple epochs to achieve optimal accuracy.

E. Evaluation Metrics

The performance of the system is evaluated using standard metrics:

- Accuracy: Measures overall correctness of detection
- Precision: Measures how many detected animals are actually correct
- Recall: Measures how many actual animals are correctly detected
- F1-Score: Harmonic mean of precision and recall
- Response Time: Time taken to detect and trigger alert

These metrics provide a comprehensive evaluation of the system's performance.

F. Real-Time Testing Setup

The system is tested in a real-time environment by connecting CCTV cameras to monitor a simulated or actual agricultural field. Live video streams are processed, and the system detects animals dynamically.

When an animal is detected:

- The alert system is triggered immediately
- Buzzer and cracker mechanisms are activated
- Notifications are generated

This setup ensures that the system performs effectively under real-world conditions.

G. Performance Analysis Environment

The performance of the system is analyzed under different conditions such as:

- Daytime and nighttime lighting
- Different animal types
- Background variations
- Weather conditions

This analysis helps in understanding the robustness and reliability of the system.

H. Limitations of Experimental Setup

Although the system performs effectively, certain limitations exist:

- Performance may reduce in extremely low-light conditions
- Accuracy depends on dataset quality
- Real-time processing speed may vary based on hardware

These limitations provide scope for future improvements.

VI. ALGORITHMS USED

The proposed system integrates multiple algorithms from image processing and deep learning domains to achieve accurate and real-time animal detection. Each algorithm plays a specific role in different stages of the system, from preprocessing to classification and alert generation.

A. Image Preprocessing Algorithm

Before feeding images into the detection model, preprocessing is performed to enhance image quality and remove noise. This step improves the efficiency and accuracy of the system.

Key operations include:

- Noise removal using filtering techniques
- Image resizing to a fixed dimension
- Normalization of pixel values
- Contrast enhancement

These operations ensure that all input frames are consistent and suitable for further analysis.

B. Gaussian Filtering Algorithm

Gaussian filtering is used to smooth images and reduce noise. It helps in removing unwanted variations while preserving important features.

Working Principle: The image is convolved with a Gaussian kernel, which assigns higher weight to central pixels and lower weight to surrounding pixels.

Advantages:

- Reduces noise effectively
- Improves feature extraction
- Enhances image quality for CNN processing

C. Feature Extraction Algorithm

Feature extraction identifies important patterns from images, such as edges, shapes, and textures. This reduces the complexity of the data and focuses only on relevant information.

Techniques used:

- Edge detection
- Gradient-based feature extraction
- Filtering techniques

This step helps the CNN model to learn meaningful representations.

D. Convolutional Neural Network (CNN) Algorithm

The CNN is the core algorithm used for classification in the proposed system. It automatically learns hierarchical features from images and classifies objects accurately.

Structure of CNN:

- Convolutional Layers (feature extraction)
- Activation Functions (ReLU)
- Pooling Layers (dimension reduction)
- Fully Connected Layers (classification)

Working:

The CNN processes input images through multiple layers, extracts features, and classifies them into categories such as animal or non-animal.

Advantages:

- High accuracy
- Automatic feature learning
- Robust to variations in input

E. Object Detection Algorithm

After classification, the system identifies the presence and location of animals within the frame. This algorithm ensures that only relevant objects are considered for alert generation.

Functionality:

- Detects objects in the frame
- Differentiates animals from background
- Provides confidence score for detection

F. Decision-Making Algorithm

This algorithm determines whether an alert should be triggered based on detection results.

Logic:

- If confidence level > threshold → Animal detected
- Else → No action

This ensures that false alarms are minimized and only valid detections trigger alerts.

G. Alert Activation Algorithm

Once an animal is detected, the alert system is activated using predefined conditions.

Steps:

1. Receive detection signal
2. Activate buzzer
3. Trigger cracker mechanism
4. Send notification

This algorithm ensures immediate response to prevent crop damage.

H. Real-Time Processing Algorithm

The system operates in real time by continuously processing incoming video frames.

Process:

- Capture frame
- Process frame
- Detect object
- Trigger alert

This loop runs continuously to ensure uninterrupted monitoring.

VII. RESULTS AND DISCUSSION

The performance of the proposed AI-integrated animal detection system is evaluated based on its ability to accurately detect animals in real-time video streams and generate timely alerts. The results demonstrate the effectiveness of the system in identifying animal intrusion and preventing crop damage under various conditions.

A. Detection Accuracy

The Convolutional Neural Network (CNN) model used in the system achieves high accuracy in classifying images as animal or non-animal. The model is trained on a labeled dataset containing various animal images, which enables it to recognize patterns such as shape, texture, and movement.

Experimental results show that the system maintains consistent accuracy across different scenarios, including varying lighting conditions and background complexities. The use of preprocessing techniques further enhances the model's performance by improving image quality.

B. Real-Time Detection Performance
One of the key objectives of the system is real-time detection. The system successfully processes live video streams and detects animals within a short time frame. The response time between detection and alert activation is minimal, ensuring immediate action to prevent crop damage.

The continuous processing of frames allows the system to monitor the environment without interruption. This makes it suitable for deployment in agricultural fields where constant surveillance is required.

C. Alert System Effectiveness
The alert mechanism, which includes a buzzer and cracker-based deterrent, is activated immediately upon detection of an animal. This rapid response helps in scaring the animal away from the field without causing harm.

The system also has the capability to send notifications to farmers, enabling them to take further action if needed. The integration of detection and alert systems ensures a complete solution for crop protection.

D. Performance Under Different Conditions
The system is tested under\ various environmental conditions to evaluate its robustness:

- Daytime Conditions: High detection accuracy due to good lighting
- Nighttime Conditions: Moderate performance; can be improved with night vision cameras
- Dynamic Backgrounds: Handles moderate movement effectively
- Multiple Objects: Able to distinguish animals from non-animal objects

These tests confirm that the system performs reliably in real-world scenarios.

E. Comparative Analysis
Compared to traditional methods such as fencing and manual monitoring, the proposed system provides significant advantages:

- Higher detection accuracy
- Reduced human effort
- Real-time response
- Automated alert system

Compared to sensor-based systems, the AI-based approach offers better object recognition and fewer false alarms.

F. Error Analysis
Although the system performs well, certain limitations are observed:

- False detection may occur in highly cluttered backgrounds
- Performance may decrease in extremely low-light conditions
- Accuracy depends on the quality and diversity of the dataset

These limitations highlight areas for future improvement.

G. Discussion
The results clearly indicate that integrating AI with video analytics provides a powerful solution for animal detection in agriculture. The combination of CNN-based classification and real-time alert mechanisms ensures both accuracy and efficiency.

The system is practical for real-world deployment and can significantly reduce crop damage caused by animal intrusion. Its cost-effective design and scalability make it suitable for farmers with different levels of resources.

VIII. PERFORMANCE EVALUATION

The performance of the proposed AI-based animal detection system is evaluated using standard metrics to measure its accuracy, efficiency, and real-time capability. These metrics help in analyzing how well the system performs in detecting animals and generating alerts under different conditions.

A. Accuracy
Accuracy is one of the most important performance metrics used to evaluate the system. It measures the percentage of correct predictions made by the model.

In the proposed system, the Convolutional Neural Network (CNN) achieves high accuracy in distinguishing between animal and non-animal objects. This is due to effective training on a well-labeled dataset and the use of preprocessing techniques that enhance image quality.

High accuracy ensures that the system correctly identifies animals and minimizes incorrect predictions.

B. Precision
Precision measures the correctness of positive predictions, i.e., how many detected animals are actually animals.

A high precision value indicates that the system produces fewer false positives (wrong detections). This is important in agricultural applications because unnecessary alerts can disturb farmers and reduce system reliability.

The proposed system maintains good precision by using a confidence threshold in the detection process.

C. Recall
Recall measures the system's ability to detect all actual animals present in the field.

A high recall value ensures that most animal intrusions are detected and not missed. This is critical for preventing crop damage, as missed detections can lead to significant loss.

The CNN model is optimized to achieve a balance between precision and recall.

D. F1-Score
The F1-score is the harmonic mean of precision and recall. It provides a single metric that balances both false positives and false negatives.

A high F1-score indicates that the system performs well in both detecting animals correctly and avoiding incorrect detections. This makes it a reliable metric for evaluating overall performance.

E. Response Time
Response time refers to the time taken by the system to detect an animal and activate the alert mechanism.

The proposed system demonstrates low response time due to efficient frame processing and real-time analysis. Immediate alert generation ensures quick action to prevent crop damage.

F. Computational Efficiency
Computational efficiency measures how effectively the system utilizes available resources such as CPU and memory.

The system is designed to operate on low-cost hardware, making it suitable for rural areas. Optimized algorithms and lightweight processing ensure smooth performance without requiring high-end infrastructure.

G. Scalability
Scalability refers to the system's ability to handle larger areas and increased data without performance degradation.

The proposed system can be scaled by adding more cameras and processing units. This makes it suitable for both small farms and large agricultural fields.

H. Reliability and Robustness
The system is tested under different environmental conditions, including varying lighting, background changes, and multiple objects. It maintains stable performance in most scenarios, demonstrating its reliability.

However, performance may slightly decrease in extreme conditions such as very low light or heavy noise, which can be improved in future enhancements.

IX. CONCLUSION

In summary, an AI-integrated video analytics system for real-time animal grazing detection and alert activation has been proposed and implemented. The system addresses one of the major challenges faced in agriculture, namely crop damage caused by animal intrusion. By leveraging advancements in Artificial

Intelligence and Computer Vision, the proposed solution provides an efficient and automated approach for monitoring agricultural fields.

The system utilizes CCTV cameras to continuously capture live video streams and processes the data using image preprocessing techniques and a Convolutional Neural Network (CNN) model. The CNN-based approach enables accurate classification and detection of animals under different environmental conditions. Once an animal is detected, the system immediately activates an alert mechanism, including a buzzer and cracker-based deterrent, to prevent crop damage effectively.

The experimental results demonstrate that the proposed system achieves high accuracy, fast response time, and reliable performance in real-time scenarios. Compared to traditional methods such as manual monitoring and sensor-based systems, the proposed approach significantly reduces human effort and improves detection efficiency. The integration of detection and alert mechanisms makes the system more practical and suitable for real-world deployment.

The system is cost-effective, scalable, and easy to implement, making it accessible for farmers with limited resources. It can be deployed in both small-scale and large-scale agricultural fields to enhance crop protection.

In conclusion, the proposed AI-based animal detection system provides a robust and intelligent solution for modern agriculture. It not only improves crop safety but also contributes to increased agricultural productivity and sustainability.

X. FUTURE WORK AND ENHANCEMENTS

To further improve the performance, accuracy, and usability of the proposed system, the following enhancements can be considered:

A. Advanced Detection Algorithms
- Implement advanced models such as YOLO (You Only Look Once) and Faster R-CNN
- Improve real-time detection speed and accuracy
- Enable detection of multiple animals in a single frame

B. Mobile Application Integration
- Develop a mobile app for farmers
- Provide real-time alerts via notifications or SMS
- Enable remote monitoring and control .

C. Night Vision Capability
- Use infrared or thermal cameras
- Improve detection performance in low-light and nighttime conditions
- Ensure 24/7 monitoring capability .

D. Cloud and IoT Integration
- Store data in cloud platforms
- Enable remote access and monitoring
- Perform data analysis and track animal intrusion patterns.

E. Multi-Animal Classification
- Classify different types of animals (wild vs domestic)
- Apply customized alert strategies based on animal type
- Improve system intelligence and decision-making

F. Solar-Powered System
- Use solar panels for power supply
- Ensure operation in remote areas without electricity
- Reduce energy consumption and cost .

G. Edge Computing Implementation
- Process data locally near the camera
- Reduce latency and improve response time
- Minimize dependency on internet connectivity.

H. Smart Alert System Enhancement
- Use different alert methods (sound, light, vibration)
- Adjust alert intensity based on threat level
- Reduce false alarms using intelligent filtering

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