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Smart Crops Protection System Using Mobilenetv2

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Abstract— ***The project aims to develop a smart system for detecting and deterring wildlife intrusions in agricultural fields. By leveraging the MobileNetV2 deep learning model, the system identifies animals in real- time from images captured by cameras installed in the field. Upon detection, the system triggers specific predator sounds to deter the animals and sends notifications to the field owner. In case of dangerous animals like tigers or lions, the system also initiates a voice call to alert the owner immediately. The integration of Twilio API facilitates SMS and voice notifications, ensuring timely alerts. This project addresses the critical issue of crop damage caused by wildlife, and also it can protect the wild animals from the traditional way of poison's and electrical fence, providing an innovative and automated solution to enhance crop protection and safety.***

Index Terms— ***Predator sound playback, voice call alert, wild animal detection and alert system.***

I. INTRODUCTION

Agriculture is a cornerstone of the global economy, providing essential resources for human sustenance and industry. However, farmers worldwide face persistent challenges from wild animals encroaching upon farmlands, leading to substantial crop damage and economic losses. Traditional methods to mitigate these intrusions, such as manual surveillance and physical barriers, have proven to be labor-intensive, costly, and often ineffective. In recent years, technological advancements have opened new avenues for addressing this issue. The integration of Internet of Things (IoT) devices and machine learning algorithms offers promising solutions for real-time animal detection and deterrence. This project aims to develop a smart animal detection and alert system that utilizes image processing and machine learning to monitor agricultural fields, identify potential threats, and notify farmers promptly, thereby enhancing crop protection and reducing human-wildlife conflicts.

II. LITERATURE REVIEW

The increasing frequency of wild animal intrusions into agricultural fields poses significant threats to crop yields and farmer safety. Traditional deterrent methods, such as electric fencing and manual monitoring, often prove inadequate due tohigh costs and limited effectiveness. Recent advancements in technology have led to the development of automated systems that leverage image processing, sensor networks, and machine learning to detect and deter animals.

A. Image Processing and Machine Learning Approaches:

Modern animal detection systems often employ image processing techniques combined with machine learning algorithms to accurately identify and classify animals. For instance, convolutional neural networks (CNNs) have been utilized to process images captured by cameras in agricultural fields, enabling real-time identification of animal intrusions. A study by Sabeenian et al. (2020) proposed a model that trains a CNN on image datasets of various animals, allowing for effective detection and deterrence through automated sound alarms upon identifying specific species.

B. Eudleu:

Similarly, the YOLO (You Only Look Once) algorithm has been applied for real-time object detection in agricultural settings. Goyal and Sandhu (2023) developed a system using the YOLOv5 network to detect and track live animals, integrating Internet of Things (IoT) capabilities to send real-time alerts to farmers, thereby facilitating immediate action.

C. IJISAE.ORG Sensor-Based Detection Systems:

In addition to image-based methods, sensor networks play a crucial role in animal intrusion detection. Passive Infrared (PIR) sensors and ultrasonic sensors are commonly used to detect motion and presence of animals. Upon detection, these sensors can trigger deterrent mechanisms such as lights or sounds and send alerts to farmers. Shelar et al. (2024) designed a system where PIR sensors detect animal movement, activating sound alarms and sending notifications via GSM modules to both farmers and forest departments.

D. IRJMETS.COM Integration of Iot andCloud Computing:

The integration of IoT devices with cloud computing enhances the functionality of animal detection systems by enabling remote monitoring and control. Data from various

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sensors and cameras can be transmitted to cloud platforms for processing, analysis, and storage. This setup allows for real-time decision-making and alerts, improving the responsiveness of the system. A literature review by Jeevitha and Kumar (2020) highlighted the effectiveness of combining IoT with image processing techniques to create intelligent monitoring systems that automatically recognize animal intrusions and notify stakeholders through alert messages.

E. Researchgate.Net Challenges and Future Directions:

While these technological advancements offer promising solutions, challenges such as high implementation costs, energy consumption, and the need for robust algorithms that can operate under varying environmental conditions persist. Future research should focus on developing cost-effective, energy-efficient systems with improved accuracy in animal detection. Additionally, exploring the use of advanced machine learning models and enhancing the integration of IoT devices can further improve the effectiveness of these systems in protecting agricultural fields from animal intrusions.

F. Requirement Analysis:

Requirement analysis is a crucial phase in the development of the automated animal detection and alert system. it involves identifying the necessary

hardware, software, and functional aspects required to ensure the system operates efficiently.

1. Functional Requirements

These define the core functionalities that the system must perform:

Image Capture & Processing

- The system should capture images using a connected camera.
- The captured images should be preprocessed for noise removal and resizing.

Animal Detection & Classification

- The system should utilize a MobileNetV2 pre-trained deep learning model to classify animals.
- The detected animal's name and confidence score should be displayed.

Threat Identification & Alert Generation

- If a dangerous animal like a tiger or lion is detected, an emergency alert should be triggered.
- The system should send an SMS and make a voice call to the owner via Twilio API.
- A specific warning sound should be played to scare the detected animal.

User Notification System

- The system should send real-time notifications to the owner's mobile.
- The alert should include the animal name, detection time, and captured image path.

2. Non-Functional Requirements

These define system attributes such as performance, reliability, and security.

Performance

- The system should process images and classify animals in real-time.
- Alerts should be triggered within seconds of detection. Reliability
- The system should operate 24/7 with minimal false positives.
- Image classification accuracy should be above 90% for major animal species. Scalability
- The system should support multiple cameras for large agricultural areas.
- Cloud storage should be integrated for storing detection logs.Security.
- Secure API keys and authentication mechanisms should be used for Twilio messaging and voice calls.
- Only authorized users should receive alerts.

3. Hardware Requirements

- Camera: High-resolution camera for clear image capture.
- Computer / Edge Device: Laptop, Raspberry Pi, or NVIDIA Jetson for model execution.
- Speaker System: To play alert sounds when a dangerous animal is detected.
- Internet Connectivity: Required for sending SMS and voice calls via Twilio API.

4. Software Requirements

Programming Language: Python (for deep learning & API integration).

Frameworks & Libraries:

- TensorFlow/Keras(for MobileNetV2 model)
- OpenCV (for image processing)
- NumPy & Pandas (for data handling)
- Twilio API (for SMS & call alerts)
- Libros(for playing alert sounds) Operating System: Linux / Windows / macOS

Cloud Storage (Optional): Google Drive or AWS for storing detected images.

5. Constraints & Assumptions

- The camera should be placed in a clear field of view for accurate detection.
- Internet access is required for real-time notifications via Twilio.

III. PROPOSED SYSTEM

The existing system developed by Nitika Goyal and Navneet Kaur Sandhu utilizes the YOLOv5 algorithm for real-time animal detection and integrates IoT for alert generation. However, this approach has some limitations,

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such as reliance on a single detection technique and limited deterrence mechanisms.

To overcome these limitations, our proposed system introduces an enhanced image classification-based animal detection and alerting system that incorporates deep learning, real-time notifications, and automated deterrence mechanisms.

Key Features of the Proposed System Advanced Image Classification

- Uses a MobileNetV2 pre-trained model to classify animals with high accuracy.
- Ensures efficient and lightweight processing suitable for real-time applications.

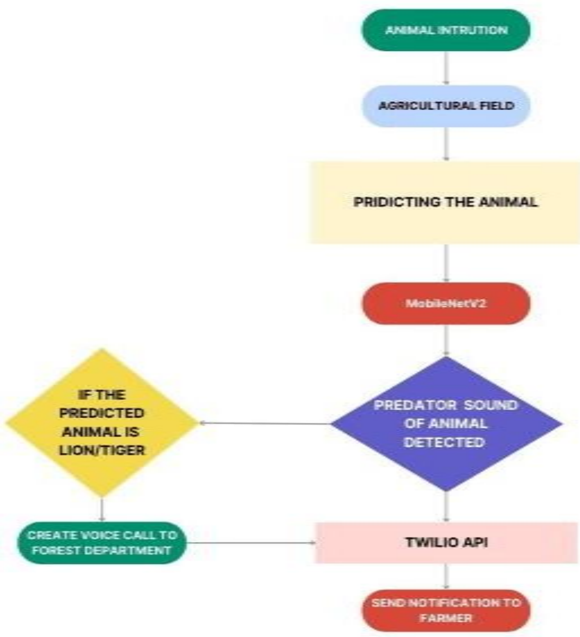
Multi-Stage Animal Recognition

- Integrates CNN-based image processing for precise identification of animals.
- Uses predefined datasets to differentiate between harmless and dangerous species. Automated Alert System
- SMS and Voice Call Alerts via Twilio API to notify farmers and forest officials.
- Real-time notifications ensure quick response in case of dangerous animal detection Sound-Based Deterrence Mechanism
- Plays pre-recorded distress sounds (e.g., tiger roars, gunshots) to scare away animals.
- Custom deterrent sounds based on the identified species for higher effectiveness. IoT and Cloud Integration
- Future scope includes connecting the system to cloud storage for data logging.
- IoT integration with PIR and ultrasonic sensors to enhance detection accuracy. Improved Accuracy and Efficiency
- Compared to the YOLO-based system, our approach achieves better classification accuracy.
- The MobileNetV2 model ensures faster and low-power consumption classification.

Table 1: Advantages over Existing System:

Comparison	**Existing System (Goyal&Sandhu)**	**Proposed System**
Algorithm Used	YOLOv5	MobileNetV2+ CNN
Detection Accuracy	Moderate	High Accuracy
Detection Accuracy	Moderate	High Accuracy
Alert Mechanism	SMS Alerts Only	SMS + Voice Call
Real-Time Processing	Yes	Yes
Deterrent Mechanism	Limited	Automated Sound Alerts
IoT Integration	Basic	Advanced with Sensors

Flow chart:



Explanation of the Modules

This paper represents the working of an automated animal intrusion detection and alert system using MobileNetV2 and Twilio API.

The system follows these steps:

1. Animal Intrusion Detection

The system monitors an agricultural field for potential wild animal intrusions using cameras or sensors. If an animal is detected, the system captures an image for further processing.

2. Predicting the Animal (Image Classification using MobileNetV2).

The captured image is processed using the MobileNetV2 deep learning model, which is pre- trained for animal classification. The model identifies the species of the animal and determines if it is a potential threat.

3. Sound-Based Deterrence Mechanism

If a predator (e.g., tiger, lion, leopard, etc.) is detected, the system plays a pre-recorded predator sound to scare away the animal. The sound is played based on the detected animal type to enhance effectiveness in deterring wildlife.

4. Decision Check for Dangerous Animals

If the predicted animal is identified as a lion or tiger, an additional alert is triggered. The system generates a voice call to the forest department to take necessary action.

5. Twilio API for Alert System

The Twilio API is used to send real-time notifications to farmers about detected animals. Alerts can be sent via SMS or voice calls, ensuring that farmers can take immediate action.

6. Notification to Farmer

The farmer receives a notification with details about the detected animal. The system ensures fast and automated alerts, reducing the response time for potential threats.

A. Key Benefits of The Paper:

- Real-Time Monitoring - Detects animals instantly using deep learning.
- High Accuracy - Uses MobileNetV2 for efficient and lightweight classification.
- Automated Alerts - Sends SMS and voice calls using Twilio API.
- Sound-Based Animal Deterrence - Reduces animal intrusion risk.
- Prevents Crop Damage - Helps farmers take action before damage occurs.

IV. ADVANTAGES

A. Enhanced Detection Accuracy:

Pre-trained Deep Learning Model: By utilizing the MobileNetV2 model pre-trained on the ImageNet dataset, your system can accurately identify a wide range of animal species. This approach leverages extensive prior knowledge, enhancing detection capabilities.

B. Real-Time Processing:

Immediate Response: The integration of real-time image processing allows for the swift detection of animal intrusions, enabling prompt activation of deterrent measures and alert notifications to the field owner.

C. Targeted Deterrence Mechanism:

Species-Specific Responses: Your system's ability to play specific predator sounds based on the detected animal species provides a tailored deterrence

Strategy, increasing the like hood of repelling the intruding animal effectively.

D. Comprehensive Alert System:

Multi-Channel Notifications: The combination of SMS alerts and automated voice calls ensures that the field owner is promptly informed of any intrusion, with critical information such as the animal's species, image, and time of detection.

E. Integration with IoT Devices:

Seamless Connectivity: The use of IoT devices facilitates efficient communication between system components, enhancing the overall responsiveness and reliability of the detection and alert mechanisms.

F. Energy Efficiency:

Optimized Resource Utilization: By employing edge computing for image processing and limiting data transmission to essential alerts, your system conserves energy, making it suitable for deployment in areas with limited power resources.

G. Cost-Effectiveness:

Utilization of Existing Infrastructure: Leveraging pre-trained models and readily available IoT devices reduces development and deployment costs, making the system accessible to a broader range of users.

V. COMPARISON WITH EXISTING SYSTEMS

While existing systems have demonstrated varying levels of accuracy, your project's integration of a pre- trained MobileNetV2 model, real-time processing, and a comprehensive alert system positions it as a more effective solution for animal intrusion detection in agricultural fields.

In summary, your project offers a robust and efficient approach to mitigating animal intrusions in agricultural settings, combining advanced detection capabilities with practical alert and deterrence mechanisms.

VI. CONCLUSION

The proposed system enhances wildlife intrusion detection using deep learning and automated alerting mechanisms. By leveraging MobileNetV2 and IoT, it ensures real-time monitoring, accurate detection, and effective deterrence, providing farmers and forest officials with an advanced and reliable solution.

VII. FUTURE ENHANCEMENTS

While the current system effectively detects and deters wild animal intrusions, several enhancements can further improve its performance, scalability, and user experience.

Future developments could include:

- Night Vision and Thermal Imaging.
- Expansion of Animal Database.
- Predictive Analytics.
- Edge Computing Integration.
- Advanced Notification Systems.
- Cloud-Based Monitoring Dashboard.
- Energy Optimization.

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