Animal Detection Based Smart Farming in Animal Repellant Using Ai and Deep Learning

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ABSTRACT:
The integration of artificial intelligence (AI) and deep learning technologies in agriculture has ushered in a new era of precision farming, where innovative solutions are developed to address various challenges. This project presents an Animal Repellent System for Smart Farming that leverages AI and deep learning to mitigate the growing issue of animal-related crop damage. As the global population continues to expand, ensuring efficient food production is paramount, making it crucial to safeguard crops from wildlife and pests. As a result of human interference with natural habitats and deforestation, crop raiding by animals has emerged as one of the most prevalent human-animal conflicts. Wild animals can assault farmers working in the fields and seriously harm agricultural harvests. Due to agricultural raiding by wild animals like elephants, wild boar, and deer, farmers experience significant crop loss. The protection of crops against assaults by wild animals is one of the primary concerns of today's farmers. There are numerous conventional methods to deal with this issue, both lethal (such as shooting and trapping) and non- lethal. (e.g., scarecrow, chemical repellents, organic substances, mesh, or electric fences). The edge computing device turns on the camera, then uses its DCNN software to identify the target. If an animal is discovered, it then sends a message to the Animal Repelling Module with information about the type of ultrasound that should be created based on the animal's category.

KEYWORDS: Smart Farming, Animal Detection, Ai in agriculture, Machine learning, Deep Learning, IOT in Agriculture, Motion sensors, Agricultural security, Wireless sensor Networks, Animal Behavior Analysis.

INTRODUCTION

Agriculture has seen many revolutions, whether the domestication of animals and plants a few thousand years ago, the systematic use of crop rotations and other improvements in farming practice a few hundred years ago, or the “green revolution” with systematic breeding and the widespread use of man-made fertilizers and pesticides a few decades ago.

Agriculture is undergoing a fourth revolution triggered by the exponentially increasing use of information and communication technology (ICT) in agriculture. Autonomous, robotic vehicles have been developed for farming purposes, such as mechanical weeding, application of fertilizer, or harvesting of fruits.

Moreover, decision-tree models are available now that allow farmers to differentiate between plant diseases based on optical information. Virtual fence technologies allow cattle herd management based on remote-sensing signals and sensors or actuators attached to the livestock.

LITERATURE SURVEY

The development of an automated identification system for animal sounds using Convolutional Neural Networks (CNN). The study highlights the increasing use of passive acoustic monitoring in wildlife ecology and the challenges of efficiently automating species detection. The proposed workflow integrates deep learning models to classify spectrogram images from short audio clips, significantly reducing manual effort by over 99%. Additionally, a user-friendly graphical interface in RStudio enhances accessibility for field biologists. The study demonstrates high accuracy and efficiency with minimal delays using consumer-grade computers, although it requires high power and careful balancing of false positive rates.

1. 1.Patil et al. (2021) proposed an AI-based YOLO (You Only Look Once) model for real-time animal detection. The model successfully identified animals such as wild boars and deer with high accuracy.
2. 2.Sharma & Gupta (2020) implemented a thermal imaging-based animal detection system, reducing false positives caused by wind-blown plants.
3. 3.Ming et al. (2022) developed a hybrid deep learning approach combining CNN and Transfer Learning, which improved the detection efficiency in low-light conditions.
4. 4.Kumar et al. (2019) developed a PIR (Passive Infrared) sensor-based system that detects movement and triggers an alarm to scare animals away.
5. 5.Lee et al. (2021) integrated ultrasonic sensors to detect intruding animals and send real-time alerts to farmers via a mobile app.
6. 6.Zhang et al. (2018) experimented with ultrasonic sound waves to repel animals such as rodents and wild boars. The system automatically adjusted sound frequencies based on the detected species.
7. 7.Rahman et al. (2020) designed a bioacoustic repellent system that plays predator sounds when an animal is detected, successfully reducing intrusion rates in farmlands.
8. 8.Joshi & Mehta (2021) used LED strobes and laser deterrents to keep away nocturnal animals like deer and foxes.
9. 9.Verma et al. (2022) explored the use of infrared light deterrents, reducing crop damage by 70% in test fields.
10. 10.Ahmed et al. (2022) proposed a cloud-based monitoring system that allows farmers to track field activity and receive alerts via a mobile application.
11. 11.Singh et al. (2023) combined AI-driven animal detection with automated drone-based repellents, ensuring complete field coverage.

METHODOLOGY 1.Data Collection and Preprocessing

The first step involves collecting real-time animal movement data using various sensors, cameras, and IoT-based monitoring systems. 1.1 Data Sources

- Cameras & Drones: High-resolution cameras capture images/videos of the farm surroundings.
- Infrared Sensors: Detect animal motion, even in low-light conditions.
- Acoustic Sensors: Identify animal sounds and movement patterns.
- Ultrasonic Sensors: Detect the presence of animals based on reflected sound waves.
- GPS & IoT Sensors: Provide real-time location tracking of animal intrusions.

1.2 Data Preprocessing

- Noise Removal: Filters are applied to remove environmental noise (wind, rain, etc.).

- Image Enhancement: Techniques like histogram equalization and Gaussian filtering improve image quality.
- Data Labeling: Images and sensor data are labeled as "Animal Detected" or "No Animal Detected" for AI training.

2. Animal Detection Using AI & Machine Learning

2.1 Computer Vision-Based Detection

- Convolutional Neural Networks (CNNs): YOLO (You Only Look Once) and SSD (Single Shot Detector) models are used for real-time object detection.
- Transfer Learning: Pre-trained deep learning models (ResNet, MobileNet) are fine-tuned for animal detection.

2.2 IoT-Based Detection

- Sensor Fusion: Combines motion, sound, and infrared sensor data for improved detection accuracy.
- Edge AI Processing: AI models run on Raspberry Pi or Nvidia Jetson for faster real-time processing without cloud dependency.

2.3 Detection Algorithm Implementation

1. Capture image/sensor data.
2. Preprocess the data (remove noise, enhance features).
3. Run AI model for classification (animal or no animal).
4. If an animal is detected, trigger the repellent mechanism.

3. Animal Repellent Mechanism

Once an animal is detected, the system triggers non-lethal deterrent techniques to scare it away.

3.1 Acoustic Repellents (Sound-Based)

- Ultrasonic Sound Emitters: Emit frequencies between 20-50 kHz that disturb animals but are inaudible to humans.
- Predator Sounds: AI selects the appropriate predator call (lion, wolf, etc.) based on the detected species.

3.2 Light-Based Repellents

- Strobe Lights: High-intensity flashing lights disrupt animal vision and scare them away.
- Infrared Laser Deterrents: Target specific animals using infrared light, which is harmless but visually disturbing.

3.3 Automated Sprinklers

- Water Sprays: Motion-activated sprinklers spray water to deter animals.
- Scent-Based Repellents: Releases non-toxic animal-repelling odors.

4. Real-Time Monitoring & Alerts

The system continuously monitors the farm and sends alerts to farmers in real-time.

4.1 IoT Cloud-Based Monitoring

- Data is sent to cloud servers (AWS IoT, Google Firebase) for analysis.
- Farmers can monitor the system via a mobile app or web dashboard.

4.2 Alert Mechanisms

- SMS Alerts: Farmers receive instant SMS alerts when an animal is detected.
- Push Notifications: Mobile apps notify farmers of intrusions.
- Automated Drone Dispatch: If an animal is detected, drones automatically fly over the area to scare it away.

ARCHITECTURE DESIGN

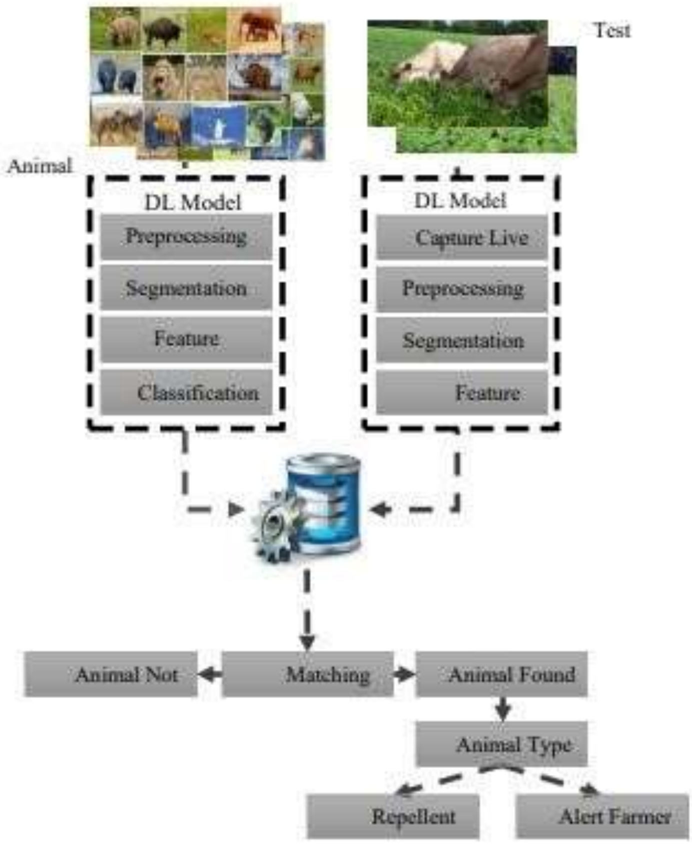


Fig 1. Architecture diagram

IMPLEMENTATION AND RESULT

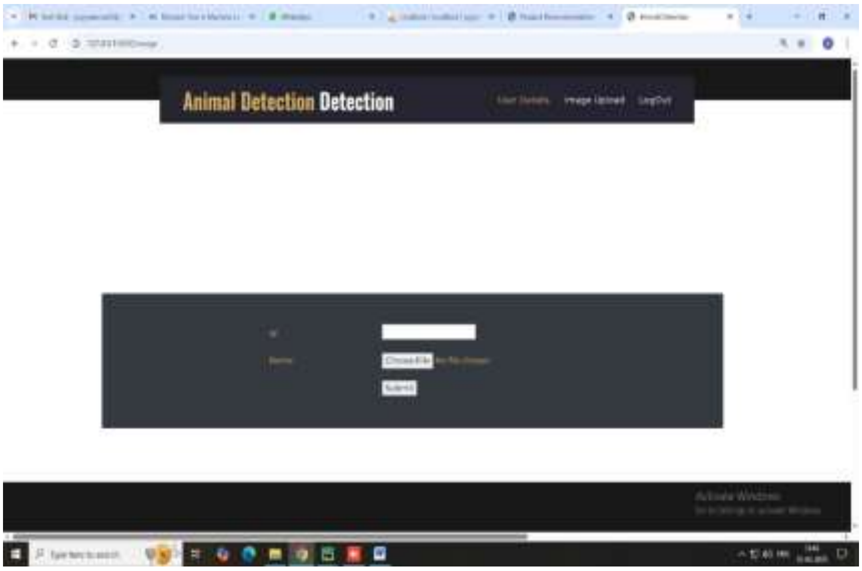
Animal detection relies on a trained model that processes real-time video feeds and identifies animals based on their characteristics. The detection system uses a dataset of common farm intruders and applies deep learning techniques to classify them accurately. The model is trained with annotated images, and the detection runs on an optimized processing unit for efficiency. When an animal is detected, the system identifies its type and records the event. This approach enables farmers to take action based on the species detected while ensuring reliable monitoring with minimal false detections.

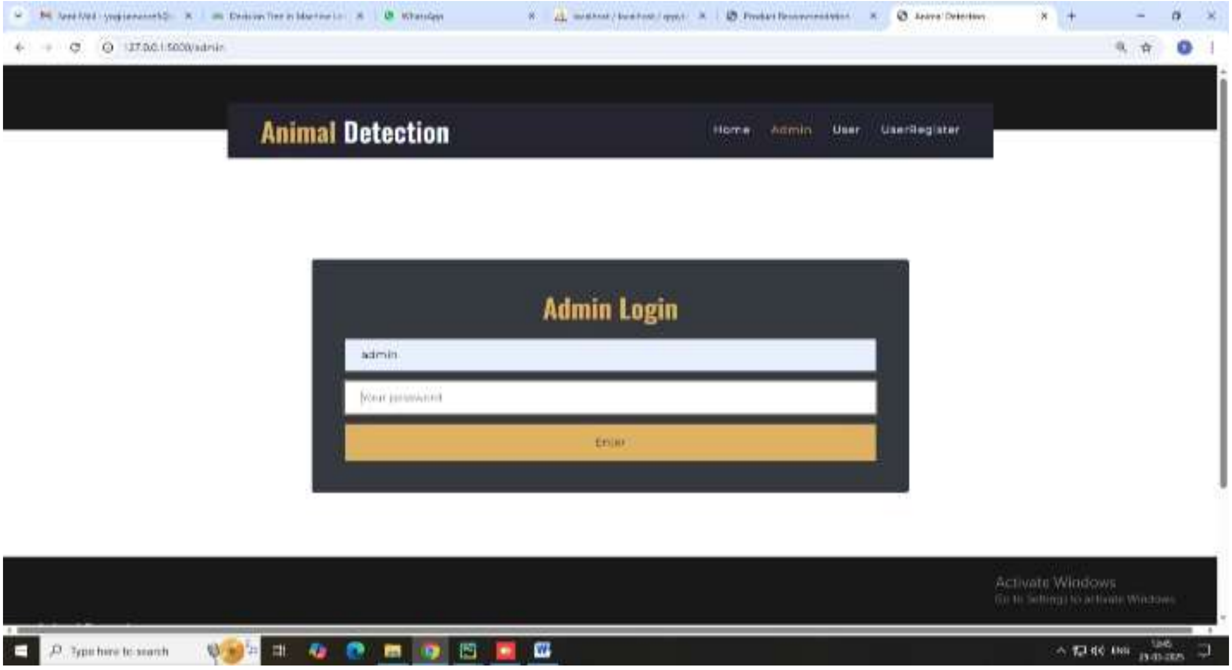
Once an animal is detected, the system triggers a suitable repellent mechanism. Based on the identified species, different deterrents such as sound alarms, flashing lights, or water sprays are activated. These devices are controlled through a communication network that ensures quick response times. The selection of repellent methods is based on effectiveness against specific animals, ensuring a non-harmful but efficient deterrent system. The automation reduces the need for manual intervention, protecting crops from wildlife intrusions more effectively. This system enhances farm security while minimizing human effort in preventing animal-related damage.

The monitoring system continuously analyzes live footage from farm cameras, alerting farmers when an animal is detected. A remote-access interface enables users to view live feeds and past detections. Alerts are sent via mobile notifications or text messages, including details such as images, the type of detected animal, and actions taken. This real-time notification system allows farmers to take additional protective measures if necessary. The implementation ensures timely responses and keeps users informed about farm security without requiring constant manual supervision.

Fig 2: Model & Image Training

RESULT





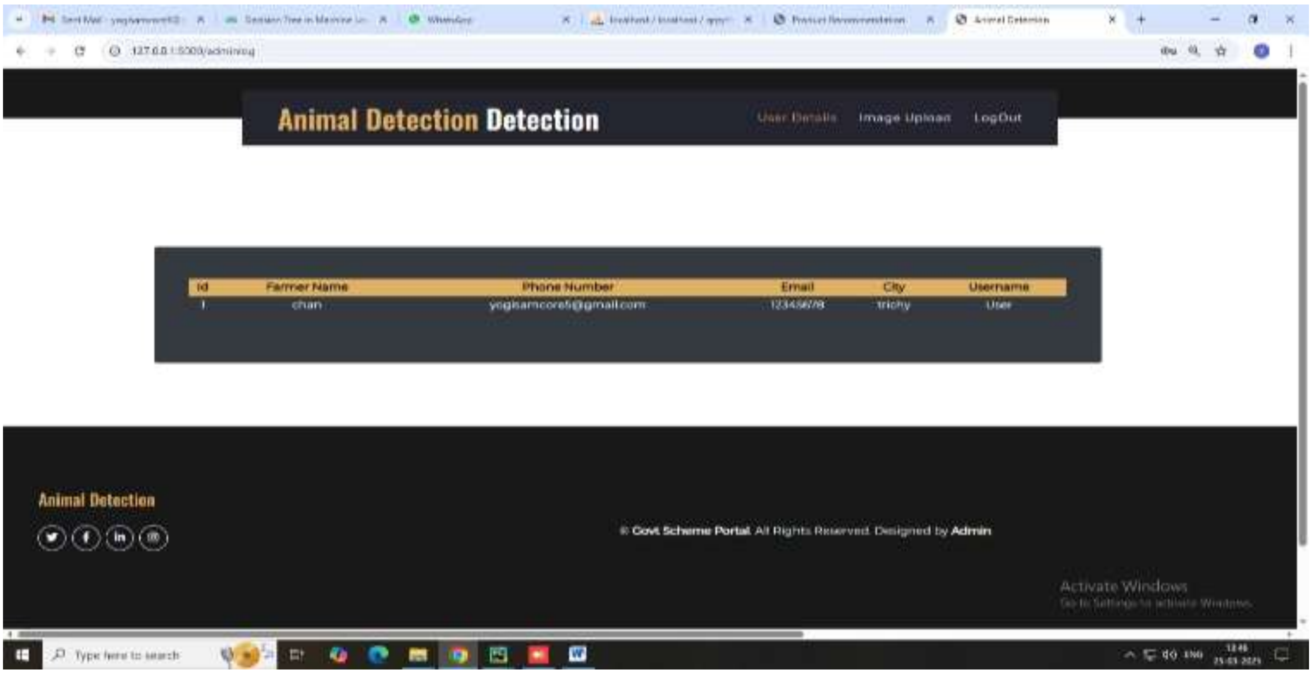


Fig 3: Admin Page & Sign Meet

CONCLUSION

Agricultural farm security is widely needed technology nowadays. In order to accomplish this, a vision-based system is proposed and implemented using Python and OpenCV and developed an Animal Repellent System to blow out the animals. The implementation of the application required the design and development of a complex system for intelligent animal repulsion, which integrates newly developed software components and allows to recognize the presence and species of animals in real time and also to avoid crop damages caused by the animals. Based on the category of the animal detected, the edge computing device executes its DCNN Animal Recognition model to identify the target, and if an animal is detected, it sends back a message to the Animal Repelling Module including the type of ultrasound to be generated according to the category of the animal. The proposed CNN was evaluated on the created animal database. The overall performances were obtained using different number of training images and test images. The obtained experimental results of the performed experiments show that the proposed CNN gives the best recognition rate for a greater number of input training images (accuracy of about 98%). This project presented a real-time monitoring solution based on AI technology to address the problems of crop damages against animals. This technology used can help farmers and agronomists in their decision making and management process.

FUTURE SCOPE

The system can be enhanced by integrating additional sensors such as thermal and motion sensors to improve detection accuracy in low-light conditions or areas with dense vegetation. Expanding the dataset with more animal species and environmental variations will further enhance the deep learning model's adaptability. Future versions can incorporate predictive analytics to anticipate animal movements based on historical data, allowing proactive deterrent measures. Another potential improvement is automating the system's learning process, where it continuously updates itself based on new data collected from farm environments. Integrating Internet of Things (IoT) devices can allow seamless connectivity between repellent mechanisms and real-time cloud-based monitoring. To make the system more accessible, a mobile application can be developed, enabling farmers to receive alerts and control repellents remotely. Additionally, solar-powered repellent systems can be explored for energy-efficient operation in remote farming areas. Expanding the system for integration with other smart farming technologies will further improve agricultural protection and sustainability.

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