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AI Based Animal Detection and Repellent System

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Abstract - Wild animals entering agricultural fields has become a growing concern, especially for farmers living near forest areas and wildlife corridors. In many regions, farmers experience significant crop damage when animals wander into their fields in search of food, most often during the night. Due to rapid urbanization, deforestation, and the gradual loss of natural habitats, wild animals are forced to move closer to human settlements as their traditional food sources become scarce.

Farmers have traditionally relied on methods such as electric fencing, staying awake to guard fields at night, or using firecrackers to scare animals away. However, these methods are often temporary, costly to maintain, physically exhausting, and sometimes unsafe for both humans and animals. In many cases, they also fail to provide a long-term or sustainable solution.

To overcome these challenges, this project proposes an AI-Powered Animal Intrusion Detection and Repelling System that offers an intelligent, automated, and humane approach to field protection. The system uses the advanced YOLOv11 object detection model to identify different animal species in real time through live video captured by an IP camera installed in the field. The model runs on a GPU-enabled laptop, ensuring fast and accurate detection with minimal delay.

Once an animal is detected, the system automatically activates non-lethal deterrent mechanisms such as water spraying, flashing lights, and species-specific sound alerts. These methods are designed to safely scare the animal away without causing injury. At the same time, important details such as the time of detection, the type of animal identified, and the confidence level of the prediction are stored in a Firebase Realtime Database. Instant notifications are also sent to farmers through a user-friendly Android application developed using Kodular, allowing them to monitor their fields remotely.

Overall, this system provides continuous real-time monitoring, remote access through a mobile application, cost-effective operation, and humane animal control. By combining Artificial Intelligence, IoT technology, and smart automation, the proposed solution aims to significantly reduce crop losses while promoting peaceful coexistence between humans and wildlife.

Key Words: Artificial Intelligence, Human–Wildlife Conflict, YOLOv11, Object Detection, Smart Agriculture, IP Camera Monitoring, IoT System, Firebase Database, Android App, Real-Time Alerts, Non-Lethal Animal Repellent, Automated Field Protection.

1.INTRODUCTION

Agriculture continues to be the backbone of livelihood for millions of people around the world, especially in developing countries like India. In rural areas, a large number of families depend directly on farming not only for income but also for their daily food and survival. Beyond supporting individual households, agriculture plays a crucial role in ensuring national food security, generating employment, and maintaining economic stability.

However, in recent years, the relationship between human settlements and wildlife has become increasingly strained. Rapid urbanization, deforestation, climate change, and the expansion of agricultural lands into forest regions have significantly reduced natural habitats and food sources for wild animals. As a result, animals such as elephants, wild boars, deer, and monkeys are frequently forced to enter agricultural fields in search of food and water. These intrusions usually occur at night and often lead to severe crop damage, heavy financial losses, and even safety risks for farmers who attempt to guard their fields.To protect their crops, farmers traditionally rely on methods such as electric fencing, night patrolling, firecrackers, scarecrows, and other visual or sound-based deterrents. While these methods may offer temporary relief, they have several drawbacks. Electric fencing can be dangerous and requires regular maintenance. Manual monitoring is physically exhausting and impractical for large farmlands. Static scare techniques gradually become ineffective as animals learn to ignore them. Similarly, basic sensor-based systems that use infrared or motion detection can trigger frequent false alarms due to wind, moving plants, or small animals. Most importantly, these systems cannot accurately identify the type of animal or assess the level of threat.With the rapid development of artificial intelligence and computer vision technologies, smarter and more reliable solutions have become possible. Deep learning–based object detection models, especially those from the YOLO (You Only Look Once) family, are known for their ability to perform real-time detection with high accuracy and minimal delay. These models can detect and classify multiple objects simultaneously, even in challenging lighting and environmental conditions.

In this work, we propose an AI-driven animal intrusion detection and humane repellent system that combines the advanced YOLOv11 model with cloud-based IoT automation. The system is designed to accurately detect wild animals entering agricultural fields and automatically activate non-lethal deterrent mechanisms such as water spraying, flashing lights, and sound alerts. At the same time, farmers receive real-time notifications through a mobile application, allowing them to monitor their fields remotely.By integrating intelligent detection, automated response, and remote monitoring, the proposed system aims to minimize crop losses, improve farmer safety, and support a more sustainable and peaceful coexistence between agriculture and wildlife.

2. LITERATURE REVIEW

With the rapid growth of artificial intelligence, edge computing, and IoT technologies, wildlife detection and crop protection systems have become smarter and more efficient. Many researchers have explored deep learning–based methods to detect, classify, and repel wild animals in agricultural and forest areas. For example, Natarajan et al. (2023) developed a hybrid deep learning system that combines YOLOR for object detection with VGG19 and Bi-LSTM models for classification and alert generation [1]. Their system analyzes large animal image datasets and sends automated SMS alerts with details about animal activity and location to forest officers. Although this approach improves detection accuracy and communication, it depends on computationally heavy models, which may not be ideal for low-power devices used in remote farming areas.

Researchers have also focused on reducing energy consumption in such systems. Sato et al. (2022) [15] introduced techniques like adjusting motion sensor sensitivity, using frame difference methods to avoid unnecessary deep learning processing, and implementing distributed nodes to minimize idle power usage. Their work highlights the importance of energy efficiency, especially for field devices that operate continuously.

In addition to detection, improving repelling strategies has been another key research area. Lee et al. (2021) proposed a reinforcement learning–based bird repelling system that adapts its sound patterns based on bird behavior. Unlike traditional fixed sound deterrents, their system learns over time, preventing birds from becoming habituated and increasing long-term effectiveness [4].

Edge AI–based crop protection solutions have also gained attention. Reddy et al. (2024) [7] introduced the EvoNet system, which combines laser-based perimeter detection with AI-powered cameras to classify animal species and activate targeted sound and light deterrents. Similarly, Adami et al. (2022) developed an embedded Edge-AI repelling system using YOLO and Tiny-YOLO models deployed on platforms like NVIDIA Jetson Nano and Raspberry Pi, enabling real-time detection without relying on cloud connectivity.

Finally, lightweight model optimization has been explored to make deep learning more suitable for resource-constrained devices. Ibraheam et al. (2023) modified the YOLOv2 architecture by reducing redundant layers, merging multi-level features, and adding deformable convolutions to enhance accuracy while lowering computational complexity [2]. Their work demonstrates that real-time animal detection can be effectively implemented even on limited hardware, making intelligent crop protection systems more practical and accessible.

3. RELATED WORK

In recent years, many researchers have explored the use of Artificial Intelligence and IoT technologies to monitor wildlife and detect animal intrusions in agricultural areas. Some studies have proposed hybrid deep learning models that combine convolutional neural networks with recurrent architectures to recognize animal activity and automatically generate alert messages. Others have focused on deploying lightweight YOLO-based models on embedded or edge-AI devices to achieve faster detection while reducing energy consumption. Researchers have also developed adaptive repellent systems using reinforcement learning, where deterrent patterns are continuously changed to prevent animals from becoming familiar with fixed sounds or signals. Although these approaches show promising results, many existing systems still face real-world challenges such as high implementation costs, limited real-time automation, unreliable performance in outdoor environments, or reliance on delayed SMS-based notifications. In contrast, the proposed system emphasizes smooth integration of real-time AI detection, cloud-based communication, and IoT-controlled actuation. By combining the advanced YOLOv11 model with Firebase cloud services and a NodeMCU controller, the system creates a practical, scalable, and efficient solution that ensures accurate detection, immediate response, and humane animal repelling for modern smart agriculture.

4. SYSTEM ARCHITECTURE

The proposed AI-driven Animal Intrusion Detection and Repelling System is designed as a smart and well-connected framework that brings together intelligent monitoring, automatic response, cloud communication, and user interaction into one seamless system. Its architecture follows a layered structure to ensure smooth data flow and reliable real-time performance in outdoor farm environments. At the first level, an IP camera is installed in the agricultural field to continuously capture live video footage. This visual data is sent to a GPU-enabled laptop, where the trained YOLOv11 deep learning model processes each frame in real time to detect and identify animals. When the system recognizes a predefined animal with a confidence level above the set threshold, it treats the event as an intrusion.

Once an intrusion is detected, the system automatically shifts into action mode. A command is sent to the D1 Mini microcontroller, which controls relay modules connected to deterrent devices such as a water pump, LED lights, and a speaker system. These components are activated instantly to repel the animal using safe and non-lethal methods. At the same time, important details like the time of detection, animal type, and confidence score are uploaded to the Firebase Realtime Database. Farmers can then receive instant notifications and monitor activity through an Android application developed using Kodular. By organizing the system into sensing, processing, control, cloud, and user interface layers, the architecture ensures accurate detection, quick automated response, remote accessibility, and scalability, making it a practical and reliable solution for modern smart agriculture.

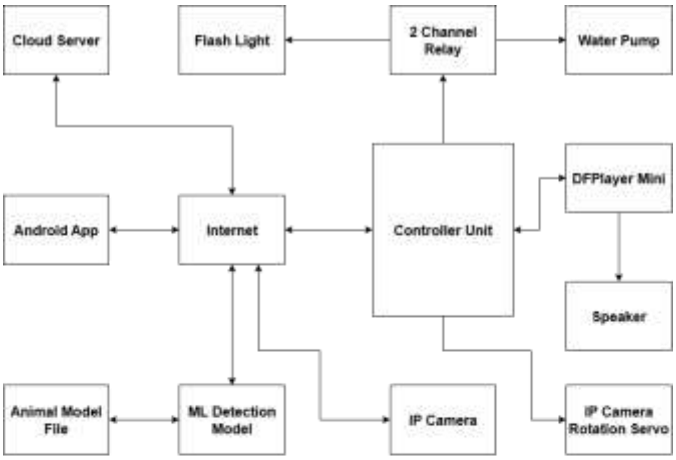

Fig- 1 Block Diagram

5.METHODOLOGY

The methodology of the proposed AI-Powered Animal Intrusion Detection and Repelling System is designed in a clear and practical manner, combining artificial intelligence, embedded hardware, and cloud technology to provide reliable field protection. The entire process is organized into four main stages: data preparation, model development, system integration, and real-time deployment.

In the first stage, a dataset of animals commonly responsible for crop damage—such as elephants, deer, wild boars, monkeys, and cattle—is collected from reliable sources. Each image is carefully labeled by drawing bounding boxes around the animals so that the model can learn to recognize them accurately. To improve performance in real-world conditions, preprocessing techniques like resizing, normalization, and image augmentation are applied. These steps help the model handle variations in lighting, weather, and background conditions commonly found in outdoor agricultural environments. The prepared dataset is then used to train the YOLOv11 deep learning model.

The second stage involves training and evaluating the model using a GPU-enabled system to ensure faster processing and better learning efficiency. During training, the YOLOv11 model learns to identify important visual features of different animals and classify them correctly. Its performance is assessed using standard evaluation metrics such as precision, recall, F1-score, and mean Average Precision (mAP). Once the model achieves satisfactory accuracy and reliability, it is finalized and prepared for real-time deployment.

In the third stage, the trained model is integrated into a Python-based application that captures live video from an IP camera using OpenCV. The system continuously analyzes each frame in real time. When an animal is detected with a confidence level above a predefined threshold, the application sends a command via serial communication to the Mega 2560 Pro microcontroller. The controller then activates deterrent devices such as a water pump, LED lights, and a speaker system to safely repel the animal.

In the final stage, all detection details—including timestamp, animal type, and confidence score—are uploaded to the Firebase Realtime Database. The Android application retrieves this information and immediately notifies farmers, allowing them to monitor their fields remotely. This step-by-step methodology ensures accurate detection, quick automated response, and effective remote supervision, making the system both practical and dependable for real-world agricultural protection.

Fig- 2 : Methodology

6.CIRCUIT DESIGN

The circuit diagram of the AI-Powered Animal Intrusion Detection and Repelling System shows how all the electronic components are connected to work safely and efficiently in the field. The design is divided into two main parts: the control section and the load section, ensuring proper voltage regulation and safe switching between low-power control devices and high-power equipment.

In the control section, the D1 Mini controller acts as the main control unit and operates on a regulated 5V supply. Its digital output pins are connected to a relay module,

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which allows the system to switch high-power devices safely. The DFPlayer Mini audio module is connected through serial communication (TX and RX pins) to play warning sounds through a speaker. If a servo motor is used to rotate the camera, it is connected to a PWM pin and powered separately to maintain stable operation.

In the load section, devices like the water pump and high-intensity LED light are connected through the relay's COM and NO terminals, powered by an external 12V supply. When the relay is activated, the connected device turns ON; when deactivated, it turns OFF. All components share a common ground to ensure smooth functioning. If solar power is included, a solar panel and battery system provide regulated power to the circuit. Overall, the circuit ensures safe switching, reliable performance, and efficient automated operation in agricultural environments.

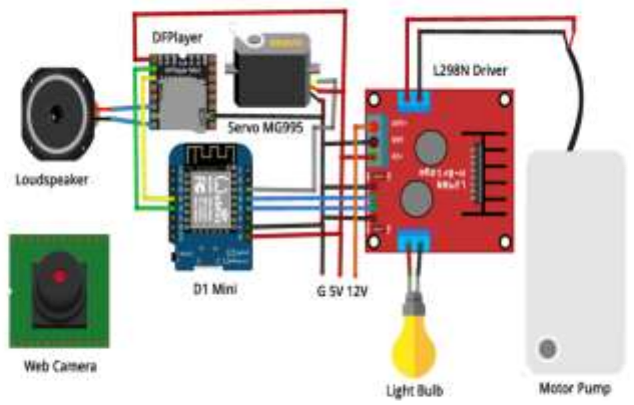

Fig- 3 Circuit Diagram

7. EXPIRIMENTAL RESULT

The experimental evaluation of the proposed AI-Powered Animal Intrusion Detection and Repelling System was conducted to thoroughly assess its real-world performance, reliability, and practical usability in agricultural environments. The primary objective of the testing phase was to measure detection accuracy, response time, system stability, and the effectiveness of the automated deterrent mechanisms under different operating conditions.

To evaluate the detection capability, the trained YOLOv11 model was tested using both live video streams from the installed IP camera and pre-recorded datasets containing images and videos of animals such as elephants, deer, wild boars, monkeys, and cattle. The system was observed under various scenarios, including different animal positions, movement speeds, and distances from the camera. Under normal daylight conditions, the model demonstrated high accuracy with very few false detections. Even when animals appeared partially visible or at moderate distances, the system was able to correctly identify and classify them. Performance was analyzed using standard evaluation metrics such as precision, recall, F1-score, and mean Average Precision (mAP). The results confirmed that the model maintained strong detection performance and consistency across different test cases.

The cloud and communication components were also evaluated during testing. Detection details, including timestamp, animal type, and confidence level, were successfully uploaded to the Firebase Realtime Database without interruption. The Android application reliably retrieved this data and delivered instant notifications to the farmer, enabling remote monitoring and timely awareness. Throughout the testing period, the system operated smoothly without major interruptions, showing stable performance in continuous monitoring mode.

Overall, the experimental results indicate that the system performs efficiently and reliably in real-time agricultural conditions. It provides accurate animal detection, quick automated deterrence, and seamless remote monitoring. These outcomes confirm that the proposed solution is practical, responsive, and suitable for protecting farmlands while promoting a safer and more sustainable approach to managing human–wildlife interactions.

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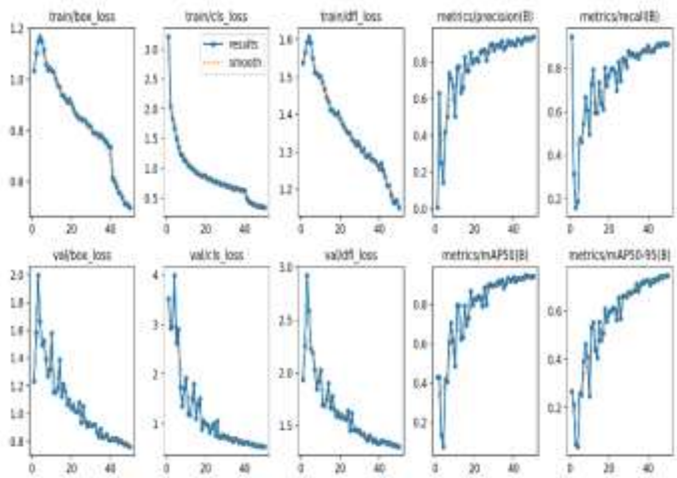

Fig- 4 Result

8. FUTURE WORK

Although the proposed AI-Powered Animal Intrusion Detection and Repelling System performs well in its current form, there is still room for meaningful improvements that can make it even more practical and scalable for real-world use. One major future enhancement would be deploying the system on compact edge AI devices such as NVIDIA Jetson or Raspberry Pi with AI accelerators. This would remove the need for a GPU-enabled laptop and transform the setup into a fully standalone, portable, and field-ready solution that farmers can easily install and maintain across large agricultural areas.

Another important improvement is the use of thermal or infrared cameras to strengthen detection during nighttime or low-light conditions. Since many animal intrusions occur at night, this addition would significantly improve reliability when standard cameras face visibility challenges. The system could also be expanded to support multiple cameras, allowing coverage of wider farmlands and improving overall surveillance capability. Beyond detection, advanced data analytics can be incorporated to study past intrusion patterns and identify high-risk time periods or specific zones within the field that are frequently targeted. This would help farmers take preventive measures more effectively. Additionally, developing animal-specific deterrent strategies—where different species trigger customized repelling actions—could improve long-term effectiveness and reduce habituation.

Sustainability can also be enhanced by optimizing solar power integration and implementing intelligent energy management systems, especially for rural areas with limited or unreliable electricity supply. Introducing a cloud-based dashboard with detailed analytics, visual reports, and intrusion history tracking would further improve monitoring and record-keeping. With these future upgrades, the system can become more robust, energy-efficient, scalable, and adaptable for large-scale agricultural deployment, ultimately contributing to a safer and more sustainable solution for reducing human–wildlife conflict.

9. CONCLUSION

The AI-Powered Animal Intrusion Detection and Repelling System clearly shows how modern technology can be used to solve a real and practical problem faced by farmers. By combining the YOLOv11 deep learning model with embedded hardware components such as the Mega 2560 Pro controller, relay modules, water pump, LED lights, and speaker system, the project creates a smart setup that can monitor fields continuously and respond instantly when an animal is detected. The system analyzes live video in real time and activates safe, non-lethal deterrents to drive animals away without causing harm, helping to protect crops in a humane manner.

The addition of Firebase Realtime Database and an Android application makes the system even more practical, as farmers can receive instant alerts and monitor their fields remotely. This reduces the need for manual night guarding and improves overall safety. Compared to traditional methods like electric fencing or constant patrolling, the proposed solution offers better automation, fewer false alarms, and more reliable performance. Experimental results confirm that the system responds quickly with minimal delay between detection and action. Overall, this project presents a cost-effective, scalable, and sustainable approach to smart agriculture, helping reduce crop losses while encouraging a safer and more balanced coexistence between humans and wildlife through the effective use of AI and IoT technologies.

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