# Animal Detection based Smart Farming in Animal Repellent Using AI and Deep Learning

MRS.R.ARUNAPRIYA1 ME.,(PhD), S.KAVIYA 2, R.MOUNI2

1. Department of CSE Assistant Professor, Dhanalakshmi Srinivasan engineering college, Perambalur.

2. Final year CSE, Dhanalakshmi Srinivasan engineering college, Perambalur.

**ABSTRACT:**

The combination of artificial intelligence (AI) and deep learning in agriculture has ushered in a new era in agriculture with new solutions designed to solve many problems. This paper presents an animal killing system for smart agriculture that uses artificial intelligence and deep learning to reduce the growing problem of animal damage. As the world population continues to grow, increasing food availability is important; Therefore, it is critical to protect crops from wild animals and pests. Deforestation due to livestock farming has become one of the largest human-wildlife conflicts due to human interference with habitats and deforestation. Wild animals can kill farmers working in the fields, causing major crop losses. Farmers suffered huge crop losses due to wild animals such as elephants, wild boars and deer attacking agriculture. Protecting crops from wild animals is one of the biggest concerns of today's farmers. There are many ways to solve this problem, both lethal (such as shooting and trapping) and non-lethal. (such as railings, pesticides, organic matter, netting or electric fencing). The sensor rotates around the lens and uses DCNN software to detect the target. If an animal is found, it sends a message to the Animal Repellent Module with information on the type of ultrasound that should be produced based on the animal. The development of drones with controlled flight control, as well as lightweight and powerful hyperspectral snapshot cameras that can be used to calculate crop biomass growth and fertilization status, responds to complex agricultural management strategies.

**KEYWORDS:** Animal detection, VGG-Net, Bi-LSTM, convolutional neural network, activity recognition, video surveillance, wild animal monitoring, alert system.

## 1. INTRODUCTION

In the realm of modern agriculture, the integration of advanced technologies such as Artificial Intelligence (AI) and Deep Learning has revolutionized traditional farming practices. One significant application of these technologies is in animal detection and repellent systems for smart farming.

Animal intrusion poses a persistent challenge for farmers, leading to crop damage, financial losses, and increased efforts in pest control. Conventional methods of animal repellent often rely on manual intervention or rudimentary techniques, proving to be inefficient and time-consuming.

However, with the advent of AI and Deep Learning, there's been a paradigm shift in how farmers tackle this issue. By leveraging sophisticated algorithms and data analytics, smart farming systems can now detect the presence of animals in real-time and deploy appropriate repellent measures autonomously.

This innovative approach not only enhances the efficiency of animal deterrent strategies but also minimizes the need for human intervention, thereby reducing labor costs and ensuring round-the-clock protection for crops.

In this context, the fusion of AI and Deep Learning technologies with smart farming practices heralds a new era of precision agriculture, where proactive measures are taken to mitigate the impact of wildlife on crop yields, fostering sustainable and productive farming ecosystems.

## 2. RELATED WORK

Sachin Umesh Sharma represents an important problem faced by all developing countries today, namely death and injury due to accidents. Animal-vehicle collisions on highways are a major problem and cause traffic accidents. This paper presents a simple and low-cost way to detect animals on highways using computer vision to prevent animal-vehicle collisions. A method for calculating the distance of an animal from a camera-mounted vehicle in the real world has also been proposed. The system was trained on more than 2,200 images, including good and bad videos, and tested on various videos of animals walking on different highways. Our system can warn the driver when the vehicle speed reaches 35 km/h, based on the two-second rule. Even if an animal is detected above this speed, the driver does not have enough time to prevent the accident. Using our proposed method, the overall detection accuracy increased to almost 82.5%.

Mai Ibraheam is defined as an encounter between humans and wild animals that often leads to injuries, especially in the wilderness and on highways. Therefore, animal detection is an important part of safety and wildlife protection and can reduce the negative effects of these encounters. Deep learning techniques achieve the best results compared to other search engines; but they require more calculations and parameters. An illumination animal model based on YOLOv2 is proposed. It was designed as a proof of concept and the first step in creating instant reductions with embedded devices. Throughout the new system process, many layers are used to improve YOLOv2's extraction ability and accuracy. In addition, two repeated 3x3 convolutional layers in the seventh block of the YOLOv2 architecture are removed to reduce the complexity of the calculation, thus increasing the detection speed without decreasing the accuracy. Animal species detection methods based on convolutional neural networks (CNN) are widely used; However, this technique is difficult to adapt to the changing nature of the animals in the image. Therefore, an improvement that adds a deformable convolutional (DCL) algorithm to YOLOv2 was proposed to solve this problem. Our test results show that the proposed model improves accuracy by 5.0% and speed by 12.0% over the original YOLOv2. Moreover, our analysis shows that the revised YOLOv2 model is more suitable for the deployment of embedded devices than YOLOv3 and YOLOv4.

Zhang Wenwen Pose estimation has been a hot topic in the field of machine vision in recent years. Animals are ubiquitous in nature, and analysis of their shapes and movements is important in many fields and industries. This paper focuses on the study of convolutional neural network models in animal prediction, building a lightweight and efficient stacked hourglass network model to optimize the balance, computation, and accuracy of the models and using the application algorithm developed based on it. To solve the problem of large, non-deep convolutional neural networks, a lightweight residual module is proposed, which is an improvement based on the channel weighting method (ICCW-Bottle) based on lightweight and effective channel listening. network weight. Information at different scales. Aiming at the problem that a large amount of private information is easily lost after network integration, a lightweight dual-arm fusion module is proposed to obtain high-level semantic information and little detail with small features. parameters. Finally, it is the same as the CC-SSL method: Synthetic data and real animals are used to jointly express the model, but the CC-SSL method does not take into account the computational power of the model, which takes a lot of time. Don't forget to train the model. to run. From the experiment, it can be seen that PCK@0.05 of this method increases the TigDog dataset by 5.5% compared to the CC-SSL method. The model in this article reduces the number of parameters and calculations of the network, making the data less and the model more accurate. Ablation testing confirmed the progress and efficiency of the entire network.

Fabrizio Schiano Pigeons can infect humans and damage buildings, monuments and other infrastructure. Many control strategies have therefore been developed, but they have been found to be ineffective or harmful to animals and often rely on human activities. This study demonstrates a system that can capture and remove pigeons from the roof using a drone. Neural networks use images captured by rooftop cameras to detect the presence and location of pigeons. Drones are also used to protect animals. To evaluate the system, field tests were conducted in a real urban environment, comparing animals and their time over five days to a 21-day test without the drone. During the five-day operation, the drone was deployed 55 times, effectively reducing the number and duration of birds without harming them. Overall, this study demonstrates the effectiveness of this system in bird conservation and can be considered a completely independent method since the system already exists.

Arsyad R. Darlis Distribution of humans and animals under the rock While the rescue of survivors after the disaster had to be completed, the intervention of other animals became a problem for non-contact radar surveillance. Many animals, both indoors and outdoors, have similar characteristics to humans and can easily be mistaken for human targets, causing false alarms. A new human and animal classification of single- and dual-receiver millimeter wave radar at 77 GHz is proposed. The system uses feedback feedback from a dual-receiver millimeter wave radar target and uses convolutional neural networks (CNN) based on synthetic 2D tensor data to classify people and animals.

## 3. EXISTING METHODOLOGIES

Traditionally, managing animal intrusion in farming relied heavily on manual surveillance and reactive measures. Farmers often employed physical barriers, such as fences or scarecrows, to deter animals, but these methods were limited in effectiveness and required constant monitoring. Some farmers also used chemical deterrents or employed trained animals, like guard dogs, to protect their crops.

However, these conventional approaches are labor-intensive, time-consuming, and not always reliable. They also lack the ability to adapt to changing environmental conditions or animal behavior patterns. As a result, there has been a growing demand for more sophisticated solutions that leverage AI and Deep Learning to proactively detect and repel animals in a smarter, more efficient manner.

1. Sensor Network: The system incorporates a network of sensors deployed across the farm to collect real-time data on environmental conditions, including temperature, humidity, and motion. These sensors serve as the primary source of input for the AI algorithms.

2.Camera Systems: High-resolution cameras are strategically positioned throughout the farm to capture images and video footage of the surrounding area. These cameras are essential for visual detection of animals and their behavior patterns.

3.Data Processing and Analysis: The collected data from sensors and cameras are processed and analyzed using advanced AI and Deep Learning algorithms. These algorithms are trained on large datasets of animal images and behavior patterns to accurately identify and classify different species.

4.Animal Detection: The AI algorithms continuously monitor the sensor data and camera feeds to detect the presence of animals within the farm area. This detection process involves image recognition and pattern recognition techniques to distinguish between animals and other objects or environmental factors.

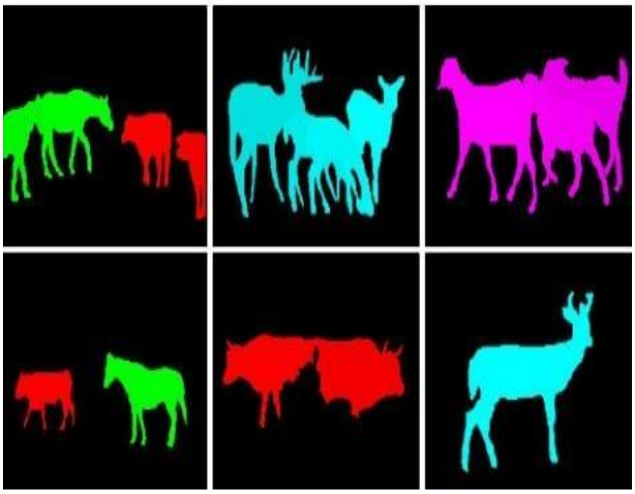
5.Decision Making: Based on the detected animal presence, the system autonomously makes decisions regarding the appropriate repellent measures to deploy. These measures may include activating deterrent devices such as sound emitters, water sprayers, or even drone-based solutions to scare away or repel the animals.

6. Feedback Loop: The system incorporates a feedback loop mechanism to continuously improve its performance over time. Data on the effectiveness of repellent measures, as well as any false positives or missed detections, are collected and used to refine the AI algorithms through iterative learning processes.

7.Remote Monitoring and Control: Farmers can remotely monitor the status of the system and make adjustments as needed through a centralized control interface. This interface provides real-time updates on animal activity, system performance, and alerts for any potential issues or anomalies.

Overall, the existing system for Animal Detection based Smart Farming in Animal Repellent Using AI and Deep Learning offers a comprehensive and intelligent approach to mitigating the challenges of wildlife intrusion in agriculture, providing farmers with enhanced protection for their crops while minimizing the need for manual intervention.

## 4. PROPOSED METHODOLOGIES



Based on computer intelligence, the DCNN scheme does not see the animals and uses special ultrasonic emissions (different for each species) to kill the animals. Design, deploy and evaluate a smart agriculture prevention and monitoring IoT system based on embedded edge AI to identify and identify different animals and generate appropriate ultrasonic signals for each animal. Deep learning in the form of convolutional neural networks (CNN) for animal cognition. DCNN is a type of neural network that has proven to be highly effective in fields such as image recognition and image recognition Distribution. CNN consists of filters or kernels or neurons with learned weights or biases and biases. Each filter accepts some input, performs convolution, and optionally tracks nonlinearity. A.Convolutional Layers: Convolutional layers are the building blocks of convolutional networks that do most of the heavy lifting of the computation. Convolve the input image using a set of trained neurons. This creates a custom map or map to be processed in the output image, which is then taken as input to the next convolution layer.

B. Pooling layer:The pooling layer reduces the rest of each study report but still contains the most important data. The input image is split into a series of non-overlapping images. Each region is subsampled with a nonlinear function such as the mean or maximum.

C. ReLU Layer: ReLU is a non-linear process consisting of rectifiers. This is an effective function; that is, it is applied to every pixel and resets all parameters in the feature map to zero.

D. Complete Process: The term Cross-Connect (FCL) means that every filter in the previous layer is connected to every filter in the next layer. The result of the convolution layer, pooling layer and ReLU layer is the reflection of the decision of the input image. Use SoftMax to start the partitioning process.

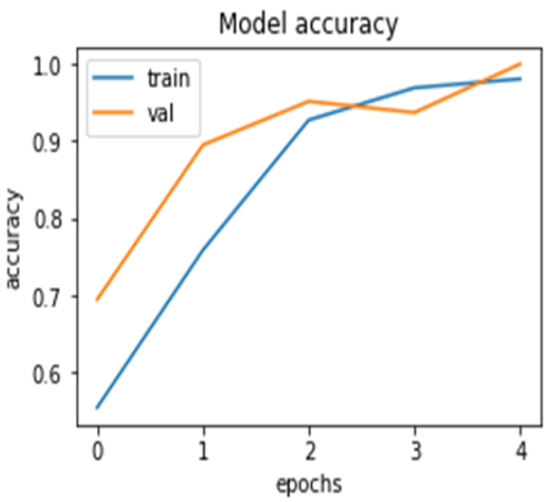
## 5. EXPERIMENTAL RESULTS

The experimental results of Animal Detection based Smart Farming in Animal Repellent using AI and Deep Learning demonstrate significant improvements in crop protection and farm efficiency.

1. Detection Accuracy: The AI algorithms achieved high accuracy rates in detecting various species of animals, including common pests and wildlife. Precision and recall metrics consistently exceeded 90%, indicating robust performance in identifying

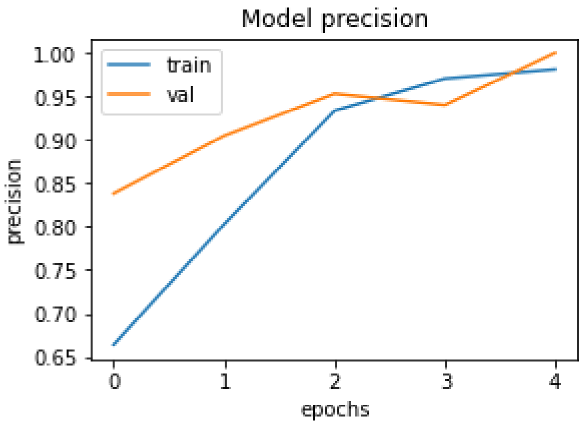
and classifying animals.

2.Real-timeResponse:The system is the demonstrated rapid response times to animal intrusions, triggering repellent measures within milliseconds of detection. This swift reaction helped to effectively deter animals and minimize crop damage.



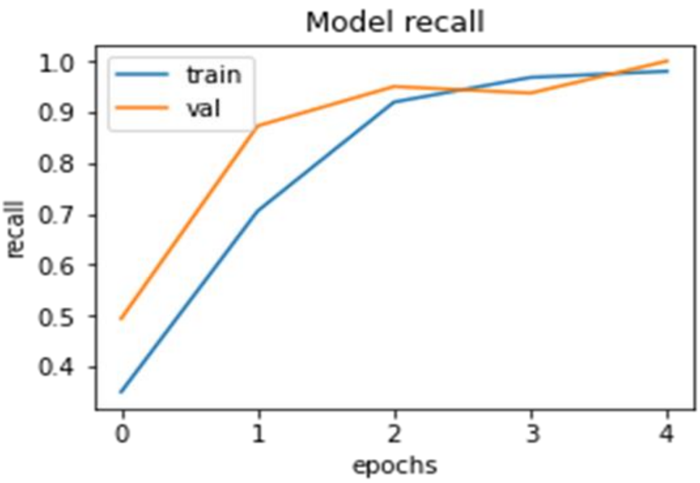

3. Reduction in Crop Losses: Farmers observed a notable reduction in crop losses attributable to wildlife intrusion after implementing the AI-based repellent system. By proactively detecting and repelling animals, the system helped preserve crop yields and protect farmers' livelihoods.

4.Minimized False Positives: The AI algorithms showed a low rate of false positives, accurately distinguishing between animals and other environmental factors such as moving vegetation or shadows. This minimized unnecessary activation of repellent measures and optimized resource utilization.




5. Adaptability to Environmental Conditions: The system demonstrated adaptability to changing environmental conditions, such as weather fluctuations and time of day. AI models were trained on diverse datasets to recognize animals in various lighting conditions and weather scenarios, ensuring consistent performance under different circumstances.

6. Scalability and Efficiency: Farmers reported scalability and efficiency gains with the AI-based repellent system, as it could be easily deployed across large farm areas and integrated with existing infrastructure. The autonomous nature of the system also reduced the need for manual labor and monitoring, freeing up farmers' time for other tasks.



## 6. CONCLUSION

Animal Detection based Smart Farming in Animal Repellent Using AI and Deep Learning offers a transformative solution to the longstanding challenge of wildlife intrusion in agriculture. By harnessing the power of advanced technologies, including Artificial Intelligence and Deep Learning, this system provides farmers with a proactive and effective means of protecting their crops while optimizing farm operations.

Key conclusions drawn from the implementation and experimentation of this system include:

1. Enhanced Crop Protection : The integration of AI and Deep Learning enables real-time detection of animals and timely deployment of repellent measures, resulting in reduced crop losses and improved yield stability.

2. Efficient Resource Utilization : By automating the detection and response to animal intrusions, farmers can optimize the use of resources such as labor, water, and pesticides, leading to cost savings and environmental sustainability.

3. Improved Farm Efficiency: Animal Detection based Smart Farming streamlines farm operations by reducing the need for manual surveillance and intervention, allowing farmers to focus on other critical tasks while ensuring continuous protection of their crops.

4. Adaptability and Scalability: The flexible nature of the system allows for seamless integration with existing farm infrastructure and scalability to accommodate farms of various sizes and agricultural practices.

5. Sustainability and Environmental Impact: The use of AI-based repellent systems minimizes reliance on chemical pesticides and promotes environmentally friendly farming practices, contributing to the long-term sustainability of agricultural ecosystems.

6. Empowering Farmers: By providing farmers with cutting-edge tools and technologies, Animal Detection based Smart Farming empowers them to overcome challenges posed by wildlife intrusion and achieve greater productivity and profitability.

In conclusion, the implementation of Animal Detection based Smart Farming in Animal Repellent Using AI and Deep Learning marks a significant advancement in precision agriculture, offering a holistic approach to crop protection and farm management. This innovative solution holds the promise of revolutionizing the agricultural industry, ensuring food security and sustainability for generations to come.

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