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Design and Evaluation of AI-Driven Acoustic Repellent Systems for Species – Specific Animal Control in Agricultural Settings

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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 paper 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: Animal Detection, YOLO(DCNN), Wildlife Intrusion, Movement Detection, Convolutional Neural Network, Image Enhancement, Real Time Monitoring, Crop Production.

I. 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. The development of unmanned aerial vehicles with autonomous flight control, together with the development of lightweight and powerful hyper spectral snapshot cameras that can be used to calculate biomass development and fertilization status of crops, opens the field for sophisticated farm management advice. 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. Although it falls well short of the human brain's capacity to cluster data and generate remarkably accurate predictions, deep learning aims to emulate the human brain. Machine learning, which is basically a neural network with three or more layers, includes deep learning as a subset. Although they fall well short of the human brain's capacity to “learn” from vast volumes of data, these neural networks make an effort to mimic its behavior. Although a single-layer neural network can still produce rough predictions, more hidden layers can aid in accuracy optimization and refinement. Deep learning drives many artificial intelligence (AI) applications and services that improve automation, performing analytical and physical tasks without human intervention. Deep learning technology lies behind everyday products and services (such as digital assistants, voice-enabled TV remotes, and credit card fraud detection) as well as emerging technologies. The

product has been iterated over a period of time. Some of the innovative ways in which this product stands out are usage of a combination of Camera Vision to detect intrusion of any animal entering the farm, Usage of the electrical signal to trigger an alarm that repels the detected animal away. Since animals tend to get acquainted to the recurring sounds and lights in their surroundings, ordinary alarming systems will work in the beginning but its effectiveness will decrease sharply with time. To overcome this shortcoming, AniRep uses permutations and combinations of Vision and sound patterns that changes every time an intrusion is detected. This delays habituation in animals. As our system is deployed in rural areas, where energy efficiency is essential, we evaluated some HW and SW architectural alternatives for the design and implementation of the AI embedded Edge computing components to be added to our system. The main aim of the current work is to develop a device to protect crops from damage by wild animals by diverting them from the farms, without harming them physically. The objective of the project is to design, deployment and assessment of an intelligent smart agriculture repelling and monitoring IoT system based on embedded edge AI, to detect and recognize the animals, as well as generate ultrasonic signals tailored to each species of the animals. Untamed life checking and investigation are in dynamic research fields since last numerous decades. This work mainly concentrates on creature identification from common scenes gained by camera and intimates the farmland owner and also stored the images in the camera trap database. This camera trap database is utilized to track the animals which enter into the farm land and damaging the crops. By making farming more connected and intelligent, precision agriculture helps reduce overall costs and improve the quality and quantity of products, the sustainability of agriculture and the experience for the consumer. Increasing control over production leads to better cost management and waste reduction. The ability to trace anomalies in crop growth or livestock health, for instance, helps eliminate the risk of losing yields. Additionally, automation boosts efficiency. With smart devices, multiple processes can be activated at the same time, and automated services enhance product quality and volume by better controlling production processes. Smart farming systems also enable careful management of the demand forecast and delivery of goods to market just in time to reduce waste. Precision agriculture is focused on managing the supply of land and, based on its condition, concentrating based on its condition, concentrating on the right growing parameters – for example, moisture, fertilizer or material content – to provide production for the right crop that is in demand. The types of precision farming systems implemented depend on the use of software for the management of the business. Control systems manage sensor input, delivering remote information for supply and decision support, in addition to the automation of machines and equipment for responding to emerging issues and production support.

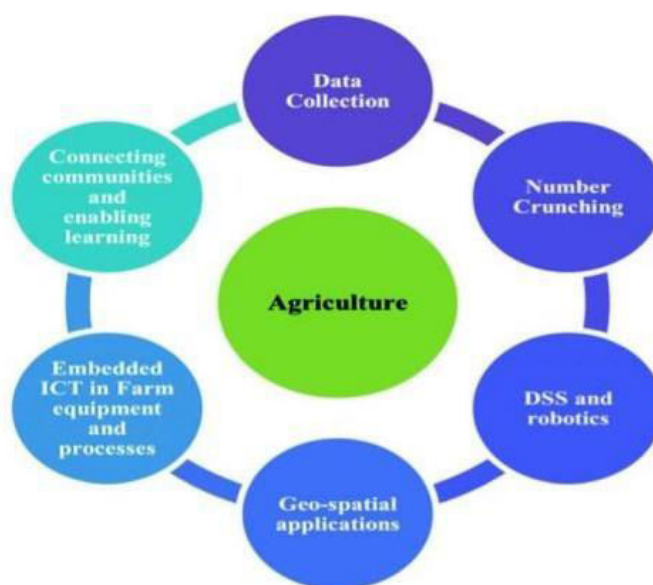


Figure: Agriculture and ICT innovation

II. RELATED WORK

Zachary J.Ruff, Damon B.Lesmeister, Cara L.Appel, Christopher M.Sullivan,...[1] The use of passive acoustic monitoring in wildlife ecology has increased dramatically in recent years as researchers take advantage of improvements in autonomous recording units and analytical methods. These technologies have allowed researchers to collect large quantities of acoustic data which must then be processed to extract meaningful information, e.g., target species detections. A persistent issue in acoustic monitoring is the challenge of efficiently automating the detection of species of interest, and deep learning has emerged as a powerful approach to accomplish this task. This article reports on the development and application of a deep convolutional neural network for the automated detection of 14 forest-adapted birds and mammals by classifying spectrogram images generated from short audio clips. This article proposes a multi- step workflow that integrates this neural network to efficiently process large volumes of audio data with a combination of automated detection and human review. This workflow reduces the necessary human effort by > 99% compared to full manual review of the data. As an optional component of this workflow, this article proposed a graphical interface for the neural network that can be run through RStudio using the Shiny package, creating a portable and user-friendly way for field biologists and managers efficiently process audio data and detect these consumer-grade computers.

R. Nikhil; B.S. Anisha; P.Ramakanth Kumar,...[2] The implemented smart agriculture system is cost effective for maximizing agricultural farm water supplies, crop prediction, and wild animal prevention. Depending on the level of soil moisture, the proposed system can be used to turn the water sprinkler on / off, thereby making the process easier to use. The system proposed can be used to predict the crop based on the soil condition which helps the farmer grow the proper crops at proper time

. Through this system it can be inferred that use of IOT and Automation there by achieving significant progress in irrigation. The proposed system is thus a solution to the problems facing in current irrigation cycle. The proposed system also helps in the prevention of trespassing wild animals in the agricultural sector. Using ultrasonic sound, the buzzer irritates wild animals and makes them leave the area. Using the alarm tone flooding techniques which requires less energy in addition to that the device is eco- friendly, because there is no harm to the ecosystem and no disruption to humans.

Henry Roberts; Avi Segev,...[3] A foundational step of any animal is the establishment of an accurate behavioural model. Building a model that is capable of defining and predicting an animal's behaviour is critical to advancing ethological theory and research, however many animal models fail to be sufficiently thorough or often do not exist at all. Great pools of data are available for improving these models through recorded video of animals posted on video hosting sites throughout the internet, however these sources are largely left unused due to their sheer quantity being too much for researchers to manually observe and annotate. This article proposed a pipeline approach for efficiently developing predictive behavioural models using a confluence of machine learning tools. Accuracy in prediction and its significance against a much longer standing time-series analysis statistical model. The results of testing proposed pipeline showed promise in that the LSTM network, trained on the JAABA annotated frames of animal behaviour and classifier function results, was able to outperform the ARIMA model.

L. G. C. Vithakshana; W. G. D. M. Samankula,...[4] The kingdom "Animalia" is used to represent all living creatures on the planet earth, which is fallen into six categories. Numerous classification techniques can be used for classification purposes, and the classification commonly can be done acoustically and visually. The classification systems are playing a considerable role, and bioacoustics monitoring was a significant field. Applying an IoT based acoustic classification system was designed using Convolutional Neural Networks (CNN), which is beneficial for those who are interested in monitoring ecosystems such as animal scientists, zoologists, and environmentalists. The hardware implementation was designed to collect the data from the place it was placed. The audio clips were pre-processed using the Mel frequency Cepstral Coefficient (MFCC). A CNN architecture based on TensorFlow was used for the training process. To train and test the network, 400 sound clips of two seconds, such that 40 per each ten animal species, which were gathered from online libraries and formatted using Audacity, were used.

Kuei-Chung Chang; Zi-Wen Guo,...[5] Agricultural production is an essential element in the development of human civilization . As the number of Taiwan Macaques increases, the original habitats cannot provide enough space and food for these macaques. So, there are many monkeys break in farm fields to obtain food and make significant agricultural damages. To prevent the crop losses, some protection and warning systems need to be deployed to detect and drive away these monkeys. This article presents a IoT- based system to recognize coming monkeys which can be used to warn the farmers and make some noises to drive out the monkeys. Also, the sensing information and images will be sent back to the server for further intelligent analysis. The system is very useful for farmers in Taiwan because the agricultural damages by monkeys become more and more serious. Also, MQTT-based IoT architecture make the system to be extended easily.

I. EXISTING METHODOLOGIES

Wild animals are a special challenge for farmers throughout the world. Animals such as deer, wild boars, rabbits, moles, elephants, monkeys, and many others may cause serious damage to crops. They can damage the plants by feeding on plant parts or simply by running over the field and trampling over the crops. Therefore, wild animals may easily cause significant yield losses and provoke additional financial problems. Another aspect to consider is that wild animal crop protection requires a particularly cautious approach. In other words, while utilizing his crop production, every farmer should be aware and take into consideration the fact that animals are living beings and need to be protected from any potential suffering.

2. ANIMAL DETECTION AND REPELLENT

Region Proposal Network (RPN) generates RoIs by sliding windows on the feature map through anchors with different scales and different aspect ratios. Animal detection and segmentation method based on improved RPN. RPN is used to generate RoIs, and RoI Align faithfully preserves the exact spatial locations. These are responsible for providing a predefined set of bounding boxes of different sizes and ratios that are going to be used for reference when first predicting object locations for the RPN. Monitoring window detecting the presence of animals then it enables repeller module to repelling them through the generation of ultrasounds, which has recently been proven as an alternative, effective method for protecting crops against predicted animals. Animals generally have a sound sensitive threshold that is far higher than humans. They can hear sounds having lower frequencies with respect to the human ear. For instance, while the audible range for humans is from 64Hz - 23KHz, the corresponding range of goats, sheep, domestic pigs, dogs and cats is 78Hz - 37KHz, 10Hz - 30KHz, 42Hz - 40.5KHz 67Hz - 45KHz and 45Hz - 64KHz respectively.

DEEP CONVOLUTIONAL NEURAL NETWORK

CNNs are a category of Neural Networks that have proven very effective in areas such as image recognition and classification. CNNs are a type of feed-forward neural networks made up of many layers. CNNs consist of filters or kernels or neurons that have learnable weights or parameters and biases. Each filter takes some inputs, performs convolution and optionally follows it with a non- linearity. The structure of CNN contains Convolutional, pooling, Rectified Linear Unit (ReLU), and Fully Connected layers.

$$(W-F+2P)/S+1$$

Convolutional Layer:

Convolutional layer performs the core building block of a Convolutional Network that does most of the computational heavy lifting. The primary purpose of Convolution layer is to extract features from the input data which is an image. Convolution preserves the spatial relationship between pixels by learning image features using small squares of input image. The input image is convoluted by employing a set of learnable neurons. This produces a feature map or activation map in the output image and after that the feature maps are fed as input data to the next convolutional layer.

Pooling Layer:

Pooling layer reduces the dimensionality of each activation map but continues to have the most important information. The input images are divided into a set of non-overlapping rectangles. Each region is down sampled by a non-linear operation such as average or maximum. This layer achieves better generalization, faster convergence, robust

to translation and distortion and is usually placed between convolutional layers.

ReLU Layer:

ReLU is a non-linear operation and includes units employing the rectifier. It is an element wise operation that means it is applied per pixel and reconstitutes all negative values in the feature map by zero. In order to understand how the ReLU operates, we assume that there is a neuron input given as x and from that the rectifier is defined as $f(x) = \max(0, x)$ in the literature for neural networks.

Fully Connected Layer:

Fully Connected Layer (FCL) term refers to that every filter in the previous layer is connected to every filter in the next layer. The output from the convolutional, pooling, and ReLU layers are embodiments of high-level features of the input image. The goal of employing the FCL is to employ these features for classifying the input image into various classes based on the training dataset. FCL is regarded as final pooling layer feeding the features to a classifier that uses SoftMax activation function. The sum of output probabilities from the Fully Connected Layer is 1.

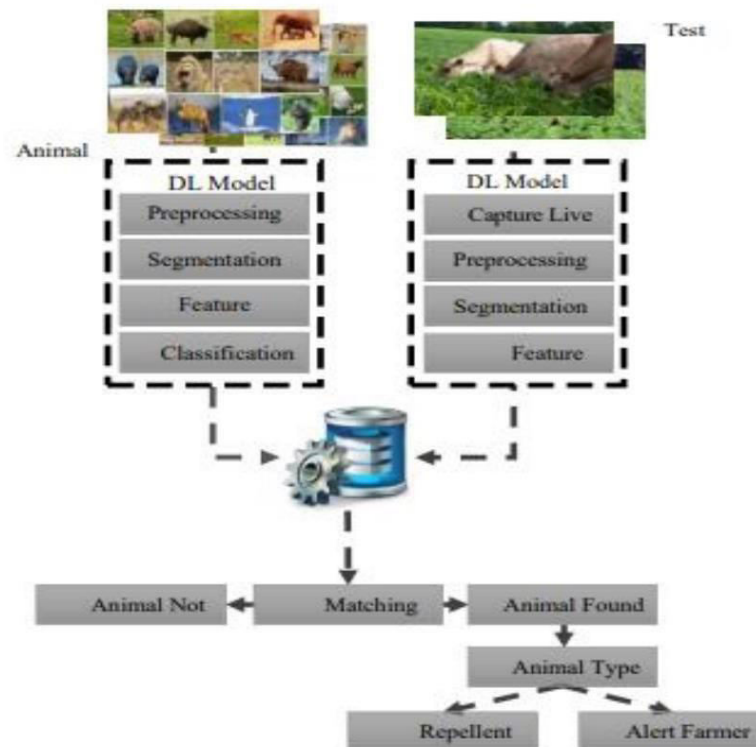


Figure: Proposed System Architecture

A deep learning-based animal repellent system designed to detect, identify, and respond to the presence of animals in agricultural fields. The system operates in two phases: training and testing. In the training phase, a dataset of animal images undergoes preprocessing, segmentation, feature extraction, and classification using a deep learning (DL) model. In the testing phase, live video or images captured from the field are processed similarly starting with image capture, followed by preprocessing, segmentation, and feature extraction. The extracted features from the live input are compared against the trained database to determine if an animal is present. If no match is found, no action is taken. If an animal is detected, the system identifies its type and triggers a corresponding response. Depending on the animal type, the system can either activate a repellent mechanism or send an alert to the farmer. This automated approach enhances crop protection and reduces human intervention. AI Computer Vision based DCNN for detecting animal species, and specific ultrasound emission (i.e., different for each species) for repelling them. design, deployment and assessment of an intelligent smart agriculture repelling and monitoring IoT system based on embedded edge AI, to detect and recognize the different kinds of animal, as well as generate ultrasonic signals tailored to each species of the animal. This combined technology used can help farmers and agronomists in their decision making and management process. Deep learning in the form of Convolutional Neural Networks (CNNs) to perform the animal recognition

III. EXPERIMENTAL RESULTS

Locations: 2 crop fields (2 acres each)

Control vs Test Zones:

Control: No repellent

Test: Acoustic repellent active upon detection

Duration: 8 weeks

Metrics:

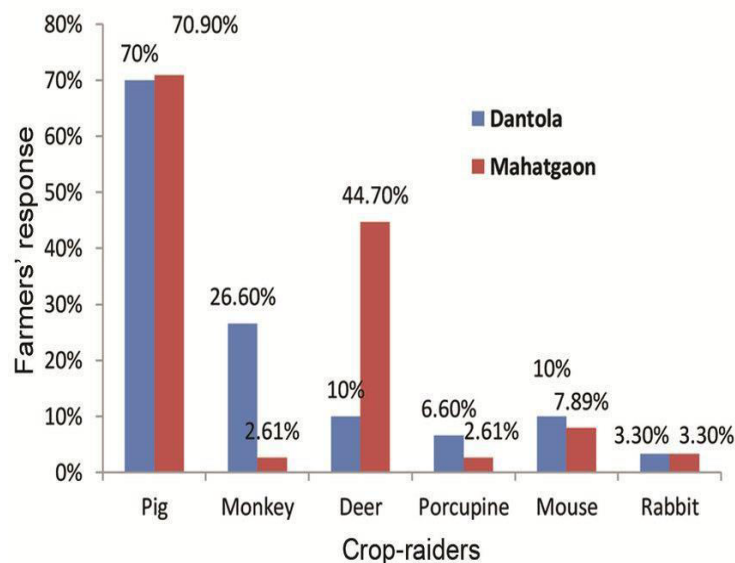
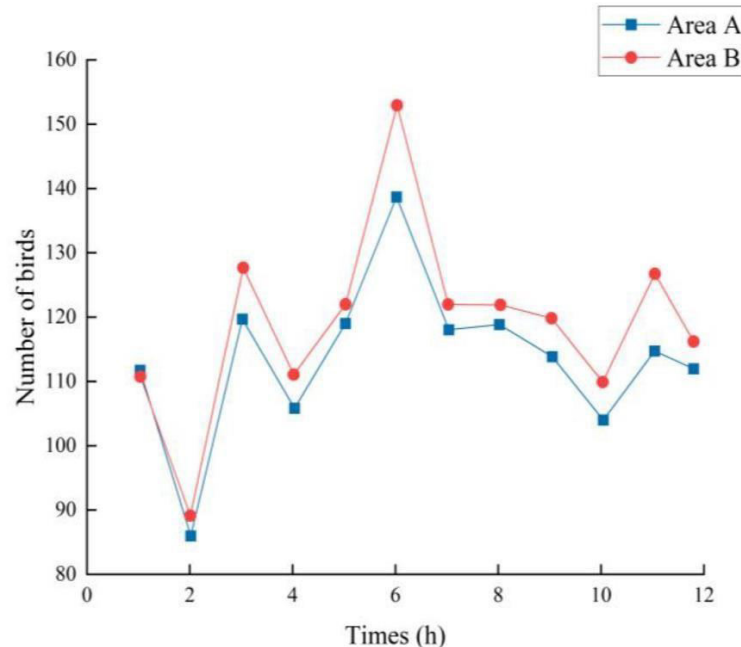
1. Animal visit frequency (via camera trap data)
2. Crop damage percentage
3. System response time (from detection to repellent activation)

Results:

Species	Avg. Visits (Control)	Avg. Visits (Test)	% Reduction	Crop Damage Reduction
Wild boar	12/week	3/week	75%	68%
Birds (Crows)	45/day	18/day	60%	54%
Monkeys	5/week	2/week	60%	50%

Latency: Average detection-to-repellent delay: 1.3 seconds

False positives: < 5% (primarily triggered by domestic animals)



IV. 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.

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