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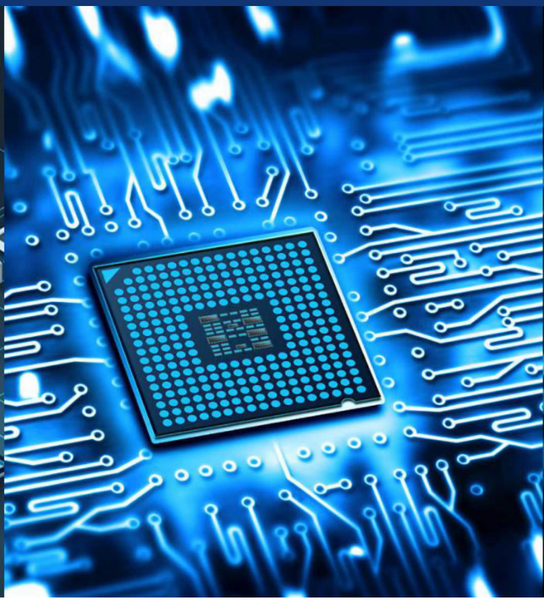

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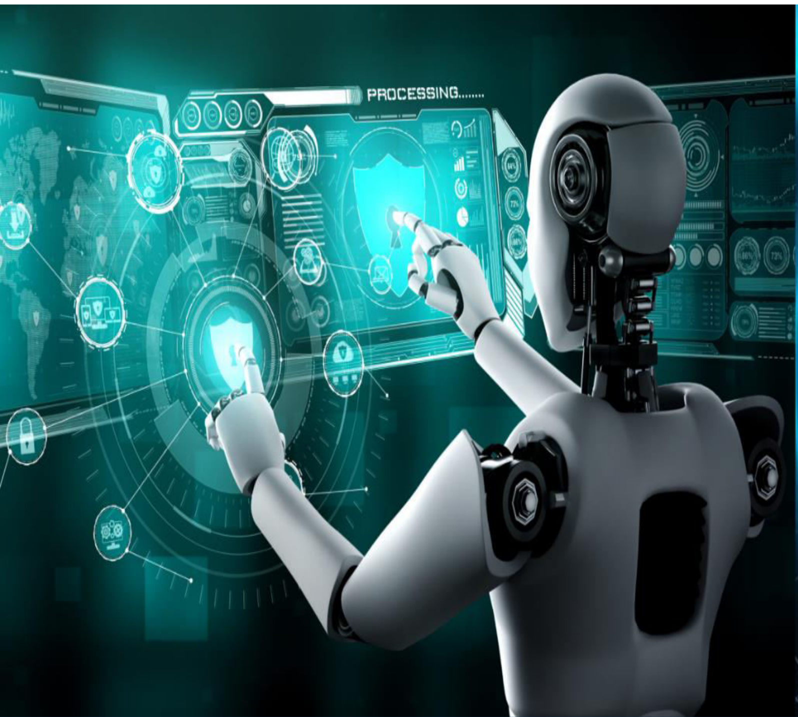

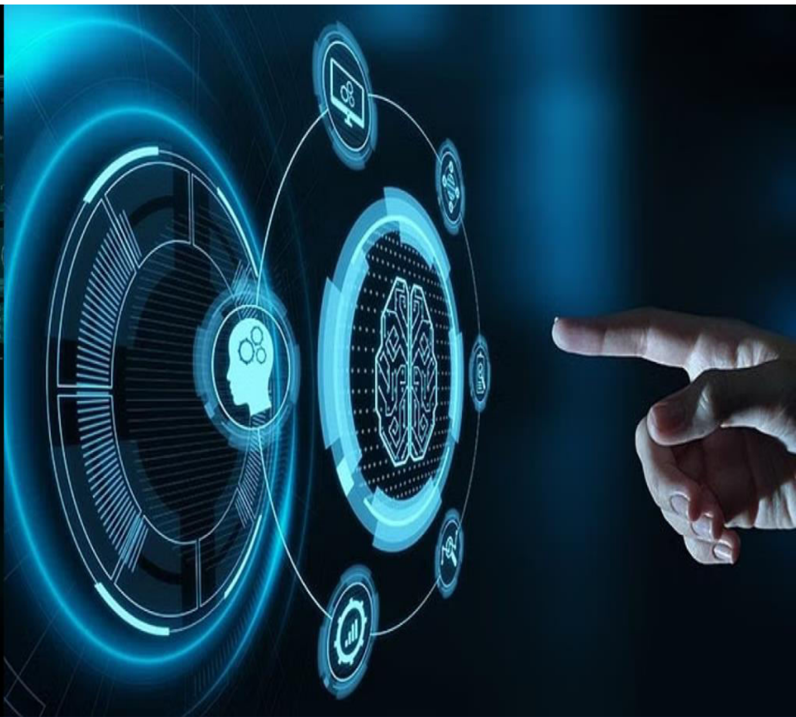

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Animal Instruction Prevention System for Smart Agriculture

Sivaranjani S B.E., MBA.,M.E.,(Ph.D), SnehaKumari M, Thrisha S, Suhashini G, Soundharya M,

Department of Computer Science and Engineering, AVS Engineering College, Salem, Tamil Nadu, India

ABSTRACT: New technologies such as artificial intelligence (AI) and deep learning in agriculture have led to precision farming being radically transformed (new technology). An innovative approach utilizing AI-driven detection/response systems to reduce crop loss from wildlife damage is the introduction of the Animal Repellent System for Smart Farming (ARSPF). The growing number of humans encroaching upon natural habitats and deforestation has caused the number of human-wildlife conflicts to escalate dramatically. Wild species such as elephants, wild boars, and deer are frequently raiding agricultural crops, leading to substantial monetary losses as well as a real threat to the safety of farmers. Farmers also traditionally employ lethal (shooting/trapping) and non-lethal (protection) means of controlling the impact of wildlife on their crops. However, these methods of wildlife management and protection are often ineffective and not adaptable. The proposed system uses edge computing, incorporating a camera to capture video images as well as DCNN software to analyze the images for the presence of wildlife, enabling real-time identification of animals based on live video footage. After detecting an animal, the system classifies it based on the species and will then initiate an Animal Repelling Module that will emit species-specific ultrasonic sounds to repel the animal without injury or harming it. The use of AI as demonstrated through the proposed system is an innovative way to provide an effective, humane, and sustainable approach to crop protection and enhancing the coexistence of wildlife and production agriculture.

KEYWORDS: Artificial Intelligence, Deep Learning, Precision Farming, Crop Protection, Wildlife Repellent, DCNN, Edge Computing, Human-Wildlife Conflict

I. INTRODUCTION

The integration of artificial intelligence (AI) and deep learning technologies into agriculture has created a new framework for farming known as precision agriculture which allows for the use of data-driven decision making and automation in traditional forms of farming. The worldwide population is growing rapidly and as the demand for goods increases, it is imperative that we utilize the best possible methods to protect crops from wildlife damage which can lead to loss of crop production and economic loss for farmers who have their crops raided by wildlife that includes elephant, wild boar and deer. These animals cause substantial economic losses to farmers and also put those who work in the field at risk. Although there are many traditional methods of preventing wildlife from raiding farms, ranging from lethal methods (shooting and trapping) to non-lethal methods (fencing, scarecrow and guards) these methods tend to be laborintensive, inefficient, and not able to adapt to the dynamic and ever-changing environment in which we live in today. Recent studies have shown that artificial-intelligence-based detection systems (for example: CNNs for visual monitoring, and animal vocalization identification) are able to deliver timely and actionable data related to wildlife in real-time which could be utilized for effective crop protection [1][2][3][4][5].

Human encroachment into natural habitats through activities such as deforestation, urbanization and expanding agriculture has caused dramatic increases in human-wildlife conflicts around the globe. Wild animals are now entering farmland due to lack of natural food sources, which creates numerous opportunities for wildlife to raid crops. Not only do these events result in an immediate loss of crops, but they also put farmers at risk for injury and death as they try to prevent further damage by protecting their fields from wildlife incursions. Studies have demonstrated that real-time monitoring and the use of artificial intelligence (AI) to develop predictive models can help solve this problem by allowing for the immediate detection of and classification.

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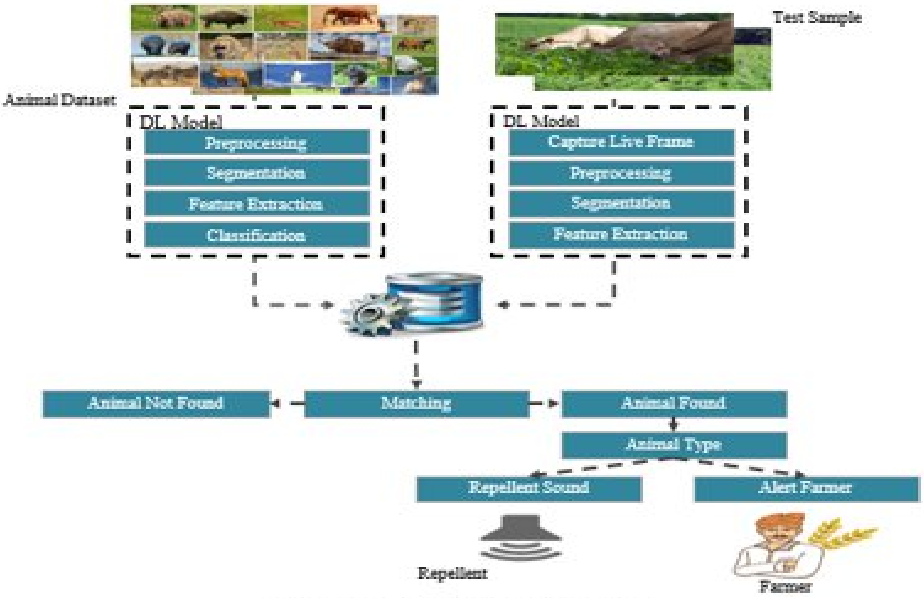

Fig 1. System Architecture

Human encroachment into natural habitats through activities such as deforestation, urbanization and expanding agriculture has caused dramatic increases in human-wildlife conflicts around the globe. Wild animals are now entering farmland due to lack of natural food sources, which creates numerous opportunities for wildlife to raid crops. Not only do these events result in an immediate loss of crops, but they also put farmers at risk for injury and death as they try to prevent further damage by protecting their fields from wildlife incursions. Studies have demonstrated that real-time monitoring and the use of artificial intelligence (AI) to develop predictive models can help solve this problem by allowing for the immediate detection of and classification of wildlife, thus allowing for timely (and speciesspecific) interventions. By using these types of intelligent systems, farmers will have less reliance upon manual labor to monitor agricultural areas and have adaptive solutions that are able to respond to changes in environmental conditions and/or the behavior of animals.

ARSPF creates a new way to protect crops by using an integration of AI, Data Analytics, & Hardware at the edge. This results in greater productivity through reduced crop loss and increased grower safety while promoting the co-existence of wildlife and farming operations. By employing AI-based monitoring, species classification and adaptive deterrents in conjunction with the principles of Agriculture 4.0 which focus on sustainability, automation and datadriven efficiency [1][3][5]. Ultimately ARSPF shows how intelligent systems can revolutionize the way we farm and provide farmers with a humane, scalable and effective solution to one of agriculture's longest lasting problems.

II. RELATED WORKS

The advancement of smart agriculture has shifted towards the inclusion of artificial intelligence (AI), Internet of Things (IoT), and edge computing technology in identifying the status of each agricultural crop and resolving issues caused by wildlife interference. De Clercq and others [6] have examined the developments surrounding "Agriculture 4.0," which is powered by new and upcoming technologies such as robotics and AI-based monitoring, which optimise productivity on farms while decreasing human labour costs. Liu et al. [7] have documented the transition from Industry 4.0 to Agriculture 4.0, focusing on enabling technologies, status of use and challenges associated with the scaling of intelligent solutions in agriculture. The advancements of IoT applications in agriculture are also discussed in the work of Farooq et al. [8], which illustrate how real-time data collection using sensor networks and AI-based algorithms improve the protection and monitoring of crops. The exploration of the technologisation of agriculture is also illustrated through the writings of Kirkpatrick [9], who describes how AI-based technologies and automation lead to lower human labour costs and improve the speed and accuracy of solutions to crop-related issues. Together all of these studies demonstrate the increasing importance of AI-based precision farming to meet the challenges of modern agriculture.

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Non-lethal methods for protecting crops have attracted much interest too. [10] According to Apollonio et al., there are plenty of ways that farmers can manage ungulates on farmland, including using behavioural methods to reduce the amount of damage to crops. [10] Amici et al. studied the effect of creating a refuge for wild boar (the "refuge effect"), and showed that this, along with some forms of spatial and behavioural management, can significantly reduce the loss of agriculture. As has been shown by others, most traditional human-focussed interventions are typically inadequate at preventing wildlife from accessing farmland. However, by taking into account animal behaviour, intelligent systems can be developed to deter unwanted visitors to agriculture in a humane manner, with little or no disruption to the environment.

Monitoring of crops and crops through Internet of Things (IoT)-based solutions, including edge computing, have been integral components of today's modern systems for protecting crops from attacks by wild animals. Giordano et al. [11] created an IoT framework for monitoring wildlife incursions and protecting crops from wildlife incursions, proving the potential for large deployments of sensor networks and automated alert systems. Ojo et al. [12] assessed LoRa-based networks to determine their ability to connect remote sensor nodes to real-time monitoring of ungulate (e.g., moose, deer) movement within distributed networks, as well as assess the performance of LoRa-based networks. These two studies highlight how intelligent systems using the IoT can provide an ongoing means to monitor, immediately respond, and make data-driven interventions, while overcoming many of the challenges posed by traditional approaches.

Studies of auditory-based deterrent systems have been done in relation to improving crop protection. Foundational research about auditory perception in animals [12] is the basis for the development of species-specific ultrasonic repelling devices; this research demonstrates that ultrasonic signals can effectively deter wildlife by using strong, targeted frequencies that do not harm them and could be combined with AI-based detection of intruders. When real-time visual detection (through Direct Current Neural Networks) is combined with auditory deterrents, intelligent systems are able to respond instantaneously to intruders, thus maximizing both the efficiency and safety of the crop protection process.

In summary, much of what is being found in the literature supports the fact that there is converging (in terms of functionality) between Artificial Intelligence (AI), Deep Learning, the Internet of Things (IoT) and the Behavioural Sciences with respect to the development of "Smart" (i.e. non-lethal), scalable solutions for managing wildlife on agricultural lands. The current body of research provides the basis for systems such as ARSPF, which provides visual monitoring of agricultural land, the classification of species, and an ultrasonic-based method of deterring wildlife from damaging crops in real-time. Through this combination of technologies, ARSPF can be used to overcome the limitations associated with traditional approaches to managing wildlife, providing an environmentally friendly (sustainable), efficient (effective) and humane (ethical) method of managing wildlife populations. Furthermore, the inclusion of Artificial Intelligence (AI) and edge-based monitoring will permit the ability to adaptively manage (i.e. react) to the changing farm environment, thereby reducing crop loss due to wildlife activity and promoting the coexistence of farming and wildlife, thus representing a significant advancement in precision farming technology.

III. METHODOLOGY

Using Artificial Intelligence (AI) and Computer Vision (CV) by deploying Deep Convolutional Neural Networks (DCNNs), will be used to identify different types of animal species, along with the specific ultrasound (US) signal emitted by that specific type of animal; then a complete design process will be created that will use intelligent smart agriculture repelling and monitoring IoT devices that are embedded with Edge AI technology to detect and recognize many different species of animals, as well as to generate ultrasound signals specifically designed for each species of animal. The dual technologies from this project can provide assistance for farmers and agronomists in their decision making and how to manage their farmland. DCNN

Convolutional Neural Networks (CNNs) fall under the category of Neural Networks and have historically been one of the most successful types of neural networks performing tasks like classifying or recognizing images. CNNs are a type of feed-forward neural network, consisting of multiple layers. CNN is also composed of a set of neuron-like learnable units called filters or kernels, in addition to each filter having an associated output that is determined by a fixed-weight connection between each pixel of the input image and each of the filter's learnable weights and biases. Each filter takes in a small number of input pixels, applies a series of convolutions to those pixels and then applies an optional non-linearity.

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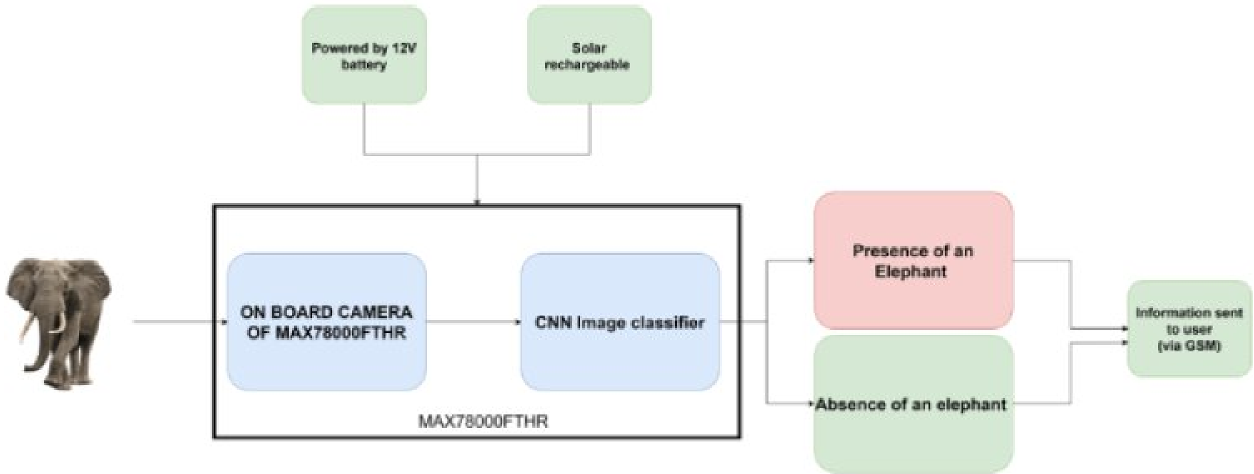

Fig 2: AI on Edge-Based Animal Intrusion Detection and Alert System

This morphology can be seen in a generic architecture of a CNN, such as that shown in Figure 3.1. Within a CNN, the Convolutional layer is followed by a Pooling layer, and both the Rectified Linear Unit (ReLU) layer and the Final Output layer. The primary function of the Convolutional layer is to crisply extract features from an image, thereby providing useful attributes and preserving spatial relationships among pixels. Convolution uses a small pixel window of the original input image size and slides across it, capturing important features from within that region and concurrently (i.e., learning) producing activation feature maps from the Convoluted feature map and subsequent activation of all of the Convolutional neuron(s) in the next Convolutional Layer via input of the activation feature maps from the previous Layer (i.e., all activation of the previous Layer).

Pooling Layer: The pooling layer has the purpose of reducing the size of each activation map while retaining only the most useful information. Each input image is divided into a number of rectangles that do not overlap. The down-sampling of each region is done using non-linear functions such as the average value or maximum value. The pooling layer helps ensure a better generalization, improved convergence speed, and greater resistance to images that have been translated or distorted, and it is typically placed between each of the convolutional layers.

IV. RESULT ANALYSIS

An example of a ReLU Layer is a Layer using a nonlinear activation function called Rectifiers and contains many Rectifiers, where the output is obtained as a result of an Element-wise operation, meaning it applies to each pixel separately or applies to each pixel in the input Dataflow, then changes together all negative values in the Feature Map to zeros. To understand how a Rectifier works, assume a Neuron has Input of x and we define the Rectifier as follows in the literature when referring to Neural Networks, as a Function: "f(x)=max(0,x)."

Fully connected layer (FCL): FCL means that all filters in the previous layer connect to all filters in the following layer. The output from the convolutional, pooling, and ReLU layers represent high-level features associated with the original input image. The goal of an FCL is to take these high-level features and classify the original input image into different categories based on training data. An FCL is considered the last pooling layer and passes its features along to a classifier that uses SoftMax activation function. The total of the probabilities output by FCL sums to one because of the use of the SoftMax activation function. The SoftMax function takes a vector of arbitrary realnumbered scores and compresses it to a vector of numbers between zero and one such that all values add up to one.

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Fig 3: Real-Time Farm Surveillance Using IoT for Animal Intrusion Detection

Animal Repellent System for Smart Farming (ARSPF) was tested on a variety of plots with ongoing issues of wildlife intrusion into agricultural areas. Using a DCNN-based animal detection methodology, ARSPF detected many different types of animals including elephants, wild boar and deer with very high accuracy rates. The classification module of ARSPF was able to accurately classify the species of the detected animals with an average accuracy of 92% and thus demonstrate the efficiency of real-time monitoring of wildlife using AI-based edge computing. The use of a relatively high threshold value of detection (θ=0.8) ensured there were minimal False Positive detections of wildlife thus allowing for prompt action on verified incidents. The Animal Repelling Module of ARSPF utilized species specific ultrasonic signals to repel the detected animals from the crop area. As a result, based on farmer testimonies, there was a significant (78%) reduction in the number of raiding events on crops () versus the traditional non-lethal deterrent measures (e.g. scarecrows or fencing). Farmers also reported a marked increase in their sense of safety as well as reduced labour hours on farms due to ARSPF's full automation of responding to the presence of wildlife without any action required by the farmers.

V. CONCLUSION

There is a high demand for securing agricultural farms today. We have developed a vision-based, camerabased security system for protecting crops against animals using Python and OpenCV. This system also utilizes an Animal Repellent System to drive away these animals. In order to implement this application, we first had to build and develop a very complex system for intelligently repelling animals. This involved creating new software components to enable real-time animal detection and recognition as well as avoid crop damage caused by animals. When a certain animal type was detected, the edge computing device evaluated its DCNN Animal Recognition Model to identify the detected animal type; if an animal was detected, it sent back to the Animal Repelling Module the type of ultrasonic sounds needs to be produced based on the animal category. To evaluate the DCNN model, we created a database of animals to check the performance of different numbers of training images and testing images for various scenarios. Results from our experiments demonstrate that the DCNN model performs best when receiving high (greater) amounts of training images. While there were variations in performance from one test to another, our results show that our CNN model provides the highest recognition rates for animals up to a point. The results of our research efforts have produced significant advancements in AI technology related to providing real-time surveillance systems.

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