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Camera Vision Based Animal Repellent System for Agriculture using Machine Learning

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***Abstract:** The human-animal conflict of crop raiding has significantly increased due to human encroachment on wildlife habitats and deforestation. Wild animals, such as elephants, wild boar, and deer, pose a substantial threat to agricultural crops and farmers working in the fields, leading to significant crop losses. To address this concern, we present a comprehensive system that combines Computer Vision using Deep Convolution Neural Networks (DCNN) for precise species detection and recognition, along with the emission of species-specific ultrasound for repelling the wild animals. An edge computing device, equipped with a camera, is activated to execute the DCNN software, identifying potential threats.*

***Keywords:** Animal Recognition, Repellent, Artificial Intelligence, Animal Detection, Deep Learning, DCNN.*

I. INTRODUCTION

Throughout history, agriculture has experienced several revolutions, including the domestication of animals and plants, advancements in farming practices such as crop rotations, and the "green revolution" involving systematic breeding and the widespread use of man-made fertilizers and pesticides. However, the current era witnesses the fourth agricultural revolution, driven by the rapid integration of information and communication technology (ICT) in agriculture. This revolution embraces autonomous robotic vehicles for farming tasks like mechanical weeding, fertilizer application, and fruit harvesting. The advent of unmanned aerial vehicles with autonomous flight control, coupled with lightweight, powerful hyper-spectral snapshot cameras, facilitates precise calculations of biomass development and crop fertilization status, revolutionizing farm management advice

II. LITERATURE SURVEY

[1] In 2021, the project "Workflow and Convolutional Neural Network for Automated Identification of Animal Sounds" focuses on automating the identification of animal sounds using Convolutional Neural Networks (CNNs). [2] In 2020, the publication "Real-Time Monitoring of Agricultural Land with Crop Prediction and Animal Intrusion Prevention using Internet of Things and Machine Learning at Edge" by R. Nikhil, B.S. Anisha, and Ramakanth Kumar P. endeavors to provide farmers with crop prediction based on soil parameters using machine learning techniques. Furthermore, the project aims to safeguard fields from wild animal intrusions [3] The 2021 project titled "IoT-Based Animal Classification System using Convolutional Neural Networks," authored by L. G. C. Vithakshana and W. G. D. M. Samankula, introduces an IoT-based acoustic classification system utilizing Convolution Neural Networks (CNNs). The system benefits researchers, zoologists, and environmentalists interested in ecosystem monitoring. [4] In 2020, Henry Roberts and Aviv Segev work on the project "Animal Behavior Prediction with Long Short-Term Memory" to efficiently convert video footage of animals into models capable of accurate behavioral prediction using Long Short-Term Memory (LSTM). [5] The project "Animal Sound Classification Using Dissimilarity Spaces," published in 2020 by Loris Nanni, Sheryl Brahnam, Alessandra Lumini, and Gianluca Maguolo, aims to automate animal audio classification using clustering methods. [6] In 2019, S. Jeevitha and S. Venkatesh Kumar conduct a study on the "Sensor-Based Animal Intrusion Alert System Using Image Processing Techniques," designing an animal intrusion alert system employing wireless sensors to automatically notify both the landowner and forest officials with an image.

III. ENHANCED SYSTEM

Design, deployment, and evaluation of an intelligent smart agriculture repelling and monitoring IoT system using embedded edge AI for the detection, recognition, and repelling of various animal species. The integrated technology utilizes AI Computer Vision with DCNN for precise animal recognition and generates species-specific ultrasonic signals tailored to each animal species. This combined approach provides valuable support to farmers and agronomists in their decision-making and management processes.

Deep learning, specifically Convolutional Neural Networks (CNNs), is employed for animal recognition. CNNs have demonstrated exceptional effectiveness in tasks like image recognition and classification.

CNNs consist of multiple layers, including convolutional, pooling, ReLU (Rectified Linear Unit), and fully connected layers, with filters having learnable weights and biases. The typical CNN architecture used in the system is depicted in Figure.

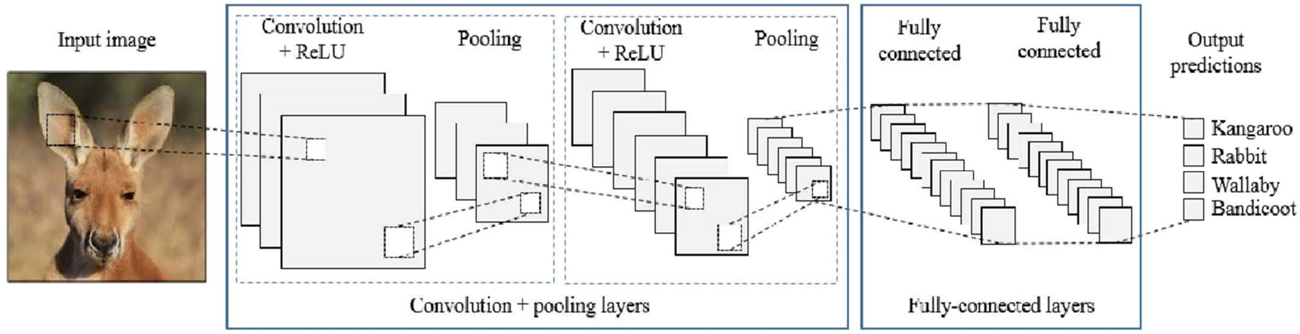

Figure 1 Training CNN

1) The Convolutional Layer serves as the fundamental building block of a Convolutional Network and performs the majority of computational tasks. Its primary function is to extract features from input images, preserving their spatial relationships. By employing a set of learnable neurons, the convolution operation learns image features through small squares of input data. This process generates activation maps in the output image, which are then passed as input data to subsequent convolutional layers.
2) The Pooling Layer reduces the dimensionality of activation maps while retaining essential information. It divides input images into non-overlapping rectangles and downsamples each region using non-linear operations such as average or maximum. This layer enhances generalization, accelerates convergence, and ensures robustness to translation and distortion. Typically positioned between convolutional layers, the pooling layer plays a crucial role in feature extraction.
3) The ReLU Layer applies a non-linear operation that involves rectifier units. It is an element-wise process, where each pixel in the feature map is recalibrated to zero for all negative values. The ReLU activation function, defined as $f(x) = \max(0, x)$, effectively modifies the neuron input (x). This operation contributes to the overall functionality of neural networks.
4) The Fully Connected Layer (FCL) establishes connections between every filter in the previous layer and the subsequent layer. It receives outputs from the convolutional, pooling, and ReLU layers, which represent high-level features of the input image. The FCL's objective is to leverage these features for image classification into various classes based on the training dataset. Serving as the final pooling layer, the FCL feeds the features to a classifier utilizing the SoftMax activation function. SoftMax ensures that the sum of output probabilities from the Fully Connected Layer equals 1, mapping the vector of arbitrary real-valued scores to a vector of values between zero and one.

a) *Generation of Repelling Ultrasound:* The animals' heightened sound sensitivity compared to humans allows them to hear lower-frequency sounds beyond the human ear's audible range. For instance, goats, sheep, domestic pigs, dogs, and cats have audible ranges of 78Hz - 37KHz, 10Hz - 30KHz, 42Hz - 40.5KHz, 67Hz - 45KHz, and 45Hz - 64KHz, respectively, while the human audible range is 64Hz - 23KHz. By generating ultrasounds within the animals' critical perceptible range, the system disturbs the animals, prompting them to move away from the sound source. Simultaneously, these ultrasounds remain imperceptible to the human ear, as the human eardrum's specific resonant frequency is far lower than that of animals, preventing it from vibrating at ultrasound frequency. This non-lethal solution poses no risk of environmental pollution and has minimal impact on the landscape.
b) *Notification System:* The detection system records the date and time of each animal detection, along with cameras and a video recording system capturing all animal movements within the enclosure. By cross-referencing the detection log with the images from the cameras, which include date and time stamps, the system ensures reliability. In the case of animal detection, an instant message alert is sent to the registered mobile number.

IV. WORKING

In this research work, a deep convolutional neural network (CNN)-based classification algorithm is developed to detect animals in both video and images. The proposed approach involves a classification model that utilizes different features and classifiers. Features such as color, gabor, and local binary patterns (LBP) are extracted from segmented animal images.

Additionally, the potential benefits of feature fusion to enhance classification performance are explored. The animal classification is achieved by employing CNN along with symbolic classifiers. Initially, features are extracted from images or frames using a pre-trained convolutional neural network from the Blink app. Subsequently, these extracted features are input into a multi-class CNN classifier for the classification task. The CNN model is constructed with a sequence of layers, including convolutional, subsampling, and fully connected layers.

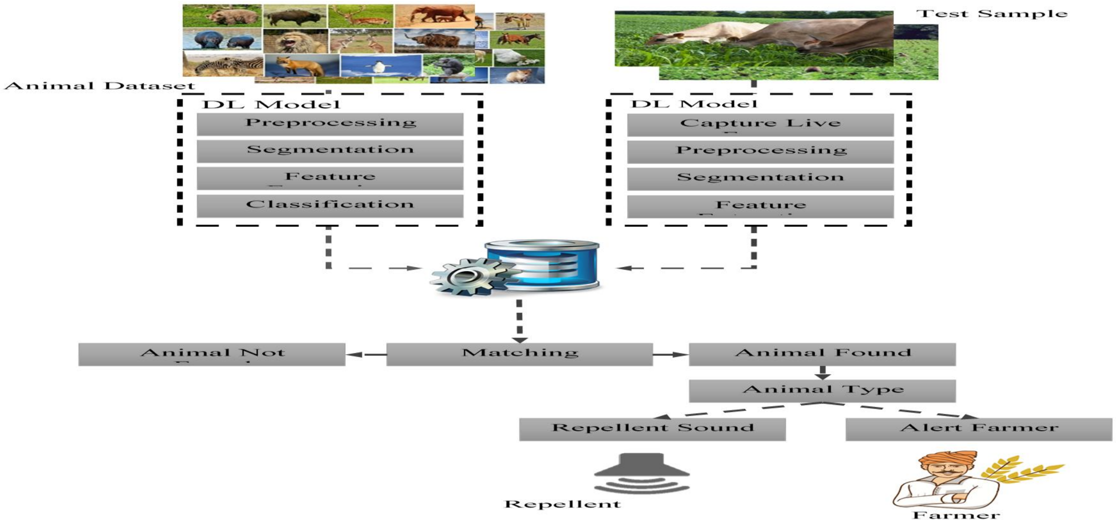

Fig 2. Working model

V. CONCLUSION

A vision-based system using Python and OpenCV is proposed and implemented for Agricultural Farm Security. The system serves as an Animal Repellent System to deter animals from crops. The complex intelligent animal repulsion system integrates newly developed software components, enabling the real-time animal presence and species recognition to prevent crop damage. Upon detecting an animal, the edge computing device activates its DCNN Animal Recognition model to identify the species and sends a message to the Animal Repelling Module to generate specific ultrasound signals based on the detected animal category. The CNN model's performance was evaluated on a created animal database, and the experimental results show excellent recognition rates, achieving about 98% accuracy with a greater number of input training images. This real-time monitoring solution based on AI technology effectively addresses crop damage issues caused by animals, benefiting farmers and agronomists in their decision-making and management processes.

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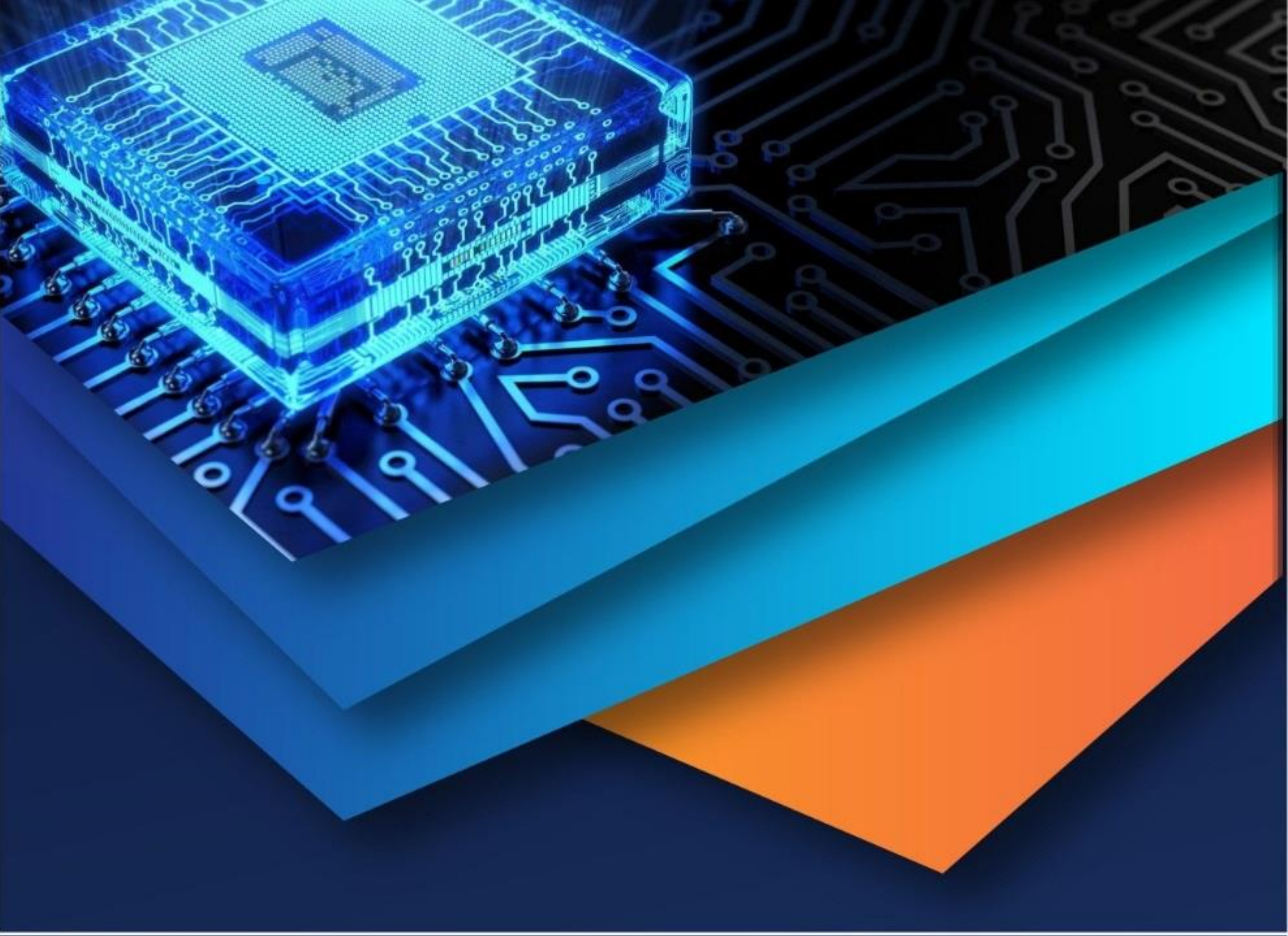

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