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Camera Vision Based Animal Beat Back System for Agriculture using Machine Learning

Mr.Deepak S
Department of Information Technologys
M.Kumarasamy College of Engineering,
Thalavapalayam, Karur, Tamil Nadu,
India – 639113
draguladeepak2807@gmail.com

Mr.Jeevanatham R
Department of Information Technologys
M.Kumarasamy College of Engineering,
Thalavapalayam, Karur, Tamil Nadu,
India – 639113
rajamalar113@gmail.com

Mr.Sanjey Kumar R
Department of Information Technologys
M.Kumarasamy College of Engineering,
Thalavapalayam, Karur, Tamil Nadu,
India – 639113
rsanj06@gmail.com

Mr.Subhikashanand G M
Department of Information Technologys
M.Kumarasamy College of Engineering,
Thalavapalayam, Karur, Tamil Nadu,
India – 639113
subhikshanand2112@gmail.com

Ms.Elankeerthana R
Department of Information Technologys
M.Kumarasamy College of Engineering,
Thalavapalayam, Karur, Tamil Nadu,
India – 639113
elankeerthanar.it@mkce.ac.in

***Abstract*— Crop striking by creatures has become one of the most well-known human creature questions because of human infringement of untamed life territories and deforestation. Wild animals can make critical harm horticultural yields and assault ranchers working in the field. Ranchers experience tremendous harvest misfortune because of yield attacking by wild animal like elephants, wild pig and deer. Crop protection from wildlife attacks is a major concern for modern-day farmers. Conventional methods for addressing this issue include lethal techniques such as shooting and trapping, as well as non-lethal methods like scarecrows, chemical repellents, natural substances, fencing, and electric barriers. Despite farmers' attempts to prevent animal attacks, such as staying up all night watching the field, traditional methods have drawbacks such as environmental contamination, high maintenance costs, limited effectiveness, and inconsistent results. The main aim of this project is to develop a system that combines Computer Vision with D-CNN to recognize and classify animal species, and to use a customized ultrasound emission (specific to each species) to keep them away. When the edge computing device activates the camera, it executes its D-CNN software's to identify the target, and if an animal is detected, it sends a message to the Creature Repelling Module, which includes the types of ultrasound that is generated based on the animal's classification.**

Keywords—Animal's Recognitions, Repellents, Artificial-Intelligence, Edge-Computing, Animal's Detections, Deep-Learning, and DCNN.

I. Introduction

Throughout these years, there have been various agricultural advancements, such as animal and plant training a few years ago, the intentional use of crop rotations and other farming techniques several years ago, and the "Green Revolution" involving systematic breeding and continuous use of synthetic fertilizers and pesticides for many years. Agriculture is experiencing a fourth disruption as a result of the rapidly expanding use of information and communication technology (ICT) in farming. Independent, automated vehicles, such as mechanical weeding, have been developed for the The purpose of cultivating, the use of manure, or the collection of natural products. The advancement of automated elevated vehicles with independent flight control, as well as the advancement of lightweight and strong hyper otherworldly depiction cameras thatcan be used to ascertain biomass advancement and Yields preparation status, opens the way for modern homestead the board guidance. Furthermore, there are now available choice tree models that enable ranchers to distinguish between plant illnesses based on optical data. Virtual wall developments Allow steers to group the board based on remote-detecting signs andsensors or actuators connected specialized advancements in various fields, including ICT and animal husbandry, are causing significant transformations in agricultural practices worldwide. These changes are impacting both developed and developing countries and are likely to continue as technological advancements (such as mobile phone usage and internet access) become more widespread and effective tools for improving farming practices, such as weather forecasting and precision agriculture.

II. Existing System

Wild animals are a special challenge for farmers throughout the world.Animals such as deer, wild boars, rabbits, moles, elephants, monkeys, andmany others may cause serious damage to crops.

1. Agricultural fences
2. Natural Repellents
3. Chemical repellents
4. Biophysical barriers; fence

III. Proposed System

Artificial intelligence PC For distinguishing creature species, vision-based DCNN is used, and explicit ultrasound discharge (different for each species) is used to repel them. plan, sending and this project aims to evaluate an intelligent agricultural monitoring and repelling IoT system based on embedded edge AI, which can detect and identify different types of animals and emit ultrasonic signals tailored to each species. This collaborative technology can assist farmers, agronomists, and managers in their decision-making processes. Convolutional Neural Networks (CNNs) utilize deep learningfor animal recognition. CNNs are a type of neural network that has shown significant success in fields like image recognition and classification.They are feed-forward neural networks with multiple layers, consisting of channels, units, or neurons with adjustable weights, biases, and thresholds. Each channel takes inputs, convolves them, and applies non-linearities alternately. As shown, common CNN's design should be visible. CNN's architecture

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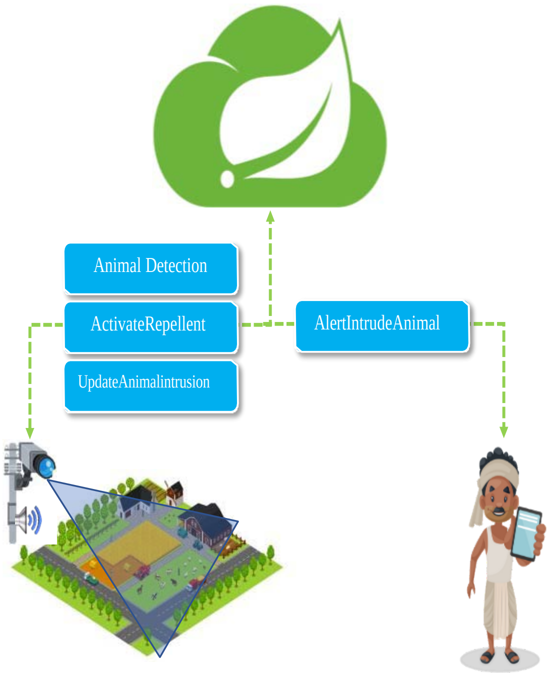
includes Convolutional, Pooling, Redressed Direct Unit(ReLU), and Completely Associated, layers.

IV. Architecture of the Proposed System



V. Module Description

A. *Animal Repellent Web Dashboard*

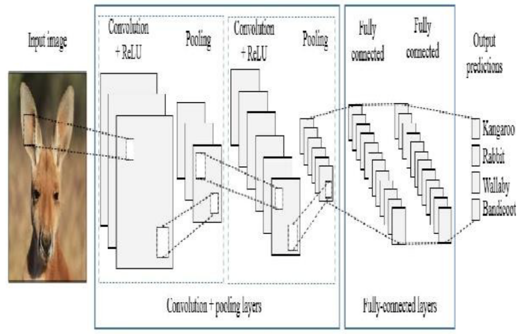
The system allows for real-time detection of animals in the fields and provides the farmer with a live view of their fields from any location through the internet. Additionally, the system includes manual bell controls that can be used if needed, giving the farmer complete control over the system. When compared to many current arrangements, such as electric walls, block facades, and manual field management, this framework is conservative. This framework is extremely effective at driving the creatures from the fields and repelling them. The need for power reduces the dangers of electric shocks.

B. *Animal Recognition*

This module starts by comment of creature dataset. These layouts then, at that point, become the reference for assessing and enrolling the formats for different stances: shift up to down, draw nearer to further, and turn left to right. Creature10N dataset contains 5 sets of mistaking creatures for a sum of 55,000 pictures. The 5 sets are as following: (feline, lynx), (panther, cheetah), (wolf, coyote), (chimpanzee, orangutan), (hamster, guinea pig). The pictures are crept from a few web-based web crawlers including Bing and Google utilizing the predefined marks as the pursuit watchword.

C. *Animal Detection*

Hence, in this module, District Proposition Organization (RPN) creates returns for capital invested by sliding windows above the element’s maps through secures with various scale and different viewpoint proportions. Creature location and division strategy considering further developed RPN. RPN is utilized to create returns for capital invested and return for money invested.



The specific spatial areas are loyally protected by Adjust. These oversee providing a predefined set of jumping boxes of varying sizes and proportions that will be used as a reference while first anticipating object areas for the RPN.

D. *Animal Identification*

Once an animal image is captured by the Farm Camera, it is processed by an animal detection module which leverages a Region Proposal Network (RPN) to identify regions within the image that are likely to contain an animal. These regions are then passed to a feature extraction module which extracts key features from the image feature extraction module uses techniques like convolutional neural networks (CNNs) to extract detailed feature representations from the image. The resulting feature vector is typically of sufficient length to accurately represent the animal image.

E. *Repellent*

A system for safeguarding crops against potential animal threats involves an observation window that detects the presence of creatures, and subsequently triggers a repeller module that uses ultrasound to deter them. Recent research has shown that ultrasound is an alternative and effective method for repelling creatures. This is because animals generally have a much higher sensitivity to sound than humans, with the ability to hear lower frequencies that are beyond the range of human hearing. For example, while the human range of hearing is typically between 64Hz to 23KHz, various animals such as goat, sheeps, pig, dog and cat can hear sounds with frequencies ranging from 78Hz to 37KHz, 10Hz to 30KHz, 42Hz to 40KHz, 37.5Hz to 45.5KHz and 45.5Hz to 64.5KHz.

F. *Monitoring And Visualizing*

The framework works continuously recognize the animals in the field, moreover the ranchers can get to the perspective on their fields from a distance. The animal recognition module can provide information on the type and number of animals present, which is then transmitted to the cloud via a Wi-Fi connection. The cloud-based system consists of a secure cloud instance running on a machine that analyzes the patterns and behaviors of wild animals using the shared data. The farmer can detect and correct any errors, and thus achieve better results from the system.

G. *Notification*

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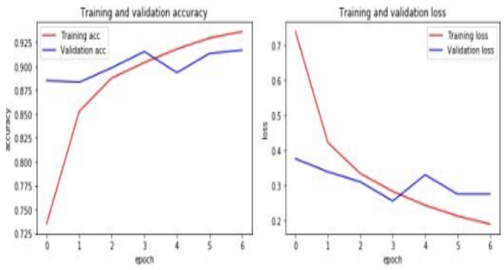
In this phase, when motion is detected, the user receives email and SMS notifications containing a captured image. The email is sent to the registered email ID, and the SMS is sent to the user's registered number on Telegram.

H. *Evaluation of System Performance*

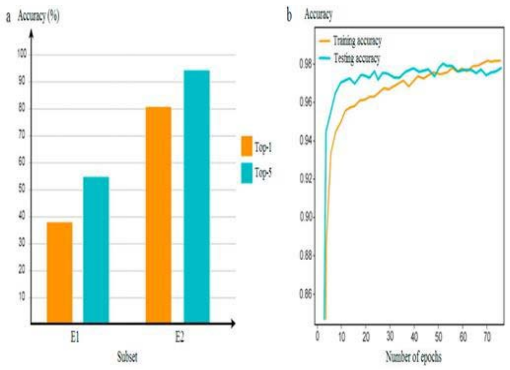
In this section, we assess the effectiveness of our system by measuring its accuracy in correctly categorizing data as either non-animal (negative class) or animal type (positive class) using three key performance indicators: Responsiveness, Specificity, and Precision. The calculations for these metrics are based on the True-Positive (TP), True-Negative (TN), False-Negative (FN), and False-Positive (FP) cases. TP represents the number of correctly identified positive cases, while FP represents the number of falsely identified negative cases. TN represents the number of correctly identified negative cases, and FN represents the number of falsely identified positive cases. The relevance of these performance metrics is analyzed within the scope of this project.

VI. Experimental Results

The generated charts in this module display the accuracy and loss during both the training and validation processes, for each iteration. The loss potential is calculated for each data item within the iteration, providing a quantitative measure of the loss at that specific iteration. The curve displayed during each iteration illustrates the loss of a portion of the complete dataset.



The project aims to create classifiers for endangered animal species by extracting appearance features of animals from the large dataset using the convolutional layers of a pre trained model. The images are then classified at the final layer of the model. Training and validation accuracy and loss graphs aregenerated to evaluate the performance of the classifiers.



The results of experiments conducted on dataset E2 demonstrate higher accuracy compared to the unbalanced dataset E1, achieving a Top-1 accuracy of 80.6% and Top-5 accuracy of 94.1% (as shown in Figure 7.2a). All training and a testing accuracy of plots for joints CNNs (Top 5) are also depicted depending on the numbers of epoch. Two experiments were performed, with the first using a single branch SVM without considering muzzle and shape features, and the second using the proposed joint CNN with decision-making rules. The resulting performance metrics, including Average-Precision (AP), Miss-Rate (MR), and False-Positives (FP), are presented in Tables 1 & 2 for a dataset (E2).

Compared to models trained from scratch, our proposed models demonstrate higher accuracy and require less time to perform tasks. This is particularly true for species with similar appearances because pre-trained models can already extract low-level features of new images. Additionally, using transfer learning eliminates the need for bounding box annotations, reducing the amount of manual work required. Assuming proper calibration, the Tfkeras-based model will be deployed effortlessly on an Android smartphone, and its potential can be broadened. It is anticipated that the precision of the model will maintained.

Animals	AP, %	MR,%	FP,%
Goat	76.96	13.3	15.8
Cow	84.67	10.5	15.7
Elephant	74.00	16.8	18.6
Deer	89.79	15.4	18.9
Horse	79.96	7.8	17.8
Pig	86.74	9.7	17.9

Animals	AP, %	MR,%	FP,%
Goat	78.86	7.4	15.9
Cow	85.8	9.8	16.8
Elephant	79.00	18.2	18.8
Deer	68.97	16.6	26.8
Horse	86.96	27.7	29.6
Pig	70.96	18.9	16.8

Thefile converter called Flat Buffer providedby TensorFlow Light is used.

VI. Conclusion

The increasing demand for agricultural farm security has led to the proposal and implementation of a vision-based system using Python and OpenCV, resulting in the development of a Creature Repellent System to protect crops from animals. A complex intelligent animal repelling mechanism was designed and developed for the system, which incorporates novel software components for real-time animal presence and species recognition to prevent crop damage. The edge computing device employs its DCNN Animal Recognition model to classify the detected animal, and if an animal is detected, it transmits a message to the Animal Repelling Module specifying the type of ultrasound to generate based on the animal's class. In this study, a CNN was tested on a custom animal dataset, with variations in the number of training andtesting images. The results demonstrated that increasing the number of input training images resulted in a higher recognition rate, with the

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proposed CNN achieving an accuracy of approximately 98%. The project aimed to address the problem of animal-induced crop damage by introducing a real-time AI monitoring system, which has the potential to assist farmers and agronomists in their management and decision-making processes.

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