AI-Powered Animal Repellent System for Smart Farming

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Abstract— **Agriculture automation is becoming more and more sophisticated, utilizing Deep Neural Networks (DNN) and the Internet of Things (IoT) to create and implement a wide range of fine-grained controlling, monitoring, and tracking applications. Managing the interaction with the factors outside the agricultural ecosystem, such wildlife, is a pertinent open topic in this quickly changing situation. One of the main concerns of today's farmers is protecting crops from wild animals' attacks. There are different traditional approaches to address this problem which can be lethal (e.g., shooting, trapping) and non-lethal (e.g., scarecrow, chemical repellents, organic substances, mesh, or electric fences). Nevertheless, some of the traditional methods have environmental pollution effects on both humans and ungulates, while others are very expensive with high maintenance costs, with limited reliability and limited effectiveness. In this project, we develop a system, that combines AI Computer Vision using DCNN for detecting and recognizing animal species, and specific ultrasound emission (i.e., different for each species) for repelling them.**

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

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. Taken together, these technical improvements constitute a technical revolution that will generate disruptive changes in agricultural practices. This trend holds for farming not only in developed countries but also in developing countries, where deployments in ICT (e.g., use of mobile phones, access to the Internet) are being adopted at a rapid pace and could become the game-changers in the future (e.g., in the form of seasonal drought forecasts, climate-smart agriculture).

II. LITERATURE REVIEW

Smart farming is a management concept focused on providing the agricultural industry with the infrastructure to leverage advanced technology – including big data, the cloud and the Internet of things (IoT) – for tracking, monitoring, automating and analyzing operations. Also known as precision agriculture, smart farming is software-managed and sensor- monitored. Smart farming is growing in importance due to the combination of the expanding global population, the increasing demand for higher crop yield, the need to use natural resources efficiently, the rising use and sophistication of information and communication technology and the increasing need for climate-smart agriculture.

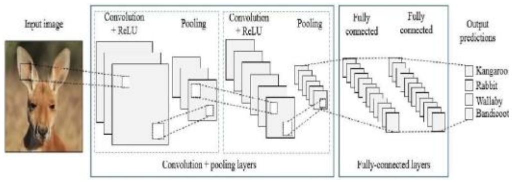
III. DESIGN IMPLEMENTATION

In this project, deep convolution neural network-based classification algorithm is devised to detect animals both in video and images. Proposed approach is a classification model based on different features and classifiers. The different features like colour, Gabor and LBP are extracted from the segmented animal images. Possibilities of fusing the features for improving the performance of the classification have also been explored. Classification of animals is accomplished using CNN and symbolic classifiers. Initially, features are extracted from images/frames using blink app pre-trained convolution neural network. Later the extracted features are fed into multi-class CNN classifier for the purpose of classification. CNN is constructed using sequence of layers like Convolutional, sub sampling and fully connected Layer.

IV. PROPOSED SYSTEM

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. DCNN and 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. A typical CNN architecture can be seen as shown in Fig.3.5. The structure of CNN contains Convolutional, pooling, Rectified Linear Unit (ReLU), and Fully Connected layers.

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.

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 thefeatures to a classifier that uses SoftMax activation function. The sum of output probabilities from the Fully Connected Layer is 1. This is ensured by using the SoftMax as the activation function.

IV. MODULAR DESCRIPTION

Dataset Description

Animals (Object) Detection dataset extracted using Google Open Images V6+. It contains about 700 medium quality animal images belonging to 7 categories: goat, pig, bear, sheep, cow, elephant, horse. Each class has a maximum of 120 images, with some classes having only 60 images. I resized every image to 224x224 to save on space.

Training Phase

This module begins by annotation of animal dataset. These templates then become the reference for evaluating and registering the templates for the other poses: tilting up/down, moving closer/further, and turning left/right.

Animal Image Acquisition:

ANIMAL-10N dataset contains 5 pairs of confusing animals with a total of 55,000 images. The5 pairs are as following: (cat, lynx), (jaguar, cheetah), (wolf, coyote), (chimpanzee, orangutan),(hamster, guinea pig). The images are crawled from several online search engines including Bing and Google using the predefined labels as the search keyword.

Pre-processing:

Animal Image pre-processing are the steps taken to format images before they are used by model training and inference. The steps to be taken are:

- Read image
- RGB to Grey Scale conversion
- Resize image Original size (360, 480, 3) —(width, height, no. RGB channels)Resized (220, 220, 3)
- Remove noise (Denoise) smooth our image to remove unwanted noise. We do this using gaussian blur.
- Binarization Image binarization is the process of taking a grayscale image and converting it to black-and-white, essentially reducing the information contained within the image from 256 shades of grey to 2: black and white, a binary image.

Animal Detection:

Therefore, in this module, 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.

Feature Extraction:

In feature extraction process, the useful information or characteristics of the image are extracted in the form of statistical, shape, color and texture features. The Transformation of the input image into features is called feature extraction. Features are extracted by using feature extraction techniques. Features are extracted based on texture, boundary, spatial, edge, transform, color and shape features. Shape-based features are divided into the boundary and region-based features. Boundary features are also called contour-based which uses boundary segments. Boundary based features are geometrical descriptors

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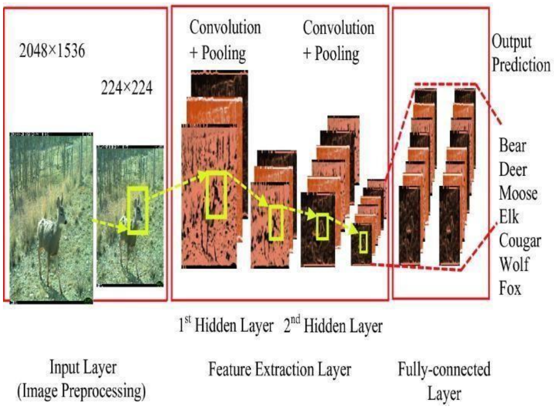
(diameter, major axis, minor axis, perimeter, eccentricity and curvature), Fourier descriptors and statistical descriptors (mean, variance, standard deviation, skew, energy and entropy). Region based features are texture features as GLCM.

Animal Classification:

DCNN algorithms were implemented to automatically detect and reject improper animal images during the classification process. This will ensure proper training and therefore the bestpossible performance.



The CNN creates feature maps by summing up the convolved grid of a vector- valued input to the kernel with a bank of filters to a given layer. Then a non- linear rectified linear unit (ReLU) is used for computing the activations of the convolved feature maps. The new feature map obtained from the ReLU is normalized using local response normalization (LRN). The output from the normalization is further computed with the use of a spatial pooling strategy (maximum or average pooling).

Animal Identification:

After capturing the animal image from the Farm Camera, the image is given to animal detection module. This module detects the image regions which are likely to be human. After the animal detection using Region Proposal Network (RPN), animal image is given as input to the feature extraction module to find the key features that will be used for classification. The module composes a very short feature vector that is well enough to represent the animal image.

Prediction:

In this module the matching process is done with trained classified result and test animal image with animal dataset classified file. Hamming Distance is used to calculate the difference according to the result the prediction accuracy will be displayed. Here, it is done with DCNN with the help of a pattern classifier, the extracted features of animal image are compared with the ones stored in the animal database. The animal image is then classified as animal type. If the animal is found corresponding repellent module is called.

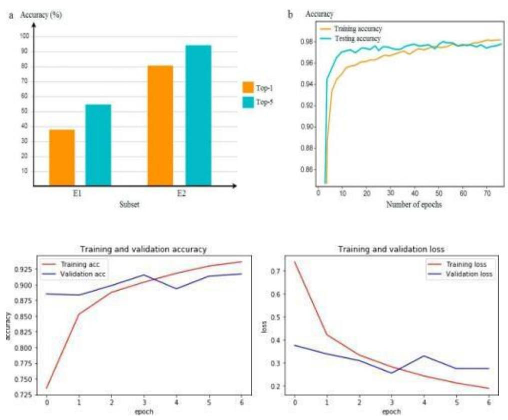
Repellent Integration:

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.

Monitoring and Visualizing:

The system works in real time detect the animals in the field, in addition the farmers can accessthe view of their fields remotely. Type of animal and also the count can be given. The animal recognition module will share the data over the cloud regularly through a Wi-Fi connection. The cloud setup will consist of a private cloud instance running on a machine. The data shared will be used to analyse the patterns and responses of wild animals. The farmer can visualize the errors if any, resolve them, and achieve better results.

Performance Analysis:



In this module we able to find the performance of our system using SENSITIVITY, SPECIFICITY AND ACCURACY of Data in the datasets are divided into two classes not animal (the negative class) and animal and type (the positive class). Sensitivity, specificity, and accuracy are calculated using the True positive (TP), true negative (TN), false negative (FN), and false positive (FP). TP is the number of positive cases that are classified as positive. FP is the number of negative cases that are classified as positive. TN is the number of negative cases classified as negative and FN is the number of positive cases classified as negative. The important points involved with the performance metrics are discussed based on the context of this project:

V. 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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