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Fortifying Fields Against Animals

Machine Learning Based Animal Repellent System for Farmers

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ABSTRACT

The rapid advancement of automation in agriculture has led to the development of various controlling, monitoring, and tracking applications. However, managing wildlife threats to crops remains an open challenge. This paper proposes a machine learning-based animal repellent system that combines computer vision using DCNN for animal detection and species recognition with specific ultrasound emissions to repel them. The edge computing device activates the camera, executes DCNN software for identification, and triggers ultrasound repellents based on the animal category.

Keywords: Animal Repellent for Farmers, Repellent, Animal Detection, Machine Learning, CNN, Agriculture.

INTRODUCTION

Agriculture has seen numerous revolutions, from animal and plant domestication to systematic breeding and the use of man-made fertilizers and pesticides. However, managing wildlife threats to crops is an ongoing challenge. Traditional approaches to protect crops from wild animals can be lethal, non-lethal, or involve the use of fences, repellents, and scare tactics. These methods have limitations, such as environmental pollution, high costs, limited reliability, and questionable effectiveness.

This paper proposes a machine learning-based animal repellent system that combines DCNN for animal detection and species recognition with ultrasound emissions tailored to each species, enabling farmers and agronomists to make informed decisions and manage their crops more effectively

RELATED SYSTEM

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.

Farmers Traditional Approach

There are different existing 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), firecrackers, bright lights, fire, beating drums, and dogs. Non-chemical control of pocket gophers. 22 rimfire rifle or a shotgun can be used to dispatch woodchucks. Some motion-activated water sprayers have been developed that spray birds when they break the motion-detecting

Agricultural fences

Fencing is a popular wild animal protection practice for that can last for many years. Agricultural fences are quite an effective wild animal protection technology. However, utilizing fences as a practice is often regulated. Some local and state entities may restrict or prevent the use of certain types of fences. Therefore, before deciding on a suitable fence, it's important to check local law regulations. The quality of fencing depends on the material and structure. Depending on how it is Some farmers prefer using natural protection made and what it is made of, some permanent fences can last up to 30 years. Farmers usually use one of the following types of fences:

Wire fences constructed of metal wires woven together forming a physical barrier. The fences are effective, long lasting, and require relatively little maintenance. However, they are expensive and recommended only for the protection of high-value crops.

Plastic fences polypropylene fences are generally less expensive and easier to install and repair than other types. Additionally, these fences are widely acceptable and meet various regulations. Their disadvantage includes their short lifespan (up to 10 years) and questionable effectiveness in areas with a higher possibility of wild animal crop damage.

Wire and Plastic Fence

Electric fences

These are constructed to inflict an electric shock to animals that come in contact with the fence, thus preventing animals from crossing the fence. These fences are long lasting and an effective crop protection measure. Costs vary depending on specific type and size of an area. Before purchasing electric fences, it's very important to make sure they are allowed for use in the specific area, and for protection against endangered animal species. Additionally, it's recommended that electric fences are marked with a warning sign to prevent any possible human contact.

Electric Fences **Natural Repellents**

measures instead of mechanical or chemical protective practices. There are various ways to protect crops from wild animals, including:

Smoke

In some areas farmers burn elephant dung or other materials that smolder and create heavy smoke

Beehive fencing

For instance, elephants are repelled by the sound of honey bees; this practice is beneficial as it serves as an extra source of income

Chili peppers

The chemical Capsaicin makes chili peppers hot; an excellent repellent against elephants, monkeys, squirrels, and some other wild animals; farmers who plant chili peppers will also benefit from an extra source of income

- Lavender, soybean, peas, and beans are excellent repellents against rabbits and are also an additional source of income
- Egg based repellent; homemade repellent against deer
- Castor oil natural repellent that keeps away burrowing animals such as moles

Beehive fence

Chemical repellents; active substances such as Anthraquinone, Butanethiol, and Methyl Anthranilate can be used to keep wild animals away from crops

Biophysical barriers; fences made of bamboo sticks, coconut tree bunches, or some other available shrubs; lowcost practice but also low efficiency in protecting crops against wild animals

Electronic repellents; effective, long lasting, and eco-friendly method for crop protection that repels animals without harming them. Farmers use one of the following two types of electronic repellents:

Ultrasonic Electric Animal Repellent

Ultrasonic electronic repellent - silent to humans, high-frequency sound waves repel wild animals

Sonic electronic repellent - audible noise that scares animals

Existing Sensor based animal intrusion detection system

PIR and IoT

IOT- based animal intrusion detection system. PIR (Passive infrared sensor) detects the movement and triggers the camera to take the animal image, once the animal is detected by the sensor the signal is passed to the camera via a microcontroller Arduino Uno. The image is classified with the sample images which is stored in the database.

RFID and GSM

Intrusion recognition in farmland through a wireless sensor network (WSN) technology. The motion sensor is placed at various locations to sense the movement and communicate to the organizer via Radio frequency transceiver. The detection raises then the organizer sends an alert call to the farm owner mobile through the Global System for Mobile (GSM) module. An Arduino board is fixed near the centralized sensor and the GSM module will be the interface along with buzzers and RFID transmitter. To differentiate authorized and unauthorized entries in farmland Radio-frequency identification (RFID) tags are used.

Existing animal intrusion system using image processing techniques

HoG

Weighted Co- occurrence Histograms of Oriented Gradients (W-Co HOG) feature vector to recognize animal. Histogram equalization is performed to reduce noise, distortions and to enhance the highlighted region of interest. The gradients are calculated in magnitude and direction is represents to convert into eight orientations. Sliding window techniques identify animals in different sizes with zoom level of the camera.

LBP and SIFT

Automated species recognition method using local cell-structured LBP (Local Binary Pattern) feature and global dense SIFT (Scale- invariant Feature Transform) descriptor for feature extraction and improvise (Sc SPM) sparse coding spatial pyramid

matching to extract dense SIFT descriptor and cell-structured LBP as a local feature. Global features generate max pooling and weighted sparse coding using multi-scale pyramid kernel.

SVM

Animal intrusion detection system based on image processing and machine learning approach. The image of an animal is segmented using a watershed algorithm to extract various objects in the image and to examine that if any threat animal is found in segmentation. This algorithm is to create a barrier which is the contour only when the marked region meets different markers. Gabor filter is extensively used in extracting a region with text to recognize facial expression in various frequencies. Linear SVM is a supervised learning algorithm to train the dataset and to classify text and hypertext.

Disadvantages

- Its disadvantages include the potential for the entire fence to be disabled due to a break in the conducting wire, shorting out if the conducting wire contacts any non-electrified component that may make up the rest of the fence, power failure, or forced disconnection due to the risk of fires starting by dry vegetation touching an electrified wire.
- Other disadvantages can be lack of visibility and the potential to shock an unsuspecting human passer-by who might accidentally touch or brush the fence
- Bee fence disadvantages are that it is only restricted to elephants and humans can also become targets of the bees
- Percentage of all intrusions in the detection area that was detected was relatively low
- Sensor Failure
- Expensive

PROPOSED SYSTEM

The proposed system utilizes DCNN, a type of feed-forward neural network, to perform animal recognition. The architecture consists of Convolutional, Pooling, ReLU, and Fully Connected Layers. The Convolutional Layer extracts features from input data (images), while the Pooling Layer reduces dimensionality. ReLU introduces non-linearity, and the Fully Connected Layer classifies input images into various classes based on the training dataset.

Ultrasound emissions are used to repel animals, as they have a higher sound sensitivity threshold than humans. Generating ultrasounds within the critical perceptible range causes animals to move away from the sound source without affecting humans.

DCNN

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.3.1. The structure of CNN contains Convolutional, pooling, Rectified Linear Unit (ReLU), and Fully Connected layers.

CNN

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 downsampled 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. 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 Re LU 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 Re LU 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. This is ensured by using the SoftMax as the activation function. The SoftMax function takes a vector of arbitrary real-valued scores and squashes it to a vector of values between zero and one that sum to one.

Generation of Repelling Ultrasound 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. Generating ultrasounds within the critical perceptible range causes animals to be disturbed, thus making them move away from the sound source. At the same time, these ultrasounds are not problems to the human ear even when the frequency range is beyond the human ear. The human eardrum has a far lower specific resonant frequency than animals and cannot vibrate at ultrasound frequency.

Notification System

The detection system recorded the date and time of each detection. In addition, there were cameras and a video recording system that recorded all animal movements within the enclosure. The detection log was compared to the images from the cameras, which also had a date and time stamp, to investigate the reliability of the system . electric shocks.

A message alert is sent to the registered mobile number.

Advantages

- Wide area surveillance
- Accurate and Fast prediction
- Cost effectiveness of available Crop protection systems.
- Easy to use and with less maintenance.
- Robust and reliable system.
- Complete security or full proof system.
- Less or no labor requirement.

- Easily adaptable by the farmers
- Remote Monitor
- Low energy consumption
- Warns and tracks
- Fully automated system
- Integra table with third-party cameras

IV Modules List

1. Animal Repellent Web Dashboard
2. Animal Recognition
3. Repellent
4. Monitoring and Visualizing
5. Notification
6. Performance Analysis

Module 1:

Animal Repellent Web Dashboard

Animal Repellent Web Dashboard This system works in real time to detect animals in the fields. The system enables the farmer to have a real-time view of his fields from any place via the internet and even provides manual buzzer controls if needed. This system is economical as compared to many of the existing solutions like electric fences, brick walls, and manual supervision of the fields. This system is very effective in driving off animals from the fields and keeping them away. It accurately determines the presence of animals in the fields and sounds the buzzer. It does not sound the buzzer due to the presence of a human being or due to some random motion. The ultrasonic buzzer is very effective against animals and causes no noise pollution. This system is totally harmless and doesn't injure animals in any way. It also doesn't cause any harm to humans. Additionally, this system has a low power requirement, reducing hazards.

Module 2:

Animal Recognition

2.1. Training & Test Data Annotation

This module begins by annotation of animal dataset.

2.2. Preprocessing

- 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. using gaussian blur.
- Binarization

2.3. Animal Detection

Therefore, in this module, Region Proposal Network generates by sliding windows on the feature map through anchors with different scales and different aspect ratios.

2.4. Feature Extraction

After the animal detection, animal image is given as input to the feature extraction module to find the key features that will be used for classification.

2.5. Animal Type Classification

DCNN algorithms were implemented to automatically detect and reject improper animal images during the classification process.

2.6. Prediction

In this module the matching process is done with trained classified result and test animal

Module 3:

Animal Identification

After capturing the animal image from the Farm Camera, the image is given to the animal detection module. This module detects the image regions which are likely to be animals. After the animal detection using Region Proposal Network (RPN), the 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 false positive (FP). True positives (TP) are the number of positive cases classified as positive, while false negatives (FN) are the number of positive cases classified as negative.

Module 4:

Repellent

The monitoring window detects the presence of animals, enabling the repeller module to repel 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.

Module 5:

Monitoring and Visualizing

The system works in real time to detect animals in the field. Farmers can access the view of their fields remotely. The animal recognition module will share 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 analyze the patterns and responses of wild animals. The farmer can visualize the errors if any, resolve them, and achieve better results.

Module 6:

Notification

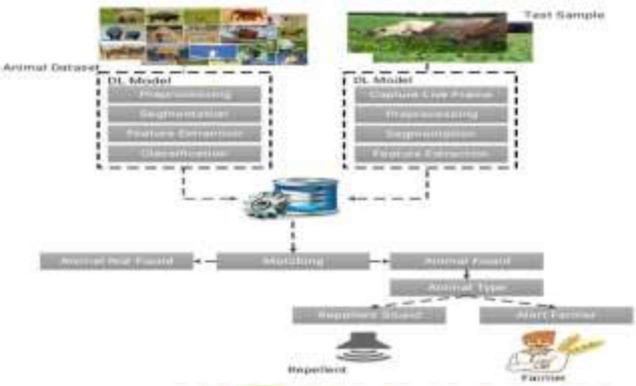
The email and SMS notification consisting of captured images is notified to the user regarding the detected motion in this phase. The email is sent to the registered email ID, and SMS is sent to the Telegram account of the user to the registered number.

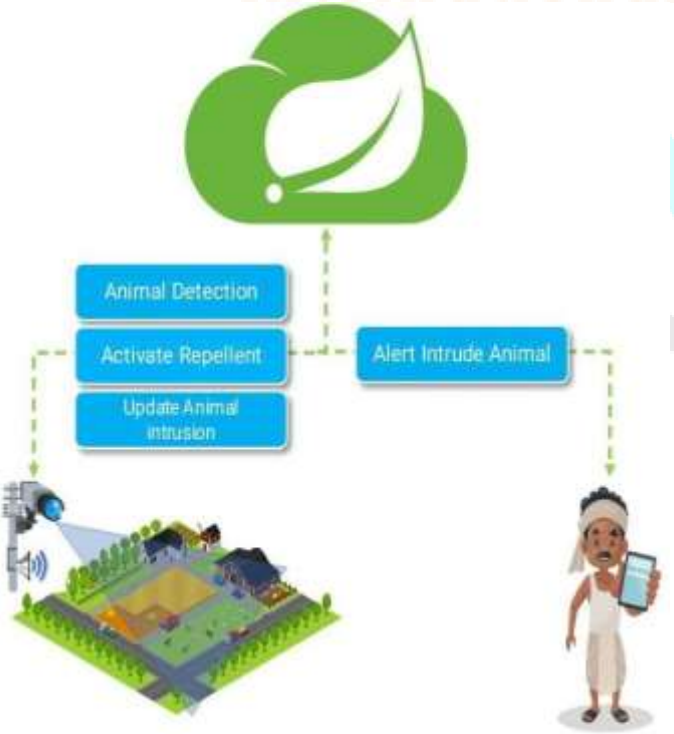
Module 7:

Performance Analysis

Performance Analysis In this module, we can find the performance of our system using Sensitivity, Specificity, and Accuracy of data in the datasets 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 number of negative cases that are classified as positive.

SYSTEM ARCHITECTURE





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 to develop 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 recognizing 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 numbers 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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