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TRENDS OF DATA ENDANGERED SPECIES USING LOGISTIC REGRESSION ALGORITHM

[1]Dr.E.Kamalanaban,B.E.,M.E.,Ph.D., , [2]M.A.Parthiban B.TECH,M.E.,

[3]Teja Kumar M.S , [4]Sandeep Vasan S , [5]Yeshwanth R

[1]Principal, [2]Assistant Professor, [3]UG Scholar [4]UG Scholar [5]UG Scholar
[1]Department of Computer Science and Engineering,
[1]Vel Tech High Tech Dr. Rangarajan Dr.Sakunthala Engineering College, Avadi, Chennai. 600062

Abstract : Crop raiding by animals hasbecome one of the most common human animal disputes as a result of human encroachment of wildlife habitats anddeforestation. Wild animals can cause significant damage to agricultural crops and attack farmers working in the field. Farmers suffer huge crop loss due to cropraiding by wild animal like elephants, wild boar and deer. One of the main concerns of today's farmers is protecting crops fromwild 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). In this project, deep convolution neural network-based classification algorithm is devised to detect animals both in video and images. The Algorithm detects and classifies the animal which has been captured by the monitoring panel and calculates the accuracy in percentage based on number of matched objects. If the accuracy of detected animal is above 45% the alert signal will be sent to the registered user through the SMS Service Provider.

IndexTerms - Animal Recognition, Repellent, Artificial Intelligence, Edge Computing, Animal Detection, Deep Learning, DCNN.

I. INTRODUCTION

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

Fig 1.Agriculture and ICT innovation

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.

SMART FARMING

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.

SMART FARMING TECHNOLOGIES:

- Sensors for soil scanning and water, light, humidity and temperature management.
- Telecommunications technologies such as advanced networking and GPS.
- Hardware and software for specialized applications and for enabling IoT-based solutions, robotics and automation.
- Data analytics tools for decision making and prediction. Data collection is a significant part of smart farming as the quantity of data available from crop yields, soil-mapping, climate change, fertilizer applications, weather data, machinery and animal health continues to escalate.
- Satellites and drones for gathering data around the clock for an entire field. This information is forwarded to IT systems for tracking and analysis to give an "eye in the field" or "eye in the barn" that makes remote monitoring possible.

Fig2. Detection Architecture

II.RELATED WORKS

The use of passive acoustic monitoring in wildlife ecology has increased dramatically in recent years as researchers take advantage of improvements in autonomous recording units and analytical methods. These technologies have allowed researchers to collect large quantities of acoustic data which must then be processed to extract meaningful information, e.g., target species detections. A persistent issue in acoustic monitoring is the challenge of efficiently automating the detection of species of interest, and deep learning has emerged as a powerful approach to accomplish this task [1].

The implemented smart agriculture system is cost effective for maximizing agricultural farm water supplies, crop prediction, and wild animal prevention. Depending on the level of soil moisture, the proposed system can be used to turn the water sprinkler on / off, thereby making the process easier to use. The system proposed can be used to predict the crop based on the soil condition which helps the farmer grow the proper crops at proper time . Through this system it can be inferred that use of IOT and Automation there by achieving significant progress in irrigation [2].

A foundational step of any animal is the establishment of an accurate behavioural model. Building a model that is capable of defining and predicting an animal's behaviour is critical to advancing ethological theory and research, however many animal models fail to be sufficiently thorough or often do not exist at all. Great pools of data are available for improving these models through recorded video of animals posted on video hosting sites throughout the internet, however these sources are largely left unused due to their sheer quantity being too much for researchers to manually observe and annotate [3].

Numerous classification techniques can be used for classification purposes, and the classification commonly can be done acoustically and visually. The classification systems are playing a considerable role, and bioacoustics monitoring was a significant field. Visual classification of animals is done by using either satellite images or established camera images. Nevertheless, due to some

circumstances, image processing techniques cannot be applied. Then the acoustical classification techniques are taken place to encounter those problems. Even with acoustical methods, a remote observing method is required due to a few issues. Applying an

IoT based acoustic classification system was designed using Convolutional Neural Networks (CNN), which is beneficial for those who are interested in monitoring ecosystems such as animal scientists, zoologists, and environmentalists [4] .

This article presents a method for classifying animal vocalizations using four Siamese networks and dissimilarity spaces. Different clustering techniques taking both a supervised and unsupervised approach were used for dissimilarity space generation. A compact descriptor is obtained by projecting each pattern into the dissimilarity spaces generated by the clustering methods using different numbers of centroids and the outputs of the four Siamese networks. The classification step is performed using a set of SVMs trained from such descriptors and combined by sum rule to obtain a highly competitive ensemble as tested on two datasets of animal vocalizations. In addition, experimental results demonstrated the diversity between the proposed approach and other state-of- the-art approaches can be exploited in an ensemble to further improve classification performance. The fusions improved performance on both audio classification problems, outperforming the standalone approaches [5].

III. TOOLS AND REQUIREMENTS

Server Side : Python 3.7.4
Client Side : HTML, CSS, Bootstrap
IDE : Flask 1.1.1
Back end : MySQL 5.

IV.EXISTING SYSTEM

Wild animals are a special challenge forfarmers throughout the world. Animalssuch as deer, wild boars, rabbits, moles, elephants, monkeys, and many othersmay cause serious damage to crops There are different existing approaches toaddress this problem which can be lethaland non-lethal

Agricultural fences: Agricultural fencesare quite an effective wild animal protection technology. However, utilizing fences as a practice is often regulated.

Natural Repellents: Some farmers prefer using natural protection measures insteadof mechanical or chemical protective practices. There are various ways to protect crops from wild animals.

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

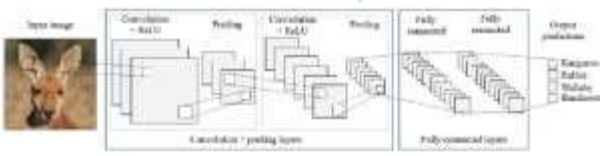
Biophysical barriers: fences made of bamboo sticks, coconut tree bunches, or some other available shrubs; low-cost practice but also low efficiency inprotecting crops against wild animals

Electronic repellents: effective, long lasting, and eco-friendly method for crop protection that repels animals without harming them.

V. PROPOSED SYSTEM

AI Computer Vision based DCNN for detecting animal species, and specificultrasound emission (i.e., different foreach species) for repelling them .design, deployment and assessment of anintelligent smart agriculture repelling and monitoring IoT system based onembedded 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

Key components of proposed system includes:



A. 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.

B. 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.

C. 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.

D. 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 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.

E. 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. In addition, such solution is non-lethal and has no effect of environmental pollution, no impact on the landscape.

F. 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. A message alert is sent to the registered mobile number.

VI. METHODOLOGY

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 color, 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, subsampling and fully connected Layer.

Overall procedure for animal detection is given below:

1. The image is fetched using the monitoring panel.
2. The fetched image is processed using the python coding.
3. The fetched image is checked for various features of objects that match with any animal of trained data set.
4. Then it detects and classifies the animal which has been captured by the monitoring panel.
5. Algorithm calculates the accuracy in percentage based on number of matched objects.
6. If the accuracy of detected animal is above 45% the alert signal will be sent to the registered user through the SMS Service Provider.

DCNN MODEL

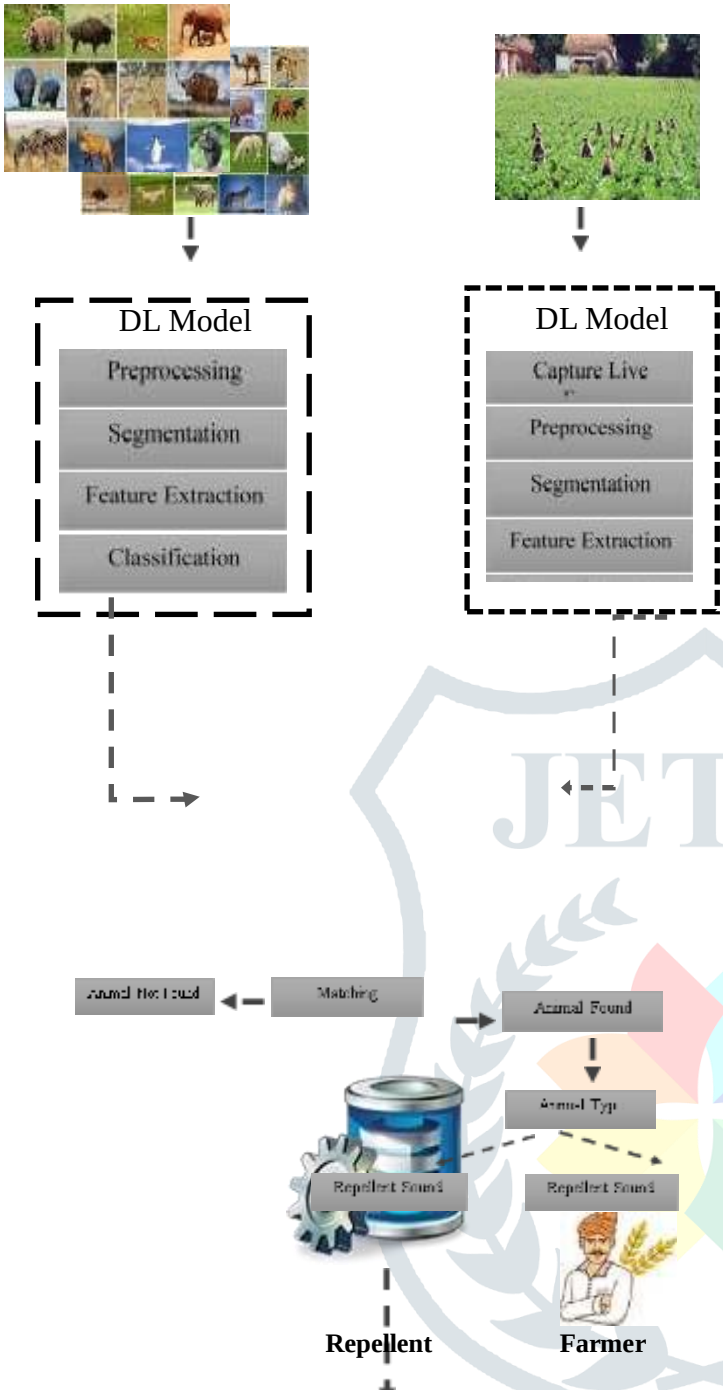


Fig 3. DCNN Model

VII. OUTPUT AND RESULT

Fig 4. Home Page

Fig 5. Admin Login

Fig 6.Admin Data Training

Fig 7.Training

Fig 8: Trained Images

Fig 9. User (Farmer) Login/Signup

Fig 10: Animal Prediction

VIII. CONCLUSION

Agricultural farm security is widely neededtechnology nowadays. In order to accomplish this, a vision-based system is proposed and implemented using Python and Open CV and developed an Animal Repellent System to blow out the animals.The proposed CNN was evaluated on the created animal database. The overallperformances were obtained usingdifferent number of training images and test images. The obtained experimentalresults of the performed experimentsshow 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 using Open CV can help farmers and agronomists in their decision making and management process.

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