

## CAMERA VISION BASED ANIMAL BEAT BACK SYSTEM FOR AGRICULTUE USING MACHINE LEARNING

DHARMADURAI N(1903010)  
Department Of Computer Science And Engineering  
PSN College Of Engineering And Technology  
Tirunelveli.

Dr.Radhakrishnan,  
Assistant Professor,  
Department Of Computer Science And Engineering,  
PSN College Of Engineering And Technology,  
Tirunelveli.

**Abstract**—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 hyperspectral 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.

### INTRODUCTION

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)

**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 analysing 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

**Problem Identified:** Most farmers have challenges related to crop damage due to wildlife pests. Animal intrusion is a major threat to the productivity of the crops, which affects food security and reduces the profit to the farmers. Organic farmers have additional challenges because they cannot use chemical controls which are sometimes the most effective and efficient options. A need has been identified for alternative pest control appropriate for traditional and organic farmers. Three types of animal intrusion you might find include animal tracks, crop damage and animal scat or faeces. In the case of animal tracks, only one instance of tracks in the field carries a relatively low risk. On the other hand, sporadic or widespread animal tracks carry a moderate risk, and a no-harvest buffer zone may need to be created around nearby crops. Crop damage, such as bite marks or trampled plants, is riskier than animal tracks. Sporadic evidence, such as a few observations of trampled plants throughout the field, is moderately risky. Widespread crop damage is a high risk and indicates significant evidence of contamination. Marking and avoiding harvest around high-risk areas of crop damage is a good strategy to reduce the potential for contamination. Risks associated with faecal matter in the field are the highest. For even just one instance of faecal matter, the risk of contamination is moderate. Widespread evidence of faecal contamination is very high risk and would justify marking the contaminated area and creating a no-harvest buffer zone around the area where significant faeces was found. Animal activity on the farm can be a huge risk to food safety when growing fruits and vegetables, which is why preharvest wildlife scouting is so important. Existing methods like fencing can be an effective deterrent, but it may not be practical for larger farms;

however, small portions of fencing may direct animals around high value or sensitive crops to other areas and electric fences are no longer efficient in solving such conflicts, to protect their crops from getting damaged because of animal intrusions, farmers have been using electric fences around their fields and areas where the fencing don't prove efficient, farmers prefer to stay up all night and guard their fields from animal intrusions. Nuisance permits may be another option, but check with local Department of Environmental Conservation (DEC) or the National Resources Conservation Service (NRCS) before choosing this method. Practices like these have done more harm than good for us and in extreme cases, it has even costed lives of both man and animals. so, we decided to come up with a smarter solution that could protect the crops from animal intrusions without causing any harm to the wildlife. To solve this conflict by using technology such as IoT and Deep learning, which is called AIoT (Artificial Intelligence for the Infrastructure of Internet of Things).

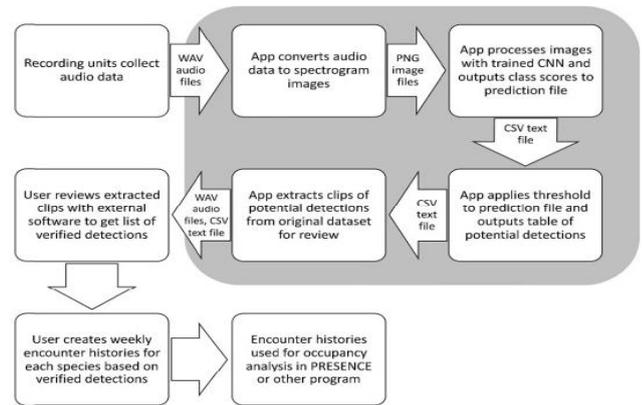
**Objective:** The main aim of the current work is to develop a device to protect crops from damage by wild animals by diverting them from the farms, without harming them physically. The objective of the project is to design, deployment and assessment of an intelligent smart agriculture repelling and monitoring IoT system based on embedded edge AI, to detect and recognize the animals, as well as generate ultrasonic signals tailored to each species of the animals. Untamed life checking and investigation are in dynamic research fields since last numerous decades. This work mainly concentrates on creature identification from common scenes gained by camera and intimates the farmland owner and also stored the images in the camera trap database. This camera trap database is utilized to track the animals which enter into the farm land and damaging the crops.

## I. LITERATURE SURVEY

### 1. Workflow and convolutional neural network for automated identification of animal sounds

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. This article reports on the development and application of a deep convolutional neural network for the automated detection of 14 forest-adapted birds and mammals by classifying spectrogram images generated from short audio clips. This article proposes a multi-step workflow that integrates this neural network to efficiently process large volumes of audio data with a combination of automated detection and human review. This workflow reduces the necessary human effort by > 99% compared to full manual review of the data. As an optional component of this workflow, this article proposed a graphical interface for the neural network that can be run through RStudio using the Shiny package, creating a portable and user-friendly way for field biologists and managers to efficiently process audio data



and detect these target species close to the point of collection and with minimal delays using consumer-grade computers.

### 2. Real-Time Monitoring of Agricultural Land with Crop Prediction and Animal Intrusion Prevention using Internet of Things and Machine Learning at Edge. Authors: R. Nikhil; B.S. Anisha; Ramakanth Kumar P.

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. The proposed system is thus a solution to the problems facing in current irrigation cycle. The proposed system also helps in the prevention of trespassing wild animals in the agricultural sector. Using ultrasonic sound, the buzzer irritates wild animals and makes them leave the area. Using the alarm tone flooding techniques which requires less energy. In addition to that the device is eco-friendly, because there is no harm to the ecosystem and no disruption to humans.

### 3. Animal Behaviour Prediction with Long Short-Term Memory. Authors: Henry Roberts; Aviv Segev

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. This article proposed a pipeline approach for efficiently developing predictive behavioural models using a confluence of machine learning tools. Accuracy in prediction and its significance against a much longer standing time-series analysis statistical model. The results of testing proposed pipeline showed promise in that the LSTM network, trained on the JAABA annotated frames of animal behaviour and classifier function results, was able to outperform the

ARIMA model.

**Existing 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.

### 1. Agricultural fences

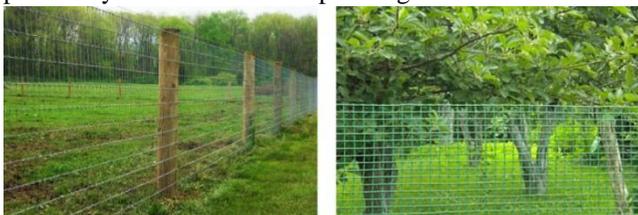
Fencing is a popular wild animal protection practice for that can last for many years. Agricultural fences are quite an effective wild animal protection technology. However, utilizing fences as a practice is often regulated. Some local and state entities may restrict or prevent the use of certain types 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 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:

### 2. 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 crop.

### 3. 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.



**2. 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.

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

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

5. 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.

**HoG: Weighted Co- occurrence Histograms of Oriented Gradients (W-CoHOG)** 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 (ScSPM) 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

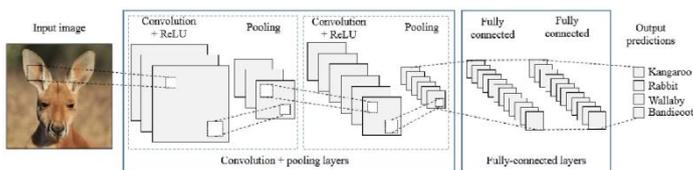
Its disadvantages include the potential for the entire fence to be disabled due to a break in the conducting wire, shorting out if the conducting wire contacts any non-electrified component that may make up the rest of the fence, power failure, or forced disconnection due to the risk of fires starting by dry vegetation touching an electrified wire.

## II. 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:

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.



**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.

**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.



**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..

**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.



**Problem Description:**

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.

corresponding to the anchor point of the feature map.

**Feature Extraction**

In feature extraction process, the useful information or characteristics of the image are extracted in the form of statistical, shape, colour 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, colour 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 (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.

**1. Animal Repellent Web Dashboard:**

This system works in real time to detect the animals in the fields. The system enables the farmer to have a real time view of his fields from any place via internet and even provides manual buzzer controls if the need arises to use them. Thus, the farmer is in effective control of the system and can manually sound the buzzer 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 the 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. Also, this system has a very low power requirement thus reducing the hazards of electric shocks.

**2. Animal Recognition:**

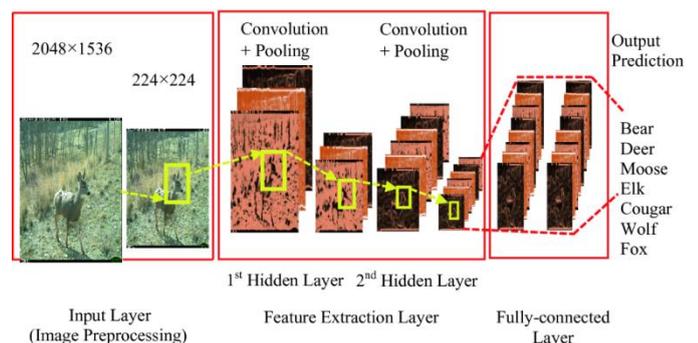
This module begins by annotation of animal dataset. These templates then become the reference for evaluating and registering the templates for the other poses: tilting up/down, moving closer/further, and turning left/right.

**Animal 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.

A Region Proposal Network, or RPN, is a fully convolutional network that simultaneously predicts object bounds and objectless scores at each position. The RPN is trained end-to-end to generate high-quality region proposals. It works on the feature map (output of CNN), and each feature (point) of this map is called Anchor Point. For each anchor point, we place 9 anchor boxes (the combinations of different sizes and ratios) over the image. These anchor boxes are centered at the point in the image which is

**Gray Level Co-occurrence Matrix:**

[1] GLCM is a second-order statistical texture analysis method. It examines the spatial relationship among pixels and defines how frequently a combination of pixels are present in an image in a given direction  $\Theta$  and distance  $d$ . Each image is quantized into 16 gray levels (0–15) and 4 GLCMs (M) each for  $\Theta = 0, 45, 90,$  and  $135$  degrees with  $d = 1$  are obtained. From each GLCM, five features (Eq. 13.30–13.34) are extracted. Thus, there are 20 features for each image. Each feature is normalized to range between 0 to 1 before passing to the classifiers, and each classifier receives the same set of features. The features we extracted can be grouped into three categories. The first category is the first order statistics, which includes maximum intensity, minimum intensity, mean, median, 10th percentile, 90th percentile, standard deviation, variance of intensity value, energy, entropy, and others. These features characterize the Gray level intensity of the tumour region.



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). Then, the use of dropout

regularization scheme is used to initialize some unused weights to zero and this activity most often takes place within the fully connected layers before the classification layer. Finally, the use of softmax activation function is used for classifying image labels within the fully connected layer.

## 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 realtime 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.

## FUTURE ENHANCEMENT

Further in the proposed architecture, some image compression techniques can be developed to reduce the time taken for notification to reach user as described above.

## REFERENCE

- [1] M. De Clercq, A. Vats, and A. Biel, "Agriculture 4.0: The future of farming technology," in Proc. World Government Summit, Dubai, UAE, 2018, pp. 11-13.
- [2] Y. Liu, X. Ma, L. Shu, G. P. Hancke, and A. M. Abu-Mahfouz, "From industry 4.0 to agriculture 4.0: Current status, enabling technologies, and research challenges," IEEE Trans. Ind. Informat., vol. 17, no. 6, pp. 4324-4334, Jun. 2021.
- [3] M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, "A survey on the role of IoT in agriculture for the implementation

of smart farming," IEEE Access, vol. 7, pp. 156237-156271, 2019.

- [4] K. Kirkpatrick, "Technologizing agriculture," Commun. ACM, vol. 62, no. 2, pp. 14-16, Jan. 2019.
- [5] A. Farooq, J. Hu, and X. Jia, "Analysis of spectral bands and spatial resolutions for weed classification via deep convolutional neural network," IEEE Geosci. Remote Sens. Lett., vol. 16, no. 2, pp. 183-187, Feb. 2018.
- [6] M. Apollonio, S. Ciuti, L. Pedrotti, and P. Banti, "Ungulates and their management in Italy," in European Ungulates and Their Management in the 21st Century. Cambridge, U.K.: Cambridge Univ. Press, 2010, pp. 475-505.
- [7] A. Amici, F. Serrani, C. M. Rossi, and R. Primi, "Increase in crop damage caused by wild boar (*Sus scrofa* L.): The refuge effect," Agronomy Sustain. Develop., vol. 32, no. 3, pp. 683-692, Jul. 2012.
- [8] S. Giordano, I. Seitanidis, M. Ojo, D. Adami, and F. Vignoli, "IoT solutions for crop protection against wild animal attacks," in Proc. IEEE Int. Conf. Environ. Eng. (EE), Mar. 2018, pp. 1-5.
- [9] M. O. Ojo, D. Adami, and S. Giordano, "Network performance evaluation of a LoRa-based IoT system for crop protection against ungulates," in Proc. IEEE 25th Int. Workshop Comput. Aided Modeling Design Commun. Links Netw. (CAMAD), Sep. 2020, pp. 1-6.
- [10] H. E. Heffner and R. S. Heffner, "Auditory perception," in Farm Animals and the Environment, C. Phillips and D. Piggins, Eds. Wallingford, U.K.: CAB International, 1992.
- [11] <https://www.indiatimes.com/news/india/in-the-battle-between-man-vs-wild-highways-railway-lines-emerge-as-new-challenges-375504.html>
- [12] <https://adventuresinmachinelearning.com/neural-networks-tutorial/>
- [13] <https://github.com/tensorflow/model>