

(A High Impact Factor, Monthly, Peer Reviewed Journal) Visit: <u>www.ijirset.com</u> Vol. 8, Issue 6, June 2019

# Smart Security and Monitoring System for Agriculture: Overview

Rahul Viswanath C<sup>1</sup>, Raniya A<sup>2</sup>, Surya K S<sup>3</sup>, Thushardath E P<sup>4</sup>, Prasad R Menon<sup>5</sup>

U.G. Student, Department of Electronics and Communication Engineering, NSS College of Engineering, Kerala, India<sup>1</sup> U.G. Student, Department of Electronics and Communication Engineering, NSS College of Engineering, Kerala, India<sup>2</sup> U.G. Student, Department of Electronics and Communication Engineering, NSS College of Engineering, Kerala, India<sup>3</sup>

U.G. Student, Department of Electronics and Communication Engineering, NSS College of Engineering, Kerala, India<sup>4</sup>

Assistant Professor, Department of Electronics and Communication Engineering, NSS College of Engineering,

Kerala, India<sup>5</sup>

**ABSTRACT:** This paper presents a solution for the rodent attacks leading to massive crop destruction in the agricultural sector. Agricultural products need safety and protection at very initial stages, like protection from attacks of rodents or insects, in field or grain stores. Security systems which are currently used are not smart enough to provide real-time notification after identifying the problem. This project solves problems like identification of rodents, crop damage and delivering real-time notification based on data analysis and processing without human intervention as the device can be controlled and monitored from a remote location. It can be implemented in agricultural fields, grain stores, and cold stores for security purposes.

**KEYWORDS:** Internet of Things(IOT); Raspberry Pi; Sensors; Convolutional Neural Network(CNN); Deep learning

### I. INTRODUCTION

The Agriculture sector in India is declining day by day which affects the production capacity of the ecosystem. There is an urgent need to solve the problem in the domain to restore vibrancy and put it back on higher growth. The notable challenge associated with security in agriculture is the interaction between security devices and to provide the intelligence acquired from learning and experience to control other electronic devices such as cameras, repellers, etc. to enhance security in various fields[9]. The security and monitoring systems must be responsible for transmitting data over the network, analyzing the information and notify the user with real-time information of surroundings.

The lack of information transmission and data analyzing has been "solved" by the integration of the internet of things with currently available security devices in order to achieve efficient food preservation and productivity. Although the food crop loss and debilitation of diseases are due to various threats such as rodents, pests, insects and grain pathogens. This research is the designing and analyzing of security device, considering depreciation to post-harvest crop by rodents and grain stores as applicable area [1].



(A High Impact Factor, Monthly, Peer Reviewed Journal)

### Visit: <u>www.ijirset.com</u>

#### Vol. 8, Issue 6, June 2019

#### II. RELATED STUDY

The aim of the project is to find an optimised solution for rodent attacks and to enhance productivity in farms. Various security approaches are being developed for the same cause.

According to a research in crop's security, developing countries, which makes use of traditional storage facilities for food crops, fails to protect them, leading to 20-30% loss of agricultural products such as rice, corn, etc[6]. Existing solutions focus only on insects, pests and grain pathogens. In Asia, there 5 to 10% loss in rice crops on average, due to damage caused by rodents[9], [10].Rodent-borne diseases are also a major cause of concern. In Asian and Pacific countries death rate due to rodent-borne diseases is higher compared to HIV-AIDS.

Animal detection and identification with deep neural networks for automated wildlife monitoring [2] proposed by Hung Nguyen, Sarah J. Maclagan, Tu Dinh Nguyen, Thin Nguyen, Paul Flemons, Kylie Andrews, Euan G. Ritchie and Dinh Phung mainly focuses on animal recognition in the wild, aiming at a fully automatic wildlife spotting system. It is performed by means of deep CNN models for image classification. Since the Wildlife dataset includes both animal and non-animal images, the wild animal identifying automation is divided into two subsequent tasks: Wildlife detection and Wildlife identification. A binary classifier capable of classifying input images into two classes: "animal" or "no animal" based on the prediction of animal presence in images is used for wildlife detection. Wildlife identification uses a multiclass classifier to label each input image by a specified species. Models hence developed provided high accuracy results.

**PROJECT DESCRIPTION** 

III.



#### FIg. 1. Block diagram

The whole idea of eradication of farm rodents is implemented in 2 sections. The first section focuses on rodent(rat, dog, etc) repulsion, while the second section deals with the detection of larger animals(elephant, pig, etc) and real-time farmer notification. The block diagram is shown in Fig. 1.



(A High Impact Factor, Monthly, Peer Reviewed Journal)

### Visit: <u>www.ijirset.com</u> Vol. 8, Issue 6, June 2019

### A. Sensing and Repelling Circuit

Sensors like PIR and ultrasonic are to detect and repel rodents like rat and mice which are sensitive to ultrasonic waves. PIR sensor acts as a motion detector and detects the presence of smaller animals like rat, mice, etc. Once the PIR sensor is activated, the output pulse is used as a trigger to activate the ultrasonic sensor, which is controlled by LM358(Fig. 1), acting as a comparator. Ultrasonic waves hence generated aids in the eradication of smaller rodents. A led is used parallel to the ultrasonic sensor to indicate the on-off state of the ultrasonic sensor.

### B. Intruder Animal Detection and Identification

The second section deals with image classification. The Pi camera captures real-time video of moving animals like an elephant. Image classification tools are used to identify the animal. Once the presence of an intruding animal is detected, a notification indicating the kind of animal is sent to the farmer, which is implemented using Twilio IoT platform.Deep

learning and convolutional neural networks(CNN) are being used to implement the animal detection part. Various concepts being employed are:

- Deep Learning: Deep learning is an extension of machine learning that teaches computers to "learn by example" [8]. Voice control in phones, tablets, TVs is based on Deep Learning. It enables driverless cars to recognize a stop sign, distinguish between pedestrian and lamp post. A computer model based on deep learning performs image, text or sound classification. Deep learning sometimes exceeds human-level performance and can achieve state-of-the-art accuracy.
- 2) CNN: A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. In primitive methods filters are hand-engineered, while ConvNets, with enough training, have the ability to learn these filters/characteristics[3]. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area,
- 3) Transfer learning: Transfer learning is a machine learning technique where a model developed for a task is reused as the starting point for a model on a second task. It is a popular approach in deep learning where pre-trained models are used as the starting point on computer vision given the vast compute and time resources required to develop neural network models on these problems and from the huge jumps in a skill that they provide on related problems. Transfer learning is related to problems such as multi-task learning and concept drift and is not exclusively an area of study for deep learning[11]. Nevertheless, transfer learning is popular in deep learning given the enormous resources required to train deep learning models or the large and challenging datasets on which deep learning models are trained [5].

Various steps involved in implementing the deep learning model are:

### STEP 1: Collecting the dataset

In order to train the machine, we need a huge amount of data so that our model can learn from them by identifying certain relations and common features related to the objects. Images of elephant, pig, and not animal are used as the dataset.



(A High Impact Factor, Monthly, Peer Reviewed Journal)

### Visit: <u>www.ijirset.com</u> Vol. 8, Issue 6, June 2019

### STEP 2: Importing libraries and splitting the dataset

To use the powers of the libraries, we first ought to import them. After importing the libraries, we need to split our data into two parts- taining\_set and test\_set. The SciKit library provides a tool, known as the Model choice library. There's a category within the library that is named 'train\_test\_split.' using this we are able to simply split the dataset into training and testing datasets in numerous proportions.

### STEP 3: Selection of CNN architecture

Selection of an efficient architecture for image classification is the most important part of this project. Raspberry Pi sets limitations on the size of the trained model to be loaded ultimately into the board. It also certain processing limitations. Hence, the selection of an optimal architecture is necessary.

We prefer using Mobilenet as it is lightweight in its architecture. It uses depthwise separable convolutions which basically means it performs a single convolution on each color channel rather than combining all three and flattening it [4]. This has the impact of filtering the input channels. It is conjointly terribly low maintenance, therefore, performing quite well with high speed. Transfer learning approach using MobileNet architecture is being used in this project.

#### STEP 4: Training the network

Once all the steps of construction are completed, it's time to train our model. With increasing number of epochs, accuracy can increase.

### STEP 5: Testing the Network

NoIR(No infrared) PI camera is interfaced with raspberry pi through a ribbon cable. The network correctly predicts the image of the object coming in front of the camera(elephant/pig/not animal). Though it is not 100% accurate, it will give correct predictions most of the times.

Once the presence of an intruding animal is detected, a notification indicating the kind of animal is sent to the farmer, which is implemented using Twilio IoT platform. The current implementation deals basically with two animalselephant and pig.

### **IV. EXPERIMENTAL RESULTS**

Figures shows the results of testing of the developed model using images of intruding animals and real time notification based on animal detection. The network correctly predicts the images of elephant and pig shown in Fig. 2 and Fig. 3. An SMS alert is sent to the farmer's phone once an elephant or pig is detected as shown in Fig. 4.



(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: <u>www.ijirset.com</u> Vol. 8, Issue 6, June 2019



Fig. 2. Elephant detection



Fig. 3. Pig detection

Sent from your Twilio trial account -Animal was detected. It is more likely to be a/an pig 99.9

Sent from your Twilio trial account -Animal was detected. It is more likely to be a/an elephant 95.9

Fig. 4. SMS alert



(A High Impact Factor, Monthly, Peer Reviewed Journal)

### Visit: <u>www.ijirset.com</u> Vol. 8, Issue 6, June 2019

#### 701. 0, 1350e 0, 501e 201

#### V. CONCLUSION

'Internet of things' is extensively used in connecting devices and collecting information. Existing agricultural security systems lack in data analysis and information transfer. This has been "solved" by the integration of the internet of things with currently available security devices in order to achieve efficient food preservation and productivity. After collecting and analyzing the data, the algorithm is designed to provide accuracy in notifying user and activation of the repeller. Once PIR sensor detects motion it activates URD sensor, which generates ultrasonic waves capable of repelling away rodents like rat and mice. A pi camera interfaced with raspberry pi continuously checks for the presence of larger animals like an elephant. Along with it, the device sends a real-time notification to the user once an intruding animal is detected. This is implemented by means of deep learning and image classification tools. Hence, the project aids in complete eradication of potential farm rodents

#### ACKNOWLEDGMENT

The authors would like to thank Prof. Asha T S, Head of ECE Dept., Nss college of Engineering, for her consistent guidance, encouragement, and motivation throughout the period of work. The authors are also grateful to Asst. Prof. Prasad R Menon, project coordinator, Nss college of Engineering, for providing necessary resources and infrastructure to conduct this project and also for his encouragement.

#### REFERENCES

- [1] Tanmay Baranwal, Nitika, Pushpendra Kumar Pateriya, "Development of IoT based Smart Security and Monitoring Devices for Agriculture" 6th International Conference - Cloud System and Big Data Engineering, 978-1-4673-8203-8/16, 2016 IEEE.
- [2] Hung Nguyen, Sarah J. Maclagan, Tu Dinh Nguyen, Thin Nguyen, Paul Flemons, Kylie Andrews, Euan G. Ritchie and Dinh Phung, "Animal Recognition and Identification with Deep Convolutional Neural Networks for Automated Wildlife Monitoring," 2017 IEEE International Conference on Data Science and Advanced Analytics (DSAA), Tokyo, 2017, pp. 40-49.
- [3] Sumit Saha, "A Comprehensive Guide to Convolutional Neural Networks-the ELI5 way," *Towards Data Science*, 15-Dec-2018. Available:https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53.[Accessed: 22-Apr-2019].
- [4] Howard, Z. Andrew G., Chen, Bo, Dmitry, Wang, Weijun, Weyand, Tobias, Marco, Adam, and Hartwig, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," *arXiv.org*, 17-Apr-2017.
- [5] Jason Brownlee, "A Gentle Introduction to Transfer Learning for Deep Learning," *Machine Learning Mastery*, 12-Dec-2018. Available: https://machinelearningmastery.com/transfer-learning/. [Accessed: 22-Apr-2019].
- [6] Tadele Tefera, Fred Kanampiu, Hugo De Groote, Jon Hellin, Stephen Mugo, Simon Kimenju, Yoseph Beyene, Prasanna M. Boddupalli, Bekele Shiferaw, Marianne Banziger. "The Metal Silo: An effective grain storage technology for reducing post-harvest insect and pathogen losses in maize while improving smallholder farmers' food security in developing countries'. Grant R. Singleton. "Impacts of rodents on rice production in Asia." IRRI Discussion Paper Series No. 45, 30 pp. (International Rice Research Institute: Los Banos, Philippines.)
- [7] "What Is Deep Learning? How It Works, Techniques & Applications," *How It Works, Techniques & Applications MATLAB & Simulink*. Available: https://www.mathworks.com/discovery/deep-learning.html. [Accessed: 22-Apr-2019].
- [8] A. F. O'Connell, J. D. Nichols, and K. U. Karanth, Camera traps in animal ecology: Methods and Analyses. Springer Science & Business Media, 2010.
- [9] Alexandros Kaloxylos, J Wolfert, Tim Verwaart, Carlos Maestre Terol, Christopher Brewster, Robbert Robbemond and Harald Sundmaker. 'The Use of Future Internet Technologies in the Agriculture and Food Sectors: Integrating the Supply Chain' in 6th International Conference on Information and Communication Technologies in Agriculture, Food and Environment. pp. 51-60
- [10] Ferhat Culfaz, "Transfer Learning using Mobilenet and Keras," Towards Data Science, 06-Nov-2018. [Online]. Available: https://towardsdatascience.com/transfer-learning-using-mobilenet-and-keras-c75daf7ff299. [Accessed: 23-Apr-2019].