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Application of IOT and machine learning in crop protection against animal intrusion

K Balakrishna*, Fazil Mohammed, C.R. Ullas, C.M. Hema, S.K. Sonakshi

Dept. of ECE, Maharaja Institute of Technology Mysore, Karnataka, India

A R T I C L E   I N F O

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A B S T R A C T

Animal intrusion is a major threat to the productivity of the crops, which affects food security and reduces the profit to the farmers. This proposed model presents the development of the Internet of Things and Machine learning technique-based solutions to overcome this problem. Raspberry Pi runs the machine algorithm, which is interfaced with the ESP8266 Wireless Fidelity module, Pi Camera, Buzzer, and LED. Machine learning algorithms like Region-based Convolutional Neural Network and Single Shot Detection technology plays an important role to detect the object in the images and classify the animals. The experimentation reveals that the Single Shot Detection algorithm outperforms than Region-based Convolutional Neural Network algorithm. Finally, the Twilio API interfaced software decimates the information to the farmers to take decisive action in their farm field.

1. Introduction

Agriculture is the backbone of the Indian economy, where more than 60% of the country's population is directly or indirectly depends on this sector. Where they need to feed this huge increasing population year by year with the decreasing land cultivating size. In near future, it is expected to have around 15-20% of food commodities to get increased within 5 years [1]. Even though a huge number of the population dependent on this sector, they are still in uncertainty to lead their life in this sector. The reason for this may be inter and intra farm field variability's such due environment, seed selection, fertilization inputs, irrigation, etc [1]. Nowadays, one more important factor causing crop loss is an animal intrusion into the farm field. The conflict between the animal and farmers is becoming common all over the region. That too in hill station area and adjacent to the forest area have major issues and the farmers suffer a huge loss. To date, they use some traditional and current methods to overcome this issue like Hellikites, Shot Gun, String and Stone, use of electrified welding mesh fence etc, but not up to the expectation of protecting their crops. Also, few attempts were tried to solve this conflict by using technology such as IoT and Machine learning, which is called AIoT (Artificial Intelligence for the Infrastructure of Internet of Things). Our proposed model uses IoT and Machine learning concepts based solution to it.

IoT (Internet of Things) controls the Things that are connected to it and transfers the data over the network. The IoT technology enables the collection of real-time data from the farm field using Sensors and various electronic components [2]. In this work, we present the coordination of Pi Camera, LED, and Buzzer interacting with the cloud a new service in the domain. The peripheral part adopted wireless technologies such as WiFi for cooperating with the data center by an advanced IoT gateway. Pi Camera is used to capture real-time images in a farm field 24 × 7 i.e., day and night. The low cost and ease of programming controller Raspberry Pi for coordination of hardware part and data transferred through ESP8266 WiFi module, which uses TCP/IP protocol [3].

Machine learning is a branch of artificial intelligence used for data analysis to automate the analytical model building, which identifies the pattern and objects to make a decision [4]. In this work, a deep machine learning algorithm for object detection and classification model is trained and tested. Twilio communication is API interface software which used to communicate throughout globally by creating its own/private network [5]. It is used to forward the decisive information to the framers, which has control through the Raspberry Pi controller. Here from all this motivated to propose an effective model to protect the crop from animal intrusion through modern technology.

2. Related works

S. Giordano et al., [6] worked and developed an IoT application for the protection of crops from animal intrusion in the crop field. To collect or monitor the crop field, authors used the wireless technologies such as 6LoWPAN, WiFi, and ZigBee with the advanced IoT gateway. An ultrasound repeller device was developed to work even in partial and total darkness using the solar panel along with LiPo batteries. To improve the efficiency of this device used PIR (Passive Infrared) sensor, which takes care of the frequency transmission and networking operation by

* Corresponding author.
E-mail address: balakrishnak_ece@mitmysore.in (K. Balakrishna).

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transmitting a small size frame at a distance of 50m. This communication happens using the RIOT-OS software, when the animal is detected it produces a sound of 120dB. The performance of this device reduces below 90% if the distance from the gateway is above 60m and it will never work if the distance crosses 100m.

Mukesh Mahajan et al., [7] worked on protecting the crop in the farm field from animals such as buffaloes, cows, goats, and birds using a PIC microcontroller. The developed model uses the motion sensor to detect the animals that are near to farm field and the sensor signals the microcontroller to take appropriate action by farmers. The PIR-based motion sensor is used to detect the animals and the buzzer is used to notify the farmers based on the microcontroller instruction. Here authors claim that this model avoids the farmers staying for 24 hours in the farm field and barricade their crops.

Iniyaa K K et al., [8] worked on protecting crops by animals using deep machine learning and Convolutional neural network algorithm. The author aims to protect the crops from animals and not harm both animals as well as humans in the conflict. Due to this, the authors developed a model to divert the animals nearer to the crop fields. The machine-learning algorithm-based model is developed to detect the animals coming nearer to the farm field using the neural network concept through the computer vision technique. In this model, the farm field is monitored using a camera placed at the farm field at a regular interval of time. The algorithm detects the animal's movement through the camera frames using various libraries function and concepts of neural networks and plays appropriate sound to divert the animals away from the farm field.

D. Kalra et al., [9] worked and developed a model to protect the crop from insects and small animals through the sensor and also for control irrigation using the IoT technologies. The Arduino UNO microcontroller works like a heart for the proposed model in managing proper irrigation and crop protection. The irrigation is managed automatically on/off water siphons depending on the dampness parameters of the farm field. The crops are protected by insects, animals, etc through the use of deliberate sensors connected in the farm field; sensors estimate the motion of insects and animals nearer to the crop and sent the signal to the Arduino Uno microcontroller for calculation of distance and all. Based on the calculated distance values, the microcontroller enables high-frequency sound.

Raksha R and Surekha P, [10] worked and developed a prototype to monitor the crops and warning the wild animals based on two emerging technologies such as IoT and Machine learning. The IoT components used are like PTZ (Pan-Tilt-Zoom) camera, GSM module, Sensors, and Arduino UNO microcontroller and Machine learning algorithm for classification of the animals are done using KNN (K-Nearest Neighbor) Algorithm, Logistic Regression, and SVM (Support Vector Machine) Algorithm. Datasets of elephants, horses, Zebra, etc are taken in total in some 605 images. SVM provides an accuracy of 89.6% compared to the KNN and Logistic Regression model for the iterated regularization parameter of C=100.

Several states of the art from the above-proposed prototype and classifier models work on IoT and detect the animals using machine learning algorithms. But still lack in achieving the expected performance, so this application is still in infancy for real-time. So here we are proposing a better model based on IoT and Machine learning algorithms to protect the farm field from intruders.

3. Proposed methodology

The crop protection from animal intrusion is done using the proposed model using IoT and Artificial Intelligence technologies as shown in Fig. 1.

The alternating current of 12V is converted into a direct current of 5V through a bridge rectifier circuit and 7805 voltage regulator to operate Raspberry pi. ESP8266 is interfaced with a Raspberry pi board to provide firebase cloud connectivity to the system [11]. Raspberry pi4 is used to run a machine learning algorithm. Pi cam is used to capture the intruder images entering the agricultural field. The images are then analyzed by the machine learning algorithm running on the Raspberry pi board and conclusions are drawn as an output of machine learning algorithm. If any danger is sensed the Raspberry pi generates sounds of different frequencies with the help of a buzzer and an input signal is sent to ESP8266 nodemcu which is in communication with the firebase IoT cloud which sends messages to the farmer through the android application [12]. If the intruder is detected at night, the LED lights and buzzer are triggered simultaneously to divert the intruder away from the field. The proposed model consists of two parts as Hardware and Software. Raspberry pi acts like a heart for the hardware part and it is interfaced with components like a voltage regulator, Pi Camera, LED lights, WiFi, and Buzzer. The software part for the hardware is done through embedded C and for computer vision prediction used machine learning models like R-CNN and SSD for object detection and predicts the animals.

a *Hardware*

The hardware section discusses the associated factors in the selection of the components for farm field regular monitoring to crop protection.

Processor

Raspberry Pi 4 controller unit is integrated with Broadcom BCM2711 and Quad-core Cortex-72 processor which works for 64-bit SoC (System-on-Chip). This controller works for a voltage of 5V and communicates easily with other connectivity such as ESP8266, Pi camera, etc. It provides a set of general-purpose input/output pins to have control over electronic components for physical computing for IoT technology, also the programming is easy and the cost is low.

Pi Camera

Pi Camera V2 module is 8-megapixel custom-designed board that is equipped with a flexible ribbon cable, making it compatible with Raspberry Pi. The camera module takes pictures in two versions i.e. Standard version and the NoIR version [13]. The Standard version; is designed to capture images in normal light and the NoIR version; is designed to capture images in dark light using the infrared light source.

WiFi Module

ESP8266 WiFi module allows the Raspberry Pi controller to connect with WiFi network using TCP/IP (Transmission Control Protocol/Internet Protocol) connection. It operates for a frequency of 2.4GHz using the serial communication UART to transmit and receive data. Two general-purpose pins such as GPIO0 and GPIO2 are used to decide to transmit/receive for serial input/output purposes, which are connected to ground and VCC.

Power

A 12V Lead-acid battery is used for the power supply of electronic components connected in the hardware part, which consists of 6 cells connected in series each producing 2.1V. The lead-acid battery can't generate the power itself, where it stores power received from another source for this it is called a storage battery. For example here the 12V battery can supply a current of 10mA for a duration of 12.5 hours, anyhow if consumption of current decreased means duration can be increased.

a *R-CNN Model*

R-CNN approach here used for the object detection uses deep models as shown in Fig. 2. The R-CNN is composed of four main parts such as selective search, pretrained CNN, category prediction, and bounding box prediction [14]. For the input images, selective search is applied to select multiple high-quality proposed regions, which are in multiple scales and different sizes and shapes. In between the selective search and output, pretrained CNN is placed. Pretrained CNN works on forward computation to extract the features for output, which gather input as required by the network through the proposed region. For object classification, multiple Support Vector Machines were trained using each proposed region of both features and labeled category. Then for the ground truth bounding box prediction linear regression model is trained using each

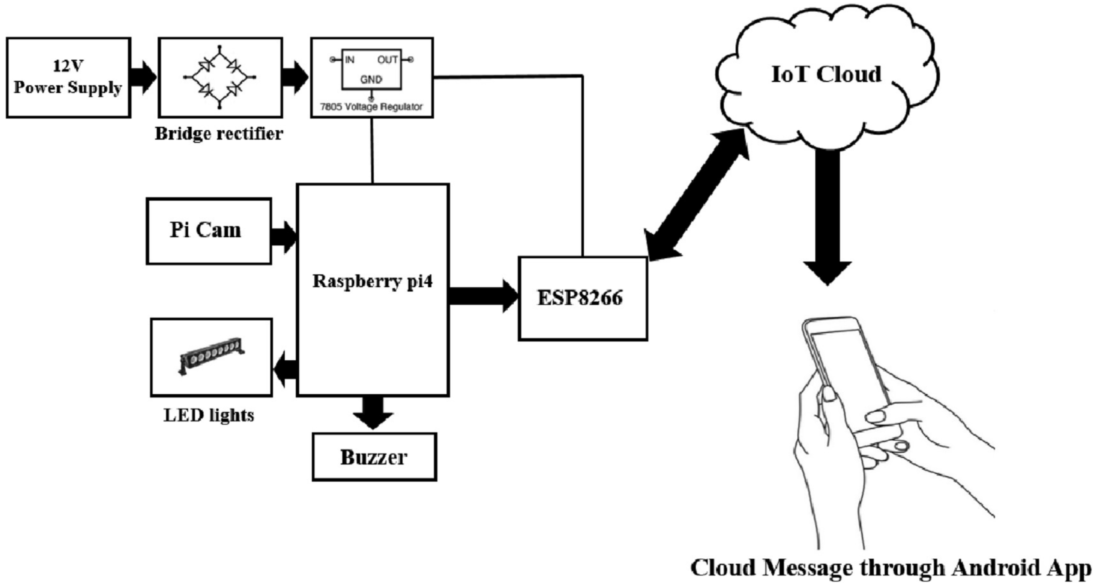


Fig. 1. Block diagram of the proposed model using IoT and artificial intelligence.

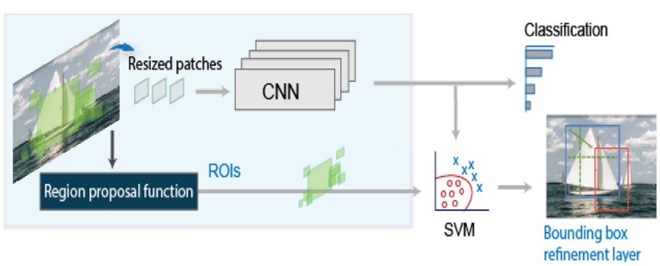


Fig. 2. Object detection using R-CNN detector architecture.

proposed region of both features and labeled bounding box hardware part and it is interfaced with components like a voltage regulator, Pi Camera, LED lights, WiFi, and Buzzer. The software part for the hardware is done through embedded C and for computer vision prediction used machine learning models like R-CNN and SSD for object detection and predicts the animals.

a *SSD Model*

Single Shot Multibox Detection (SSD) model consists series of components like a base network block and several multiscale feature blocks a shown in Fig. 3. In original images, features are extracted using the base network block based on the deep Convolutional neural network [15]. Here to detect the small objects in the original images more anchor boxes are generated using the feature map. Several multiscale feature blocks are used to reduce the size. The multiscale feature blocks detect the objects of different sizes based on the predicted bounding boxes and anchor boxes.

The SSD defines the scale value for each feature map layer manually. Conv4_3 detects objects starting from the smallest value of 0.2 then increases linearly till it reaches 0.9. Combining the scale value with the target aspect ratio value to find width and height as shown in Eq. (1) and (2), here aspect ratio kept as value 1.

$$w = scale * \sqrt{Aspectratio} \tag{1}$$

$$h = \frac{scale}{\sqrt{Aspectratio}} \tag{2}$$

Here the SSD adds an extra default box to scale as shown in Eq. (3).

$$scale = \sqrt{scale * scaleatnextlevel} \tag{3}$$

a *Tensor Flow*

Tensor Flow library is an open source library developed by Google, which is used to build a numerical computation for the deep machine learning model [16]. It offers multiple levels of abstraction to build and train models using API (Application Program Interface). While training the large machine learning tasks, it used the distributed strategy to train the model on different training on the different hardware configurations. This execution allows for immediate iteration and debugging, which makes it more flexible.

a *Twilio*

Twilio is programmable software used for communication functions using its web API such as make and receive phone calls and text messages globally. Here the Twilio is connected with electronic components, which are called as Cellular IoT connectivity.

4. Discussion

The Power supply of 12V is used here, which rectifies it to 5V using the bridge rectifier i.e., converting from alternating current into direct current using the LM7805IC. Raspberry pi controller works as a heart for the proposed hardware part with the interconnected electronic components powered by a battery of 12V. The controller and other connected components in the hardware part work for a voltage of 5V, so here regulator is used for stepping down the voltage. To monitor the field regularly, the Pi camera module is connected to the controller, which communicates with Pi using the MIPI camera serial interface protocol. The Pi camera is controlled using the Python code and the preview see-through by setting an alpha level to 200. Images were captured every 5 seconds, where delay time gives the camera sensor to sense the light levels around the field. The Raspberry Pi communicates with the ESP8266 module through predefined AT commands, UART, and specified Baud rate. Even the artificial intelligence based machine learning algorithm works on the Raspberry Pi. Images captured are analyzed using deep machine learning technique as shown in Fig. 4.

The pre-trained Convolutional neural network is taken and retrained the last layer considering the classification of animals. R-CNN uses selective search to extract the boxes in the image using the basic four regions

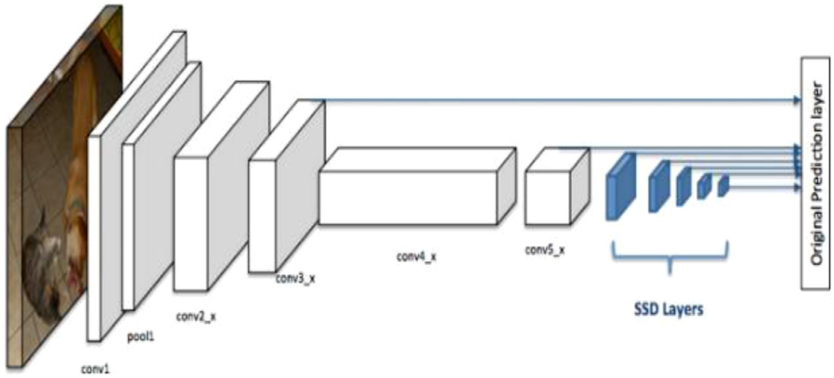


Fig. 3. Object detection using SSD detector architecture.

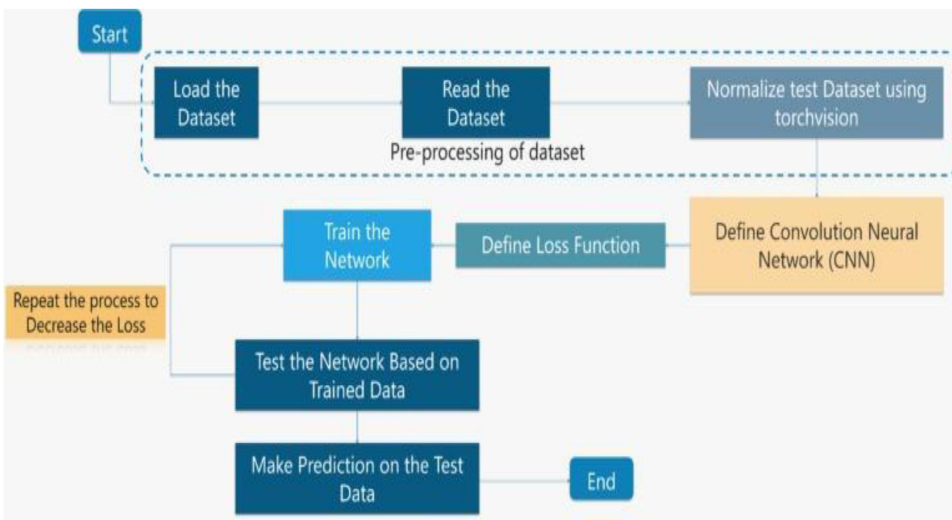


Fig. 4. Training and testing process flow in machine learning algorithm.

Table 1
SSD prediction layers and mAP.

Prediction source layers 38 × 38	19 × 19	10 × 10	5 × 5	3 × 3	1 × 1	mAP*	Number of Boxes
✔	✔	✔	✔	✔	✔	89.32	8732
✔	✔	✔				84.51	9864
	✔					79.57	8664

For classification purpose, the ResNet trained on ImageNet. SSD have advantages concerning R-CNN in speed, multiscale features, and default [17-20].

to form objects such as varying scales, colors, textures, and enclosures. All the regions are reshaped to match the input size for classifying the detected animals in the images. For the classification purpose, the Support Vector Machine (SVM) and Linear Regression model are trained. Single Shot Multibox Detection model designed to object detection and classify using boundary boxes. SSD applies 3 × 3 convolution filters to predict the object in each cell. Each cell outputs 25 channels for 21 scores for each class for one boundary box, example: In Conv4_3, four 3 × 3 filters mapped 512 channels to 25 channels as shown in Eq. (4).

$$(38 \times 38 \times 512) \overset{(4\times3\times3\times512\times(21+4))}{\rightarrow} (38 \times 38 \times 4 \times (21 + 4)) \quad (4)$$

SSD adds six auxiliary convolution layers, out of which five will be used for object detection. In three of those layers, six predictions are done instead of four. In total, SSD makes 8732 predictions using six layers as shown in Table 1. The multiscale feature map improves accuracy for object detection. Here the localization between the ground truth box and prediction box is defined with smooth loss with considering offset to the default boundary box of width and height as given in Eq. (5) to Eq. (7).

$$L_{loc}(x, l, g) = \sum\nolimits_{i\in pos}^{N} \sum\nolimits_{m\in(Cx,Cy,w,h)} x_{ij}^{k}\, smooth_{L1}(l_i^m - g_j^m) \quad (5)$$

$$L_{conf}(x, c) = -\sum\nolimits_{i\in pos}^{N} x_{ij}^{p} \log(c_i^p) - \sum\nolimits_{i\in Neg} \log(c_i^o) \quad (6)$$

$$L(x, c, l, g) = \frac{1}{N}(L_{conf}(x, c) + \alpha L_{loc}(x, l, g)) \quad (7)$$

Where, *cx, cy* are offset default boundary box of width w and height h,
l is predicted box and g is ground truth box
c gives class score and α is the weight for the localization loss
N is number of positive matched default box.

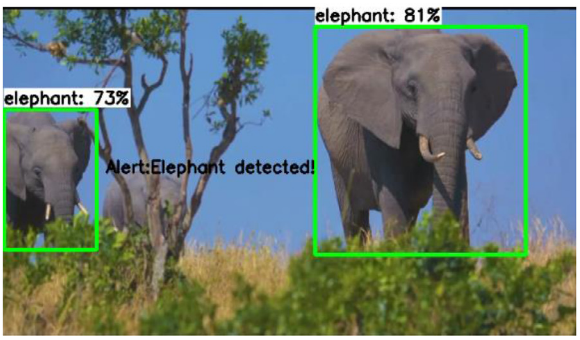
a *Datasets*

In this work created a database with 300 datasets of animal's images. For experimentation considered 5 classes of animals such as Horse, Zebra, Cheetah, Elephant and Cow, each animal 60 images were collected.

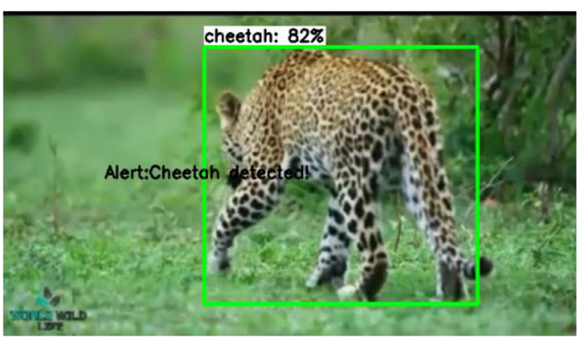
5. Results

We conducted experimentation by varying training datasets for the detection of animals and classification purposes. Fig. 5 shows the testing model for the proposed algorithm. R-CNN algorithm generates regions using selective search and extracts around 2000 regions in each image. Computation time will be much higher because of its process in making a prediction, which is around 40-50 seconds. SSD algorithm works on backbone model and SSD head contains pre-trained image classification network as a featured network. Here we have used 4 × 4 grids for detecting the objects in the region of the image. Table 2 shows the

(a)



(b)



(c)

Fig. 5. Testing model for the proposed algorithm.

Table 2
Algorithm performance comparison with State-of-the-Art.

State-of-the-Art	mAP* (%)
Proposed R-CNN	**85.22**
Proposed SSD	**89.32**
S. Giordano et al., [6]	84.51
Iniyaa K K et al., [8]	77.45

*mAP (mean Average Precision).

prediction for the algorithm, SSD outstands in predicting and classifying the animals compared to R-CNN, and also computation time will be very less. The Twilio API interface decimates the information to the farmers to take necessary action in their farm field [21-25].

The R-CNN gives a mean average precision (mAP) of 83.42%, whereas SSD gives mAP of 89.32% on 300 datasets of animal images for 5 classes as shown in Table 2. However, the architecture of R-CNN is very slow to train and takes approximately 49seconds to generate the test results. Whereas SSD training and testing results will be very faster.

Comparing with the previous works carried out by researcher S. Giordano et al., [6] and Iniyaa K K et al., [8] as shown in Table 2, SSD based detection algorithm developed here works better for the real-time classification of animals using the IoT technologies. Even the number of classification taken in this experimentation is higher compared with the related works in the field.

6. Conclusion

Crop protection from animal intrusion is important for the successful cultivation of the crops and this can be done with the IoT and Machine learning technology. This paper discusses various techniques like Raspberry Pi processor, WiFi module, R-CNN, SSD, and Twilio. SSD algorithm performance better compared to the R-CNN algorithm with computation time, accuracy and efficiency. In future work, an App-based model can be developed to make it more mobility and user friendly.

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