Image Processing based Animal Intrusion Detection system in Agricultural Field using Deep Learning

Oviya G[1]**, Prapti D**[1]**, Srividhya K**[1]

[1]Department of ECE, SVCE -Affiliated to Anna University Sriperumbudur, Chennai,India.

E-mail:Ovi13ya@gmail.com, srivi@svce.ac.in

Abstract- Agriculture is one of the most important industries in any economy since it plays a big role in the food supply chain. Agricultural fields, on the other hand, confront a number of issues, including animal encroachment, which can cause severe crop damage and loss. Traditional animal control tactics, such as electrical fences, physical barriers, and scarecrows, can be inefficient, time-consuming and a serious threat to animal lives. The animals either become entangled in the fence's wire mesh or were electrocuted by the electric lines. To overcome these problems we propose a unique method that involves image processing-based animal incursion detection system in agricultural fields using Raspberry Pi and deep learning technique, mainly the YOLOv7. This technology captures live video feeds of agricultural fields using a camera and analyses them using deep learning algorithm to detect any animal invasions. If an intrusion is detected, the system emits specific repellent sounds for specific animal via speakers in order to scare them away and alerts the farmers by sending SMS. This method provides an efficient and practical alternative for crop damage prevention and human-wildlife conflict reduction in agricultural settings.

Index Terms- *Animal Intrusion Detection System in Agricultural Fields -* *AIDSAF, Deep Learning – DL, YOLOv7, Faster RCNN, Raspberry Pi 4 model B.*

I. INTRODUCTION

Agriculture is the primary source of income for many people in many parts of the world [5]. In India, common causes of wildlife death include fencing and electrocution. Fencing is used to keep wildlife out of agricultural areas and human communities, while electric barriers keep elephants out of human populations. In 2014, a research published in the journal Oryx looked at the effect of fencing on animal mortality in India's Kanha National Park. Fencing was shown to be responsible for the deaths of various large species, including tigers, leopards, elephants, and gaurs, according to the study.

Traditional agricultural methods are ineffective, and employing guards to keep an eye on crops and keep animals at away is not a viable option [2]. However, these measures may unintentionally harm wildlife, with serious ecological and conservation consequences. A study published in 2017 in the journal PLOS One looked at the effect of electric fencing on elephant death in India. According to the research, electrocution from these fences was the top cause of elephant death in the nation, killing almost 400 elephants between 2000 and 2013. The study also discovered that using solar-powered fences lowered the frequency of elephant fatalities, indicating that alternate technologies might offset the detrimental impact of electric barriers on animals. Farmers typically employ electrical fences to safeguard their fields from animals whose electrocution with cramp causes them to behave abnormally [8]. These findings emphasize the need for more study and attention to the issue of fence and electrocution in India. It is critical to comprehend the scope of the issue, as well as the influence of various types of fences and electrical technologies on animal death. This research can help to guide the development of more effective and environmentally sustainable wildlife-human conflict mitigation methods.In addition to research, policy measures are required to solve the issue of fence and electrocution. The Indian government has taken steps such as paying farmers for agricultural loss caused by wildlife and subsidizing the building of solar-powered fences. More has to be done, however, to ensure that these policies are effective and equitable, and that they are administered in a way that considers the ecological and conservation consequences of wildlife-human conflict.

To summarize, fences and electrocution are major causes of animal death in India. More research is needed to determine the scope of the problem and to devise more effective and environmentally sustainable solutions to wildlife-human conflict. Simultaneously, policy interventions are required to ensure that these measures are effective, equitable, and take the ecological and conservation implications of wildlife-human conflict into account. In this research, we present an image processing-based AIDSAF based on Yolov7 deep learning algorithm. We construct the system using the Raspberry Pi 4 model B, a low-cost and power-efficient computer, making it a cheap and accessible alternative for farmers. The suggested technology is predicted to drastically minimize crop damage caused by animal encroachment while also improving agricultural production's sustainability and productivity.

II. LITERATURE SURVEY

[1] presents IoT technological improvements on the application layer in an understandable manner, together with the lightweight communication protocol lightweight M2M (LwM2M). The research [2] indicates that the biggest drawback is the slower computing efficiency and accuracy of CNN. [3] suggests that the YOLOv5 algorithm be used for real-time animal detection in precision agriculture. The authors employed a dataset of cows, buffaloes, and horses, and the YOLOv5 system detected animals with great accuracy. In terms of accuracy, YOLOv7 outperforms YOLOv5. On the COCO dataset, the MAP (mean average precision) for YOLOv5 is 55.0%, while for YOLov7, it is 56.8%. According to research, the adjustment resulted in a reduction of 35-40% parameters as well as half of the calculations for each (normal and embedded system). The tests in [3] used a small dataset that may not be typical of all forms of animal invasions that farmers may face. In AIDSAF the train images used are 3000 which include 8 classes of animals namely cow, bear, elephant, bird, horse, sheep, cat, and dog. Total of 4000 images were used for training and testing the model on the whole. [4] goes through many strategies such as the Raspberry Pi CPU, WiFi module, R-CNN, SSD, and Twilio. SSD method outperforms R-CNN algorithm in terms of calculation time, accuracy, and efficiency. [5] works by comparing the acquired image from the IoT model to the training dataset, splitting the image into frames, and then storing the data in the cloud, which maintains the other databases. 2 holds the identified object, and then the raspberry pi receives the data of item recognition and decides whether to activate the buzzer, LED lights, or both. Furthermore, when necessary, sends the notification to the

client/ranch. [6] created a YOLOV3 model to identify the animal in a user-supplied photograph and it takes longer to forecast the result, and we cannot choose our own pictures. The downside of [6] is that when we run the YOLO V3 model, it predicts right and inaccurate predictions, and it does not forecast for certain photographs and does not take input images correctly. The primary concept of [8] is that in order to address this difficulty, an intelligent monitoring system that can automatically monitor and recognize the image of animal ingress and send an alarm message to humans is necessary. Attempts to boost recall through tracking and multi model pooling failed in [9]. RETINA and YOLO were demonstrated to be competitive with bigger models while being lightweight enough for multi-camera mobile deployment. Giordano and colleagues worked on and created an IoT application for crop security from animal encroachment in the agricultural field. The idea in [10] employed wireless technology such as to gather or monitor crop field data and a PIR (Passive Infrared) sensor was used to improve the device's efficiency by handling frequency transfer and networking activities by broadcasting a small size frame at a distance of 50m. For this communication, the RIOT-OS software is employed, and when the animal is detected, it makes a 120dB sound. PIR sensors have lesser sensitivity and coverage than microwave sensors, and they only operate in LOS (Line of Sight) and will have difficulty in corner locations. [12] utilizes a Raspberry Pi 2 for this project since it is a low-cost single-board computer. PIR sensors are used to detect motion. It has room for development, such as enhanced motion detection employing image processing with night vision cameras.

In conclusion the image-processing based AIDSAF, the raspberry pi 4 model b excels due to specific features such as a faster processor, a 1.5-GHz Broadcom CPU and GPU, larger and faster RAM, the inclusion of USB 3 connections, multiple mini HDMI connectors (rather than a single HDMI connection), and 4K output capabilities. The YOLOv7 algorithm, which is also scored well in terms of accuracy and computing speed, is the major distinguishing feature of our project. This strategy appears to be very effective in terms of reducing crop damage and saving the lives of trespassing animals by producing customized repellant sounds for individual species and producing notifications to farmers.

III. PROPOSED ARCHITECTURE

Various technologies have been developed to detect and deter animals from entering agricultural fields in order to address this issue. Image processing-based animal incursion detection systems that involves deep learning algorithms such as Yolov7 and Faster RCNN, have emerged as a possible answer to this problem. ML, together with IoT (Internet of Things) enabled farm gear, will be critical components of the next agricultural revolution [7].

A. *Goal setting*

Objectives:

- To develop a robust and accurate deep learning model using YOLO V7 and Fast RCNN that can detect and classify animal intrusions in agricultural fields using Raspberry Pi in order to prevent crop damage and animal-deaths due to electrocution from illegal power fence.

- To train the deep learning model on a large dataset of animal images to improve its accuracy and generalization ability.

- To optimize the model's hyperparameters, such as learning rate, batch size, and regularization, to achieve the best performance on the test dataset.

- To deploy the trained model on cameras placed in the agricultural fields to detect and classify animal intrusions in real-time.

- To generate alerts whenever an animal intrusion is detected using Raspberry Pi, allowing farmers or operators to take necessary actions to protect their crops from further damage.

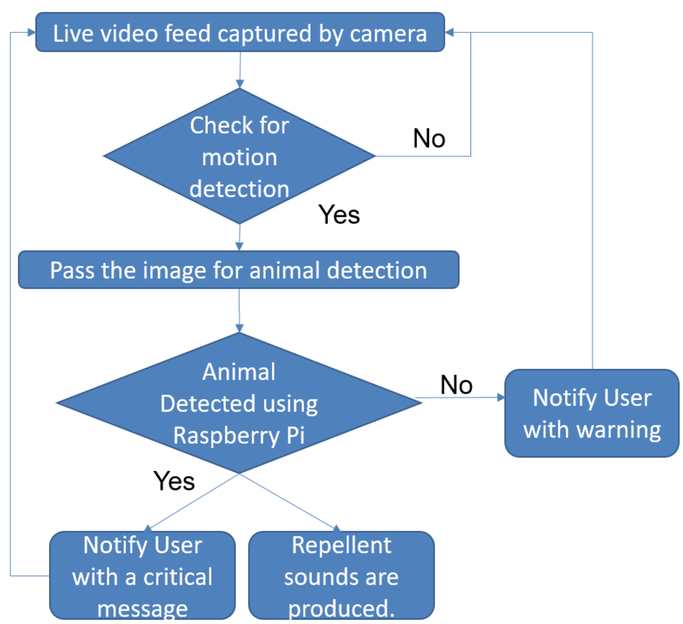


Figure 1. Model workflow

Figure 1 above shows the complete workflow of the model, starting with the live video capture by a camera in an agricultural field. The following step is to look for animal movement inside the designated area. The picture is sent to a third party for animal detection if motion or incursion is detected. A raspberry pi 4 model B with the Yolov7 algorithm built in is used to detect animals. For instance, if the animal is recognized, the user or farmer is immediately told via a crucial SMS notice, and at the same time, repellent noises are created specifically to frighten away the detected animals. A notice is left for the user if the animal cannot be recognized.

B. Model Classification

a) YOLOv7

YoloV7 is an object detection model that evolved from the YOLO (You Only Look Once) model family. It is a deep neural network-based model that detects objects in real-time video streams or pictures using convolutional neural networks (CNNs). YOLO is made up of 75 convolutional layers, with skip connections and upsampling layers taken into account [6].

The YoloV7 model is trained on a 3000 dataset of labelled pictures. The model learns to modify the weights of its parameters during training in order to minimise the discrepancy between the predicted objectness score and class probability and the ground-truth labels for the objects in the picture. This is accomplished by the use of a loss function, which penalises the model for generating inaccurate predictions.

After training, the YoloV7 model may be used to recognise objects by running an image or video stream through it. In real-time, the model predicts the position and class of objects in an image or video stream. Because of its excellent accuracy and rapid processing speed, the YoloV7 model is a popular choice for real-time object identification applications. Because the whole detection pipeline is a single network, detection performance may be optimized end-to-end [11].

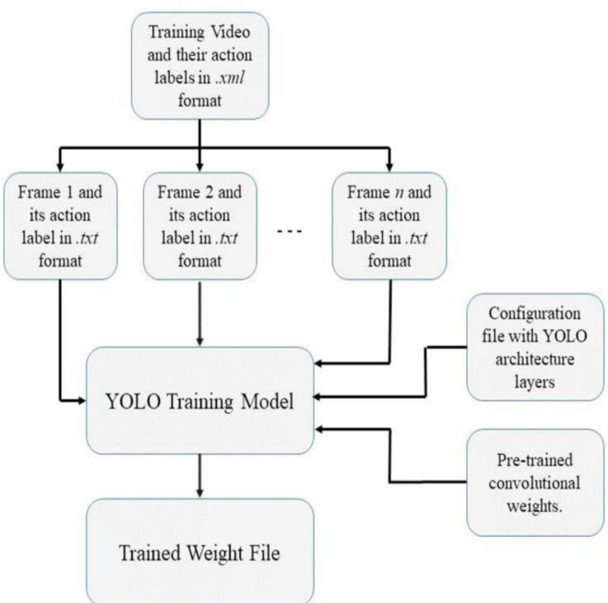


Figure 2. Yolov7 training model

The live captured video feed is analyzed by dividing the whole video into frames that is sort of images for animal detection. Layers and weights are added to the YOLO training model in order to enhance the speed and accuracy of the system in order to get best.pt file as shown in figure 2.

In summary, YoloV7 is a deep neural network-based object identification model that detects items of various sizes and shapes using anchor boxes. It is trained on a huge dataset of labelled pictures and can recognise objects in video streams or photographs in real time with great accuracy and speed.

b) Faster RCNN

Faster R-CNN (Region-based Convolutional Neural Network) is an object identification model that detects objects in images in two stages. A Region Proposal Network (RPN) and a Fast R-CNN network are the two fundamental components of the Faster R-CNN paradigm. The RPN creates a collection of candidate areas, also known as proposals, that are likely to include objects. After that, the Fast R-CNN network classifies and refines these ideas to provide the final object detection.

During training, the Faster R-CNN model is trained from start to finish with a multi-task loss function. This loss function consists of two parts: a classification loss that penalises the model for wrong class predictions and a regression loss that penalises the model for incorrect bounding box predictions. After training, the Faster R-CNN model may be used to detect objects by sending an image through it. Using the RPN, the model generates a collection of object suggestions and their objectness ratings. After that, the Fast R-CNN network classifies and refines these ideas to provide the final object detection.

In summary, Faster R-CNN is an object detection model that detects objects in images in two stages. A Region Proposal Network (RPN) creates object suggestions, and a Fast R-CNN network classifies and refines these proposals to provide the final object detection. The model is trained from start to finish with a multi-task loss function and may be used to recognise objects in photos in real time with high accuracy.

III. SYSTEM IMPLEMENTATION AND RESULT

a) Training the model

1) Collection of data:

To create data, animal photographs must first be gathered. We gathered pictures of eight different animal species: dogs, cats, horse, sheep, elephant, bear, cow and bird. We gathered at least 500 pictures of a single animal class to make a training module. So, in total, we gathered about 4000 pictures. For the picture testing, we gathered unique photographs for each class.

Figure 3. Training of images

2) Image labelling:

Data must be tagged after collection in order to produce a text document that can be used to develop a training module. The images are first accessed, and if it contains the animal classes we need, it is then picked using a bounding box. The class of animals defined after the animal is enclosed by a box, as seen in the following figure 4;

Figure 4. Labels of animals

To label images we used labelImg. This tool can detect animal for YOLOv7 and other as well. We can find more than one data in a single image. So, in 4000 images we collected more than 4000 data. In labelImg we have to classified animal from class 1 to class 8. So, we classified animals as shown in fig 5;

CLASS	ANIMALS
Class 1	Cow
Class 2	Bear
Class 3	Elephant
Class 4	Bird
Class 5	Horse
Class 6	Cat
Class 7	Sheep
Class 8	Dog

Figure 5. Class of animals

Here,

- No. of epochs = 100.
- Training Data: Images: 3000; Labels: 3000

Where, epoch is a hyperparameter that defines the number times that the learning algorithm will work through the entire training dataset and N is number of classes. To train 8 classes of animals, we have used 100 epochs. The above figures are clearly mentioned in the below table 1.

BATCH SIZE	**8**
WIDTH	**640**
HEIGHT	**640**
CLASSES	**8**

Table 1. Parameters of dataset

b) Requirements

1) Software components:
   - Python – 3.9
   - Visual studio code
   - OBS Studio
2) Hardware components:
   - Raspberry pi 4 model B
   - Webcam
   - Speakers

c) Result

- YOLOv7:

The individual accuracy of each class of animal in YOLOv7 is represented below figure 6;

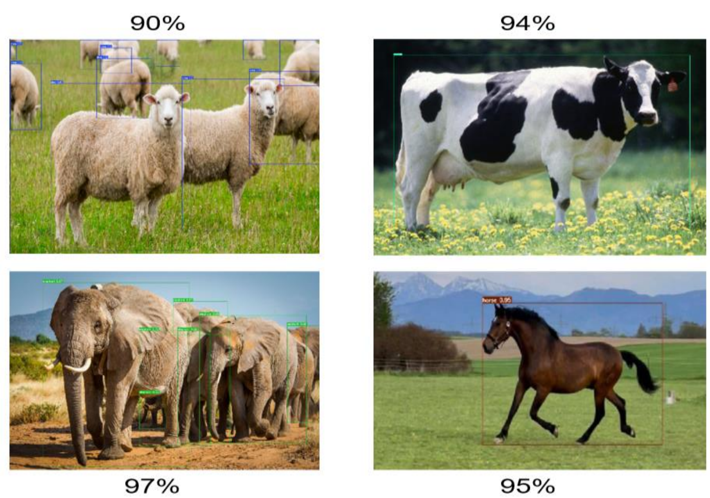


Figure 6. YOLOv7 Accuracy

- Faster RCNN:

The detection of each class of animal in Faster RCNN is represented below figure 7;

Figure 7. Faster RCNN Accuracy

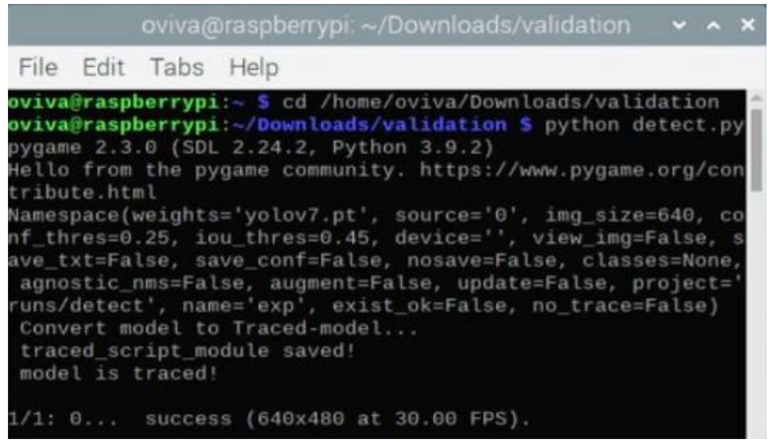
From the below table 2, we can conclude that YOLOv7 model is highly efficient in terms of accuracy as compared to Faster RCNN model. When generalizing from natural pictures to other domains such as artwork, it outperforms other detection approaches such as DPM and R-CNN [11].

CLASS	YOLOv7	Faster RCNN
Cow	96%	81%
Bear	95%	88%
Elephant	99%	92%
Bird	92%	97%
Horse	96%	90%
Cat	100%	82%
Sheep	92%	94%
Dog	97%	83%

Table 2. Accuracy comparison

- AIDSAF Result:

Using OpenCV we detect if there is any movement in live video feed captured by camera monitoring 24/7. The video feed is divided into frames to detect any animal intrusion. The AIDSAF performs at the rate of 30fps using raspberry pi for analyzing and detecting any animal intrusion in agricultural field.



```
oviva@raspberrypi: ~/Downloads/validation
File  Edit  Tabs  Help
oviva@raspberrypi:~ $ cd /home/oviva/Downloads/validation
oviva@raspberrypi:~/Downloads/validation $ python detect.py
pygame 2.3.0 (SDL 2.24.2, Python 3.9.2)
Hello from the pygame community. https://www.pygame.org/contribute.html
Namespace(weights='yolov7.pt', source='0', img_size=640, conf_thres=0.25, iou_thres=0.45, device='', view_img=False, save_txt=False, save_conf=False, nosave=False, classes=None, agnostic_nms=False, augment=False, update=False, project='runs/detect', name='exp', exist_ok=False, no_trace=False)
 Convert model to Traced-model...
 traced_script_module saved!
 model is traced!

1/1: 0...  success (640x480 at 30.00 FPS).
```

Figure 8. Code execution snippet

From the above snippet 8, we can infer the property of image to be 640 x 480, configuring threshold as 0.25 and other parameters as well.

Figure 9. Intrusion detection

When an elephant is intruded inside the specified agricultural boundary, the alerts are generated via SMS and simultaneously the repellent sound is played in order to scare away the animal. For example, in this case honey bee sound is played as elephants are irritated by this particular noise.

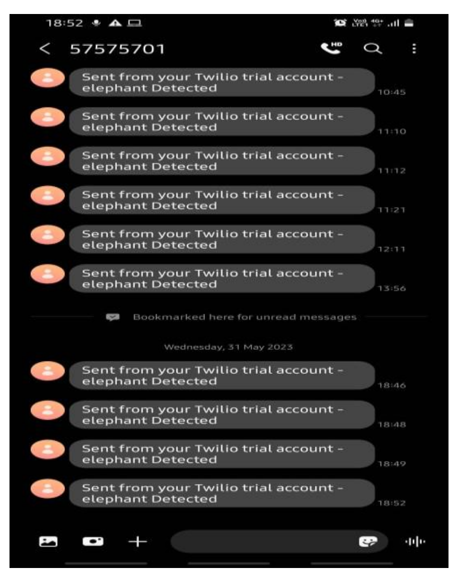


Figure 10. Alerts generated

Fig 10 shows that alert is generated to farmers via SMS notification by means of twilio which is a free service. Alerts are generated to user when a desired animal intrudes into the specified boundary. For instance, in the above fig 10. We can note that the elephant has intruded at that specific time period.

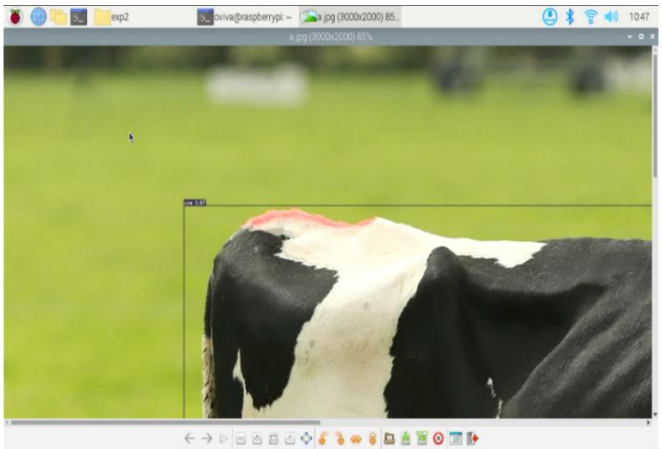


Figure 11. Animal detection

The above figure 11 shows the output of the animal detection in raspberry pi 4 model B when it enters the specified boundary. We have trained 8 classes and when the cow image is passed for testing, the yolov7 code in raspberry bi 4 model B detects the animal with a higher accuracy.

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AUTHORS

First Author –Oviya Gnanasekar, B.E ECE, Sri Venkateswara College of Engineering, ovi13ya@gmail.com.
Second Author – Prapti Dinesh, B.E ECE, Sri Venkateswara College of Engineering, praptid2002@gmail.com.
Third Author – Srividhya K, Assistant Professor ECE, Sri Venkateswara College of Engineering, srivi@svce.ac.in.

Correspondence Author – Oviya Gnanasekar, B.E ECE, Sri Venkateswara College of Engineering, ovi13ya@gmail.com,7395955220.