IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

ANIMAL DETECTION IN FARMS USING OPEN CV

[1]S Raji, [2]M Mubashira Nazneen, [3]T Sai Poojitha, [4] Y Lavanya
[1]Student, [2] Student, [3]Student, [4] Student
[1]Computer Science & Engineering,
[1]Sri Venkateshwara Institute Of Technology, Anantapur, India

Abstract : Agriculture is the most important sector of Indian Economy but the issue of damage to crops by wild animals has turned into an important social issue in current occasions. So far, many of the farmers reply on guards to guard their crops which increases the overhead costs. But, due to current climate conditions, crop failure rate has increased dramatically. Debt in agricultural sector has increased tremendously. In these situations, a farmer cannot expect further destruction of crops and neither can afford increase costs in farming.

Thus, there is need for a system to detect any intrusion which can help the farmers to drive away these animals as soon as they learn about their intrusion. Computer vision is applicable to many fields like medical field, robotics, remote sensing, machine vision, content-based image retrieval. Computer vision also applied in the security field to perform automatic surveillance and access control and attendance management. In agriculture fields near to forest areas have a severe threat from wild animals, which attacks regularly on farms.

These attacks causing huge damage to agricultural crops subsequently causes significant financial losses to farmers. Some measures are taken by the farmers by installing electrical fences to the farms, big flood lights in the farm. Some even resort to hiring guards. Installing an electrical fence is much costlier to equip huge farms and kills so many animals, which is even illegal in certain places and affects the biodiversity. Other existing techniques also are not effective due to several reasons, cost being one of them.

In this project, we proposed a new and cost effective solution for agriculture security from animals. It is a proactive solution which gives alerts to the farmers when animals come near to the farms. It also causes certain siren to be played whenever any animals are detected and is directed towards the animal in an attempt to scare them away. Here, we are implementing a solution that recognizes animals when it is captured on camera.

IndexTerms - OpenCV, Machine Learning, Artificial Intelligence, Single Shot Detector(SSD).

INTRODUCTION

Interference of animals in agricultural lands causes a huge loss of crops. Small farmers can even lose up to half of their yield to animals and they cannot take any harsh measures due to the strict wildlife laws.

Thus, there is need for a system to detect any intrusion which can help the farmers to drive away these animals as soon as they learn about their intrusion. In this project, we proposed a new and cost effective solution for agriculture security from animals. It is a proactive solution which gives alerts to the farmers when animals come near to the farms. Here, we are implementing a solution that recognizes animals when it is captured on camera.

EXISTING SYSTEM

Region-based Convolutional Neural Network (R-CNN) is a type of deep learning architecture used for object detection in computer vision tasks. RCNN was one of the pioneering models that helped advance the object detection field by combining the power of convolutional neural networks and region-based approaches.

R-CNN starts by dividing the input image into multiple regions or subregions. These regions are referred to as "region proposals" or "region candidates." The region proposal step is responsible for generating a set of potential regions in the image that are likely to contain objects. R-CNN does not generate these proposals itself; instead, it relies on external methods like Selective Search or Edge Boxes to generate region proposals.

Selective Search, for example, operates by merging or splitting segments of the image based on various image cues like color, texture, and shape to create a diverse set of region proposals.Below we show how Selective Search works, which shows an input image, then an image with many segmented masks, then fewer masks, then masks that comprise the main components in the image.

DRAWBACKS OF EXISTING SYSTEM

Computational Complexity: R-CNN is computationally intensive. It involves extracting region proposals, applying a CNN to each proposal, and then running the extracted features through a classifier. This multi-stage process can be slow and resource-demanding.
Slow Inference: Due to its sequential processing of region proposals, R-CNN is relatively slow during inference.
Overlapping Region Proposals: R-CNN may generate multiple region proposals that overlap significantly, leading to redundant computation and potentially affecting detection performance. **R-CNN is Not End-to-End**: Unlike more modern object detection architectures like Faster R-CNN, R-CNN is not an end-to-end model. It involves separate modules for region proposal and classification.

PROPOSED WORK

SSD (Single Shot MultiBox Detector) offers several advantages over RCNN (Region-based Convolutional Neural Network):

Speed: SSD is significantly faster than RCNN. RCNN involves multiple stages, including generating region proposals, extracting features, and classifying objects, which makes it computationally expensive and slow. In contrast, SSD performs object detection in a single forward pass of the network, making it much faster and more suitable for real-time applications.

Efficiency: SSD is more efficient in terms of both memory and computation. RCNN requires processing each region proposal independently through a CNN, resulting in redundant computations and memory overhead. SSD, on the other hand, integrates all detection tasks into a single network, eliminating the need for separate region proposal and feature extraction stages, which leads to improved efficiency.

- **End-to-End Training**: SSD is end-to-end trainable, whereas RCNN involves multiple separate components that need to be trained independently. In SSD, all components, including the feature extractor, bounding box regressor, and classifier, are trained jointly, allowing for better optimization and learning.
- **Simplicity**: SSD has a simpler architecture compared to RCNN. RCNN consists of multiple stages and components, including generating region proposals, feature extraction, classification, and bounding box regression, making it complex and difficult to implement. SSD, with its single-shot detection approach, simplifies the object detection pipeline, making it easier to understand and implement.
- **Multi-scale Detection**: SSD inherently captures objects at multiple scales through its feature pyramid architecture. It combines features from multiple layers in the network to detect objects of different sizes, whereas RCNN requires separate processing for objects at different scales, leading to inefficiencies.
- **Real-time Applications**: Due to its speed and efficiency, SSD is well-suited for real-time applications where fast and accurate object detection is required, such as autonomous driving, video surveillance, and robotics.

Overall, SSD's speed, efficiency, simplicity, end-to-end training capability, and suitability for real-time applications make it a superior choice compared to RCNN for many object detection tasks.

PROJECT MODULES

1. Image dataset collection
2. Image preprocessing
3. Importing modules
4. Capturing the images of animals
5. Camera interfacing

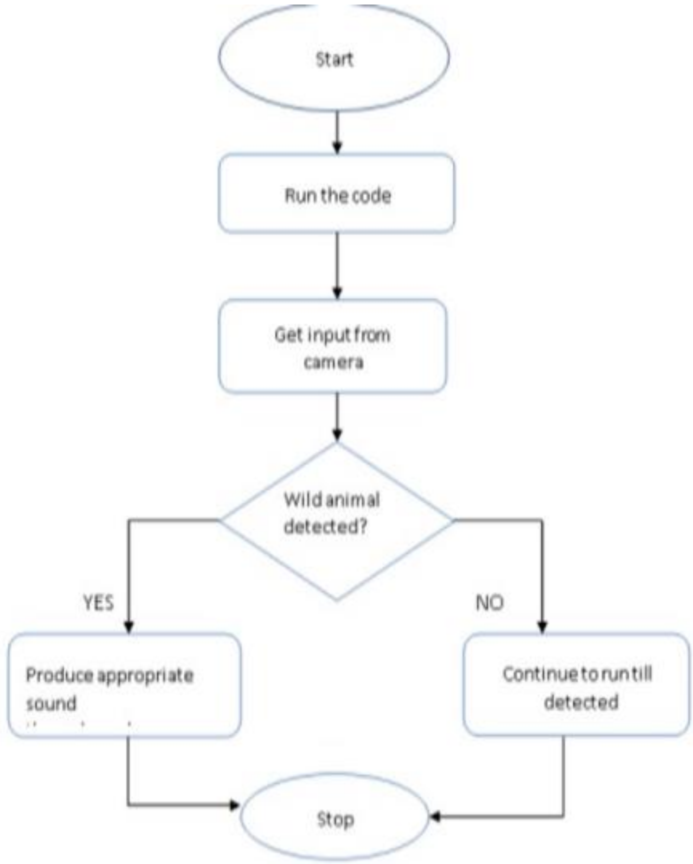

Fig: Workflow of the project

1. IMAGE DATASET COLLECTION

Define the Scope: Determine what types of animals you want to detect. This could range from common pets like cats and dogs to wildlife like bears and deer.
COCO (common objects in context): COCO is a large-scale object detection, segmentation, and captioning dataset. It contains over 200,000 labeled images and covers 80 object categories

2. IMAGE PREPROCESSING

Animal images may vary in size and aspect ratio. Resizing them to a uniform size can make processing more efficient and facilitate comparisons between different images.
Cropping can help remove irrelevant parts of the image and focus only on the region containing the animal, reducing computational overhead and improving detection accuracy.

3.IMPORTING MODULES

- OpenCV
- Imutils
- Pygame
- Numpy

4. CAPTURING THE IMAGES OF ANIMALS

Live webcams or livestreams are used to capture real-time footage of animals. These can be used to collect images for detection purposes.

5. CAMERA INTERFACING

Interfacing a camera for animal detection involves capturing images or video frames from the camera feed and processing them using computer vision techniques to detect animals.

MODULES DESCRIPTION

Upload (live): Upload a video as a live feed using a webcam (or any camera attached in a farm).
View: video can be viewed live in a dialog box.
Preprocessing: data preprocessing is used to convert the raw data into a clean data set.
Cleaning the data refers to removing the null values, removing duplicate values, removing outliers, removing unwanted attributes.
In this case, we are taking a live video feed in the form of images and resizing them to a standard size.

ALGORITHM

Input Image: The algorithm takes an input image where objects need to be detected.

Base Convolutional Network: SSD typically uses a base convolutional network (such as VGG, ResNet, or MobileNet) to extract features from the input image. These convolutional layers are pre-trained on a large dataset to learn generalizable features.

Multiscale Feature Maps: SSD uses multiple feature maps at different spatial scales to detect objects of varying sizes. These feature maps capture objects at different resolutions, allowing SSD to detect both small and large objects effectively.

Convolutional Predictor Layers: SSD adds additional convolutional layers on top of each feature map to predict bounding boxes and classify objects. These predictor layers have different aspect ratios and scales to detect objects of various shapes and sizes.

Bounding Box Regression: SSD performs bounding box regression to refine the positions of the predicted bounding boxes. It learns to adjust the
dimensions and positions of the anchor boxes to better fit the objects in the image.

1. **Object Classification**: SSD performs object classification using softmax or logistic regression to assign class probabilities to each detected object. It predicts the probability of each anchor box containing an object belonging to a specific class.
2. **Non-maximum Suppression (NMS)**: To remove duplicate detections and improve the final detection results, SSD applies non-maximum suppression. This algorithm suppresses overlapping bounding boxes with lower confidence scores, keeping only the most confident detections for each object.
3. **Output**: The final output of the SSD algorithm consists of the detected bounding boxes along with their corresponding class labels and confidence scores.

COCO DATASET

The dataset used for training the model is mobile net SSD. However, one of the datasets used for object detection tasks include:

COCO (common objects in context):

The dataset used for training the model is mobile net SSD. COCO is a large-scale object detection, segmentation, and captioning dataset. It contains over 200,000 labeled images and covers 80 object categories.Many popular deep learning models, including mobile net SSD, are often trained on subsets or the entirety of the coco dataset to learn to recognize objects in images.

SYSTEM REQUIREMENTS

- Language used : python 3.6+
- Libraries used : pygame, NumPy, OpenCV, imutils.
- IDE : PyCharm

CONCLUSION

The problem of damaging crops by wild animals has become a major social problem in the current time. It requires urgent attention and an effective solution. The proposed method allows us to detect any animal presence or intrusion in farms using video from any camera device placed in the farms. The object detection model worked almost consistently at 18 frames per second. It is a cheap and robust system. The siren scares the intruders away as well as it can alert the farmer to take action. Thus, this application can be used to protect crops in the farm. It might be very useful for agricultural purposes instead of traditional methods used today.

FUTURE ENHANCEMENT

The methods to scare away the intruders can be changed in future. We may even employ a laser based system instead of just an siren to do so. It can also be embedded in an IOT based system for easy utilization.

REFERENCES

[1] Parikh, m. Et al. "Wild-animal recognition in agriculture farms using W-COHOG for Agro-security." (2017).

[2] s. Yadahalli, A. Parmar and A. Deshpande, "smart intrusion detection system for crop protection by using Arduino," *2020 second international conference on inventive research in computing applications (ICIRCA)*, Coimbatore, India, 2020, pp. 405-408, Doi: 10.1109/icirca48905.2020.9182868.

[3] Howard, Andrew & Zhu, menglong & Chen, bo & kalenichenko, Dmitry & wang, weijun & weyand, Tobias & andreetto, Marco & Adam, Hartwig. (2017). "Mobile nets: efficient convolutional neural networks for mobile vision applications."

[4] S. Matuska, R. Hudec, M. Benco, P. Kamencay and M. Zachariasova, \"A novel system for automatic detection and classification of animal,\" 2014 ELEKTRO, 2014, pp. 76-80, doi: 10.1109/ELEKTRO.2014.6847875.

[5] Priya Sharma, Sirisha C K, Soumya Gururaj, and Padmavathi C, "Neural Network Based Image Classification for Animal Intrusion Detection System", IJPRSE, vol. 1, no. 4, pp. 1–7, Jul. 2020.

[6] Morrow-Tesch J, Dailey JW, Jiang H. A video data base system for studying animal behavior. J Anim Sci. 1998 Oct;76(10):2605-8. doi: 10.2527/1998.76102605x. PMID: 9814900.

[7] D. P. Gibson, N. W. Campbell and B. T. Thomas, \"Quadruped gait analysis using sparse motion information,\" Proceedings 2003 International Conference on Image Processing (Cat. No.03CH37429), 2003, pp. III-333, doi: 10.1109/ICIP.2003.1247249.

[8] Burghardt, T. & Calic, Janko. (2006). "Analyzing animal behavior in wildlife videos using face detection and tracking", Vision, Image and Signal Processing, IEE Proceedings -. 153. 305 - 312. 10.1049/ip- vis:20050052.

[9] Zeppelzauer, M., "Automated detection of elephants in wildlife video", J Image Video Proc 2013, 46 (2013). https://doi.org/10.1186/1687-5281-2013-46.

[10] Prajna. P, Soujanya B.S, Mrs. Divya, "IoT-based Wild Animal Intrusion Detection System", International Journal Of Engineering Research & Technology (IJERT) ICRTT – 2018 (Volume 06 – Issue 15).