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WILD ANIMAL DETECTION IN AGRICULTURE FARMS USING DEEP CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT: On account of farmlands or rural terrains reconnaissance is vital to keep unapproved individuals from accessing the region as well as to shield the region from animals. Different techniques point just at observation which is basically for human interlopers, yet we will quite often fail to remember that the primary adversaries of such ranchers are the animals which obliterate the harvests. Crop damage brought about by animal assaults is one of the significant dangers in lessening the harvest yield. Because of the extension of developed land into past wildlife territory, crop striking is becoming one of the most alienating human-wildlife clashes. Effective and solid checking of the wild animals' right in their natural habitat is fundamental. This project fosters an algorithm to identify the animals that intrudes into the agriculture land. Since there are enormous number of various animals physically distinguishing them can be a troublesome undertaking. This calculation arranges animals in view of their pictures so we can screen them all the more proficiently. This can be accomplished by applying yolo v3 algorithms which is a powerful real-time object detection algorithms. YOLOv3 detect an object with the help of the features of deep convolutional neural network.

Key words: Image Processing, Real-time Object, YOLOv3, Deep Convolutional Neural Network.

INTRODUCTION

One of the significant issues that is faced by farmers are their yields get damaged by wild animals that intrudes their crops. Wild animal interruption has forever been a continuing issue to the ranchers. A portion of the animals that go about as a danger to the yields are wild boar, deer, wild buffalo, elephants, tiger, monkeys and others. These animals might benefit from crops and furthermore go around the field without any rancher and accordingly make damage those yields. This may thus bring about critical misfortune in the yield and will make extra monetary security all together arrangement with the result of the damage.

In any case, wildlife-friendly cultivating regularly brings about lower effectiveness. In this manner, endeavors have been made to foster programmed frameworks fit for identifying wild animals in the harvest without superfluous discontinuance of the cultivating activity. For instance, a recognition framework in light of infrared sensors has been answered to lessen wildlife mortality in Germany [1]. In [2] a UAV-based framework for roe deer grovel location is introduced. The creators show that warm imaging can be utilized to identify roe deer grovels based on elevated film, but the location is as yet performed physically.

Here we are using Real-time object detection algorithms which detect an object with the help of deep convolutional neural network. It helps in identifying wild animal intrusion to the crops. For this project we need some cameras affixed at agricultural areas, so that it is clearly visible that who is entering to the particular area. Our system will identify the animal and send a warning notification to the farmer that particular animal has been entered to his crops. Now this will be easy for farmers to perform he next step to distract those animals from his crops.

OBJECTIVE

The primary goal of the project is to safe watchman the farming field from wild animals and furthermore to safeguard them by pushing them away as opposed to killing. The project additionally plans to safeguard human lives from creature assaults. We are involving an integrative methodology in the field of Deep Learning to give a checking and repulsing framework for crop insurance against creature assaults.

EXISTING SYSTEM

The current systems essentially give the observation usefulness. Additionally these systems don't give security from wild animals, particularly in such an application region. They additionally need to make moves in light of the on the kind of animal that attempts to enter the region, as various techniques are taken on to keep various animals from entering such confined regions. Likewise the ranchers resort to different techniques by raising human manikins and likenesses in their homesteads, which is ineffectual in warding off the wild animals, however is valuable somewhat to avert birds .The other usually involved strategies by the ranchers to forestall the harvest vandalization by animals incorporate structure actual obstructions, utilization of electric wall and manual reconnaissance and different such thorough and risky techniques.

STRATEGIES TO PROTECT CROPS

Fruitful farmers generally look to decide the acceptable degree of wild animal harvest assurance utilizing one of the accompanying innovations:

1. **Agricultural fences**
   - Electric fences
   - Plastic fences
   - Wire fences
   - Wood fences
2. **Natural repellents**
   - Lavender and beans
   - Chilli peppers
   - garlic emulsion
   - Smoke Fish
   - Egg based repellent

3. **Chemical repellent**
4. **Electronic repellent**
   - Sonic Electronic repellent
   - Ultrasonic Electronic repellent

SCOPE OF STUDY

1. To plan a security system for farm assurance

2. Restrict the passage of animal into the farm

3. Use GSM module for cautioning us

4. Plan a system that sounds through solar animal anti-agents when animal attempts to go into the farm

5. In night streak light will zero in on that side.

6. The camera consistently screens the fields and gives the video feed to the farmer at home 24×7 for the entire day

7. The system guarantees that the caution isn't set off by the presence of a human in the field, or by means of any arbitrary movement.

8. The system is fit for turning On/Off consequently and averting the animals in this way safeguarding the fields from any harm additionally we can arrangement a Timer according to farmer's prerequisite

CONCEPT OF THE MODEL

1. Visual recognition - to separate elements from pictures.
2. AI - Supervised learning is required for the model to order the animals.
3. Deep Learning - This gives the mental ability of breaking down the animal recognized to a specific class and consequently produce the proper result, very much like how human examinations and this can be accomplished with the assistance of CNN.
4. Keras and OpenCV : which will help in the handling of the information gained including all the above ideas.
5. Anaconda labelImg : LabelImg is a graphical image annotation tool.It is written in Python and uses Qt for its graphical interface.Annotations are saved as XML files in PASCAL VOC format, the format used by ImageNet. It supports YOLO and CreateML formats.
6. Google Colab : Colab is a free Jupyter notebook environment that runs entirely in the cloud. Most importantly, it does not require a setup and the notebooks that you create can be simultaneously edited by your team members - just the way you edit documents in Google Docs. Colab supports many popular machine learning libraries which can be easily loaded in your notebook.

PROPOSED SYSTEM

The proposed system uses YOLOv3 algorithms to detect real-time object.

YOLOv3 is a real-time object discovery algorithm that distinguishes explicit objects in recordings, live feeds, or pictures. Consequences be damned uses highlights learned by a deep convolutional neural network to recognize an object. YOLOv3 is a superior form of YOLO and YOLOv2. YOLO is carried out utilizing the Keras or OpenCV deep learning libraries

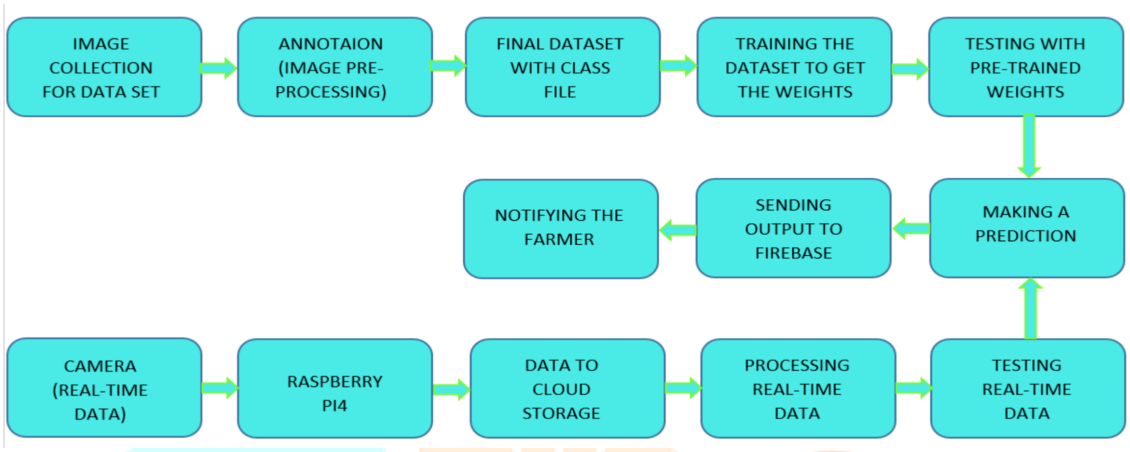

Figure 1. Overall process of proposed system.

For developing this system we have to collect some dataset. Here our datasets are images of wild animals of 8 different classes. After collecting the dataset it will go through an image pre-processing step, it is also called as annotation and we will get our final dataset for training. These dataset contains the class file, images and txt files of those images, which is automatically created after successful annotation. Now we can start to train our system, we are using google colab for training and testing. While the dataset is going through training process it will generate some weights that is later useful for testing. Training process may take approximately 12-15 hours, but testing can be done easily with the help of those trained weights. While testing the system it will check an image and look for matching class and it will predict an output which have an accuracy near to 1. After that it will send these predicted class name to firebase which is a real-time database, further the class name will be notified to the user's device

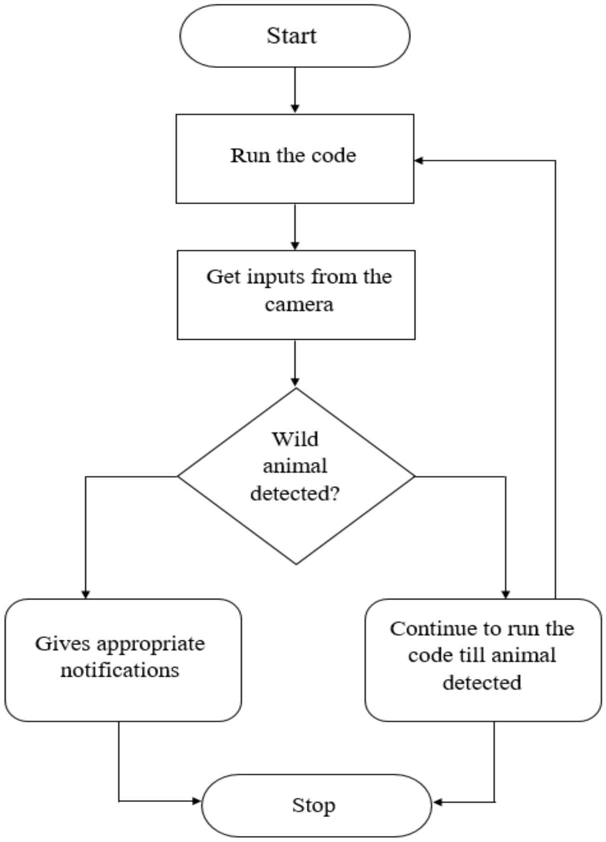

Figure 2. Flow chart of the working model

DATASET

Image dataset is used to this model. We use 8 classes, they are elephant, tiger, leopard, wild boar, deer, wild buffalo, monkey and peacock. These animals are some of the main intruders of the agriculture area and they are also threat to human life. Dataset are mainly divided into 2 parts. The majority will go for training and the other for testing

The training dataset includes:
Elephant – 523 images
Tiger – 550 images
Leopard – 670 images
Wild boar – 520 images
Deer – 560 images
Wild buffalo – 534 images
Monkey – 600 images
Peacock – 533 images

The testing dataset includes:
Elephant – 103 images
Tiger – 100 images
Leopard – 110 images
Wild boar – 90 images
Deer – 98 images
Wild buffalo – 69 images
Monkey – 80 images

Peacock – 92 images

Figure 3. Sample dataset collection of 8 classes.

YOLOv3

Object grouping frameworks are utilized by AI projects that see the subjects of interest that are explicit objects in a class. The frameworks sort objects in pictures into bunches where objects with comparative qualities are set together, while others are ignored except if customized to do in any case. As average for object finders, the elements learned by the convolutional layers are gone to a classifier which makes the identification forecast. In YOLO, it uses convolutional layer for the expectation which depends on a layer that utilizes 1×1 convolutions.

YOLO is named "you just look once" on the grounds that its forecast utilizes 1×1 convolutions; the size of the expectation map is actually the size of the element map before it. YOLO is CNN that is developed to doing an object location in real-time. CNNs are classifier-based frameworks that can interaction input pictures as organized varieties of information and distinguish designs between them (view picture underneath). YOLO enjoys the benefit of being a lot quicker than different networks nevertheless keeps up with exactness. It permits the model at the test time to take some gander at the entire picture, so it can educate the forecasts by the worldwide setting in the picture. YOLO and other CNN "score" locales in light of their likenesses to predefined classes.

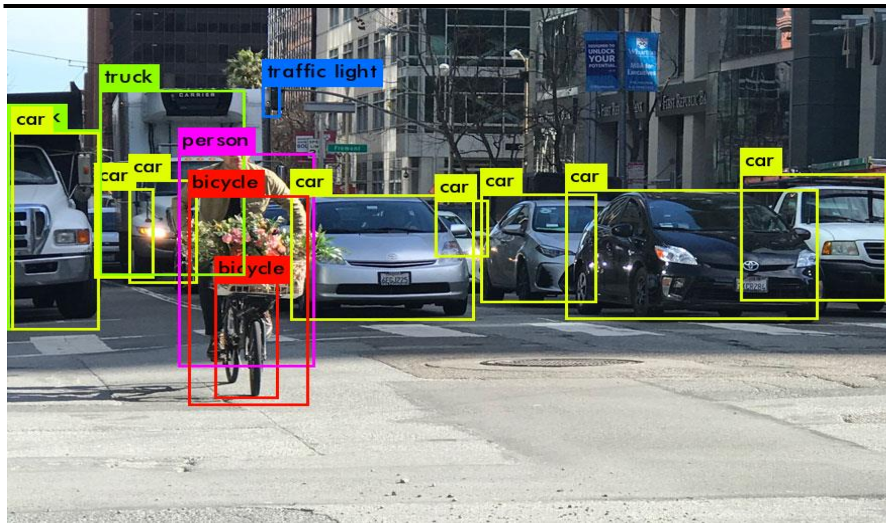

Figure 4. Example of YOLOv3 Computer Vision

HOW TO USE YOLOv3

The first step to using YOLOv3 would be to decide on a specific object detection project. YOLOv3 performs real-time detections, so choosing a simple project that has an easy premise, such as detecting a certain kind of animal or car in a video, is ideal for beginners to get started with YOLOv3.In this section, we will go over the essential steps and what you have to know for using YOLOv3 successfully.

MODEL WEIGHTS

Weights and cfg (or configuration) files can be downloaded from the website of the original creator of YOLOv3: https://pjreddie.com/darknet/yolo. You can also (more easily) use YOLO's COCO pretrained weights by initializing the model with **model = YOLOv3 ().** Using COCO's pre-trained weights means that you can only use YOLO for object detection with any of the 80 pretrained classes that come with the COCO dataset. This is a good option for beginners because it requires the least amount of new code and customization.

MAKING A PREDICTION

The convolutional layers remembered for the YOLOv3 design produce a recognition expectation in the wake of passing the elements learned onto a classifier or regressor. These elements incorporate the class name, directions of the bouncing boxes, sizes of the jumping boxes, and the sky is the limit from there. In YOLOv3 and its different renditions, the way this forecast map is deciphered is that every cell predicts a proper number of jumping boxes. Then, at that point, whichever cell contains the focal point of the ground truth box of an object of interest is assigned as the cell that will be at last liable for foreseeing the object. There is a huge load of math behind the internal functions of the forecast design.

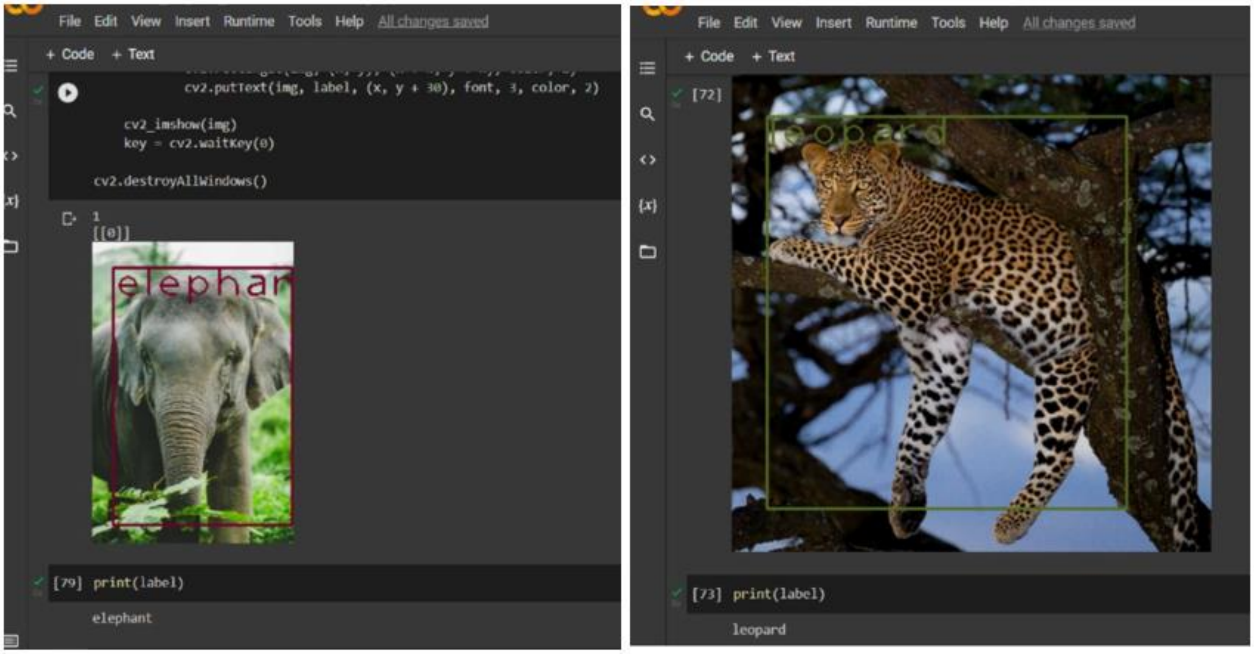

Figure 5. Output prediction.

LOSS FUCTION

YOLO uses sum-squared error between predictions (the one with highest IoU) and ground truth to calculate loss. The loss function composes of:

- The **classification loss**.
- The **localization loss**.
- The **confidence loss** (the abjectness of the box).

❖ Classification loss

$$\sum_{i=0}^{S^2} 1_i^{obj} \cdot \sum_{cc \in classes} (\mathrm{pi}(cc) - \hat{p}_i(cc))^2$$

where $1_i^{obj} = 1$ if an object appears in cell i, otherwise *0*;

$\hat{p}_i(cc)$ denotes the conditional class probability for class cc in cell i.

❖ Localization loss

$$\boldsymbol{\lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2\right] +}$$

$$\boldsymbol{\lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} \left[\left(\sqrt{w_{i_i}} - \sqrt{\hat{w}_i}\right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i}\right)^2\right]}$$

Where $1_{ij}^{obj} = 1$ if the *j*th boundary box in cell *i* is responsible for detecting

λ_{coord} Increases the weight for the loss in the boundary box coordinates.

YOLO predicts the square root of bounding box width and height in order to differentiate large and small boxes. By setting $\boldsymbol{\lambda_{coord}}$ (default: 5), we put more emphasis on the boundary box accuracy.

❖ Confidence loss

If an object is detected in the box, the confidence loss is:

$$\sum_{i=0}^{S^2}\sum_{j=0}^{B}\mathbf{1}_{ij}^{obj}\left(C_I-\hat{C}_i\right)^2$$

Where $1_{ij}^{obj}=1$if the *j*th boundary box in cell *i* is responsible for detecting the object, otherwise 0; $\hat{C}_i$ is the box confidence score of the box *j* in cell *i*.
However, if an object is not detected:

$$\lambda_{backg}\sum_{i=0}^{S^2}\sum_{j=0}^{B}\mathbf{1}_{ij}^{backg}\left(C_I-\hat{C}_i\right)^2$$

Where $\mathbf{1}_{ij}^{backg}$ is the complement of $\mathbf{1}_{ij}^{obj}$.
$\hat{C}_i$ is the box confidence score of the box *j* in cell *i*.
λ_{backg} weights down the loss when detecting background.
As most boxes do not contain any objects, we weight the loss down by a factor λ_{backg} (default: 0.5) to balance the weight.

CONCLUSION

The issue of yield destroying by wild animals has turned into a significant social issue in the current time. It requires dire consideration and a powerful arrangement. Subsequently this project conveys an extraordinary social significance as it plans to resolve this issue. Thus we have planned a shrewd installed farmland protection and observation based framework which is minimal expense, and furthermore consumes less energy. The principle point is to forestall the deficiency of yields and to shield the region from intruders and wild animals which represent a significant danger to the rural regions. Such a framework will be useful to the ranchers in safeguarding their plantations and fields and save them from critical monetary misfortunes and furthermore saves them from ineffective endeavors that they suffer for the protection of their fields. This framework will likewise help them in accomplishing better harvest yields consequently prompting their monetary prosperity.

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