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An Intelligent Animal Repellent System for Crop Protection: A Deep Learning Approach

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Abstract— ***Human Wildlife Conflicts (HWC) refers to the negative interactions between human and wild animals, with undesirable consequences both for people and their resources, on the one hand, and wildlife and their habitats on the other (IUCN 2020).HWC, caused by competition for natural resources between humans and wildlife, influences human food security and the well-being of both humans and animals. As a result of human population growth and the transformation of land use in many regions, the number of these conflicts has increased in recent decades. HWC is a significant global threat to reliable development, food security, and conservation in urban and rural landscapes alike. In general, the consequences of HWC include crop destruction, reduced agricultural productivity, competition for grazing lands and water supply, livestock predation, injury and death to humans, damage to infrastructure, etc. From farmers' perspectives, their main concern is to protect their crops from animal intrusion and crop destruction. It is necessary to have an affordable better technique for crop protection from animal attacks. Human-wildlife conflict is on the verge of its extremity. Because of the increased deforestation and human penetration into their area, the wild animals have to roam around aimlessly and intrude into the human habitats. While considering the safety of both humans and animals, it is necessary to think and act differently than the traditional solutions (like shooting, trapping, electric fences, etc). This work presents an intelligent animal repellent system, particularly for crop protection, with the advent of some deep learning techniques. This automatic intrusion and repellent system uses the MobileNet SSD model for better performance. On detection of the hazardous animal, the system produces an alarm sound and makes an alert notification to the responsible authorities to make an awareness of the detection. This rapid way of detection makes it more human-friendly and the harmless way of repulsion makes it more animal friendly at the same time. .***

Index Terms— ***Crop Protection, Human Wildlife Conflict, Intelligent Animal Repellent System, MobileNet SSD***

I. INTRODUCTION

Agriculture, or farming as it is commonly known, is the practice of growing crops and raising cattle. It contributes greatly to a country's economy. Crop damage caused by animal attacks is one of the major threats to reducing crop yield. Due to the augmented conversion of wild habitats into cultivated lands, the wild animal species have to migrate for survival. These in due course led animals to intrude into human habitats for food and shelter causing Human-Wildlife conflicts. Crop raiding has become one of the most conflicts alienating the human-wildlife relationship. Examining wild animals in their natural environment is an essential task in the ecosystem. Due to the enormous growth in human inhabitants and the increase in the hunt for economic development makes excessive exploitation of natural resources, fast, innovative, and significant changes in the Earth's ecosystems. An expanding region of the land surface has been changed by human activity, modifying the natural life populace, habitat, and behavior. In the reduction of crop yields, damage caused by animal attacks is one of the major threats. To resist these losses, humans in turn take some preventive measures. These traditional methods can be lethal (like shooting, trapping, electric fences, etc.) or non-lethal (like chemical repellents, guard dogs, etc.).But these measures are proved to be unfit due to the reasons such as having a temporary lifespan, unhealthy, very expensive and maintenance, causing environmental pollution, etc.

More fatally, many wild animals on the Earth have disappeared, and many species are locomoted into new places where they can disturb all natural and human resources. According to the studies, most wild animal fatality cases are kept unreported/unattended for months showing the overall negligence of the forest department. Even though the government performed numerous drives to eradicate illegal fences to control the overall fatality rate the cases have still occurred and to some extent are kept unreported. This shows that humans and animals both share losses equally. These conflicts and fatality rates are likely to reduce if the presence of these wild animals can be notified in time. Many wild animal repellent systems were invented based on IoT solutions, with the evolution in technology.

Deep neural networks are the collection of algorithms that have defined new records in precision for several vital problems; Convolutional neural network (CNN) is a category of deep neural networks, most generally applicable for investigating visual images. Compared to other image classification algorithms, CNNs employ fairly modest preprocessing. This liberty from past knowledge and human intervention in feature design is a key benefit of a

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Convolutional neural network (CNN). They have several applications in the field of image and video recognition, recommendation systems, image classification, and medical image processing. Recent advancements in deep learning have observed development in image classifiers that have already surpassed human accuracy, leading to high demand for AI to work effectively within the IoT domain. For example, a fully automated security wherein intruders can be detected and reported immediately. Here the basic essence of technology lies over an algorithm that pursues each frame of the video/image hoping to find something abnormal and send an alert to the concerned person.

II. RELATED WORK

This section presents a review of various strategies and technologies used for animal detection and classification. Since the related literature pertaining to animal detection is limited, an extensive review of object detection is carried out. Among the reviewed literature, the most relevant studies are detailed below.

The work in [1] focuses on a Smart Agriculture application that aims to protect crops from ungulate attacks, and therefore significantly reduce production losses, through the creation of virtual fences that make use of computer vision and ultrasound emission. This work provides a comprehensive interpretation of the design, development, and assessment of an intelligent animal repulsion system that allows to detect and recognize the ungulates as well as generates ultrasonic signals customized to each species of the ungulate. The proposed system in the work [2] aims in protecting human habitation and livestock on the outskirts of the forest area by developing an automated system that detects the intrusion of wild animals and repels them back to their habitat without causing any harm; Hence reducing the dangerous effects caused by the conflict. .

The study in [5] presents the development of the Internet of Things application for crop protection to prevent animal intrusions in the crop field. A repelling and a monitoring system are provided to prevent potential damage in agriculture, both from wild animal attacks and weather conditions. It presents the system architecture for the ultrasound repeller device, the weather monitoring system, and the back-end system implementation. In [12], it summarizes some of the most important deep learning models used for object detection tasks over the last recent years, since the creation of AlexNet in 2012. Then, makes a comparison in speed and accuracy between the most used state-of-the-art methods in object detection. The proposed work in [13] develops an algorithm to detect the animals in wildlife and classifies animals based on their images so we can monitor them more efficiently.

III. PROPOSED SYSTEM

The proposed system aims in protecting human habitation and crops from wild animal intrusion and attacks. This automated system detects the intrusion of wild animals and repels them back without causing any harm. The specified operations are performed with the touch of a deep learning technique called MobileNet SSD. Once the wild animal is detected an alarm sound is produced to drive away them back. Along with, an alert message is passed to responsible authorities to make awareness of the detection. Hence minimizing the dangerous consequences caused by the conflict and can be considered as advancement in the smart agricultural applications.

The system mainly focuses in providing an automated wild animal detection and repellent system, for human habitat and crop fields. The whole system flow can be divided into three major parts.

1. Training Model with standard datasets (Microsoft COCO).
2. Building Animal Detection model which works on real time video streaming.
3. Repelling the hazardous intruder (only wild animals if found) without harming it.

Figure 3.1 below represents the overview of the control flow diagram of the proposed system. Input will be given through real-time video by camera or webcam, based on streamlined MobileNet Architecture which uses depth-wise separable convolutions to build lightweight deep neural Networks. The input video is divided into frames and passes to MobileNet layers. The feature value can be determined as a difference between the amount of pixel intensity under the bright region and the pixel intensity under the dark area. Every one of the possible sizes and areas of the image is utilized to compute these elements. An image may contain relevant and irrelevant features that can be used to detect the object. It is the MobileNet layers that change over the pixels from the input image into highlights that describe the contents of the image. Then it passes to the MobileNet-SSD model to determine the bounding boxes and corresponding class (label) of objects. After that, the only last step is to display the output or switch to the following module.

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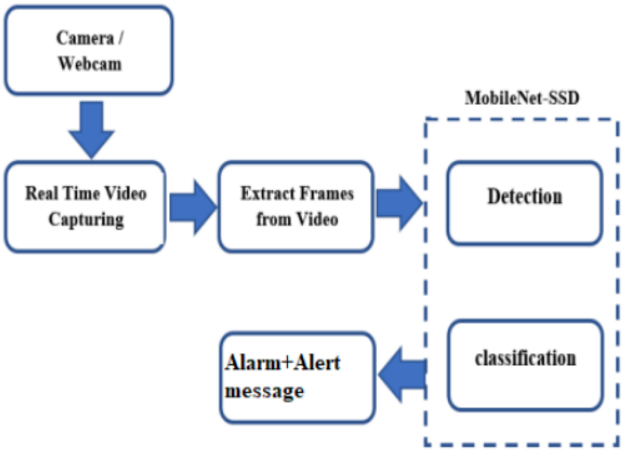


Fig.3.1. Control flow diagram of proposed system

The following are the layers of the architecture and their specific roles:

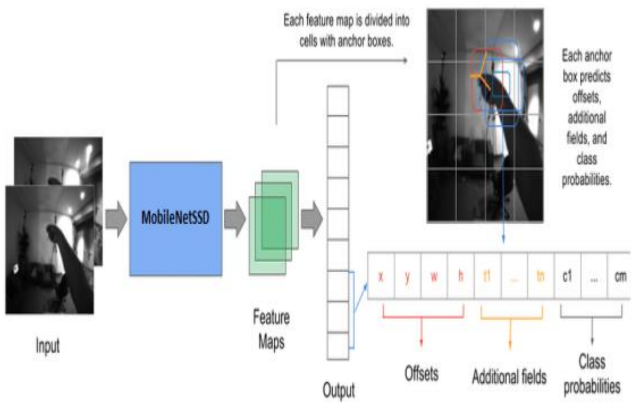
A. Camera

The camera is connected to the computation module to initiate live streaming and capture the video. The precision and confidence level of the model solely depends on the resolution and camera calibrations. The camera position and the height from the ground should be firm and fixed. The input video stream source can be anything, we might want to read from our webcam, parse an already existing video, or from an external camera connected to the network.If we are building an application that will be deployed on a server your camera will have an IP address from which you can access the video stream. The images are continuously captured from the webcam stream with the help of an infinite while loop, and then capturing the corresponding height and width of the webcam frame, and after then define the parameters of the region of interest (ROI) box in which our object can fit in by taking the corresponding height and width of the webcam frame. And then we draw the rectangle from the ROI parameters. 3

B. Animal Detection and Classification Model

This model will detect the animal species in the video using the MobileNet SSD algorithm. This algorithm for object detection computes the bounding box and category of an object from an input image. This Single Shot Detector (SSD) object detection model uses Mobilenet as a backbone and can achieve fast object detection optimized for mobile devices. An SSD-based object detection model mainly consists of four components, namely, the pre-processing, the feature extractor, and the bounding box prediction. Instead of using a sliding window, SSD divides the image using a grid and has each grid cell responsible for detecting objects in that region of the image. Detection of objects simply refers to the prediction of the class and location of an object within that region. The MobileNet layers convert the pixels from the input image into features that describe the contents of the image and pass these along to the other layers. Hence, here the MobileNet is used as a feature extractor for a second neural network.

Mobilenet SSD computes the output bounding box and class of an object from an input image. This Single Shot Detector (SSD) object detection model considers Mobilenet as a backbone and It can achieve fast object detection optimized for mobile devices. SSD Mobilenet V2 is a one-stage object detection model which has gained popularity for its lean network and novel depth-wise separable convolutions. This model is commonly deployed on low compute devices such as mobile (hence the name Mobilenet) with high accuracy performance. Mobilenet SSD takes an image as input and outputs boxes and scores. Boxes have some offset values (cx,cy,w,h) from the default box. Scores represent the confidence values for the presence of each of the object categories; the value 0 is reserved for the background.



C. Alarm and Alert Notification

The Buzzer is connected to the computation module. On confirmation detection of the Wild animal intrusion, a buzzer alarm will be initiated to divert the wild animal back to its habitat without physically harming or causing life-threatening conceptions to animals or humans in any scenario. Also, an alert notification is passed to the responsible authorities' mobile phones as pop-up text messages. This makes them aware of intrusion detection even if they are far away.

IV. IMPLEMENTATION

For implementation we need to consider software than be integrated to our computation modules. For Programming the logics and functionalities, OpenCV with Python 3 is used. This proposed system uses a pre-trained model known as SSDLite Mobilenet. It is available as a part of the torch vision module in the PyTorch framework. In fact, the complete name is ssdlite320mobilenetv3large. The 320 indicates that it internally resizes the inputs to the 320×320 and it has a

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MobileNetV3 Large backbone model. The MS COCO object detection dataset is used for training the model. It is also good to know what the input is and output format to and from the model while carrying out object detection inference

A. Major Steps involved in the Implementation

1. Load Dependencies

Dependencies are all of the software components required by your project in order for it to work as intended and avoid runtime errors. There are many different dependency management tools and methods for managing and adding dependencies to a Python project, from pip to Conda to the ActiveState Platform. Import the modules, construct the argument parser, and define the computation device and model.

2. Capture Video and Frame conversion

Get the video frames' height and width. Initialize the VideoWriter () object to save the resulting frames to disk. The total number of frames and cumulative FPS till the end will be tracked by frame-count and total-fps variables respectively. A while loop is used to loop through the video frames and detect the objects in each frame. For each frame: -We are detecting the animals. -Drawing the bounding boxes around the detected animals. -Annotating the frame with the FPS text. -Visualizing it and saving it to disk..

3. Set up the Neural Network

The get model () function accepts the computation device as the input parameter. This load the model from the torchvision module, switches it to eval() mode, loads it onto the computation device and returns the model.

4. Load the Dataset

Import all the required modules and libraries along with the COCO INSTANCE CATEGORY NAMES that are defined above. It defines a COLORS array that holds different color tuples for each of the COCO classes. These can be used to add different colors to the bounding boxes and texts for each of the classes while annotating the images with OpenCV.

5. Convert BGR images to RGB images

When the image file is read with the OpenCV function imread(), the order of colors is BGR (blue, green, red). On the other hand, in Pillow, the order of colors is assumed to be RGB (red, green, blue).Various color spaces such as RGB, BGR, HSV can be mutually converted using OpenCV function cvtColor().

6. Set Non maximal Suppression Threshold for the best Bounding box

The predict () function accepts the image, model, device, and detection threshold as input parameters. After the forward pass, this filters out all the predictions according to the threshold value. All the detections which have a confidence score below the given value are avoided. The boxes containing the bounding box coordinates, pred-classes containing the class names, and labels containing the class numbers are returned.

7. Set Intersection Over Union threshold

SSDLite with MobileNetV3 backbone tends the tradeoff accuracy for detection speed. So, maybe using a lower value as a confidence threshold will help.

8. Detect and Recognize the animals using utils module

Utils are simple functions to draw the bounding boxes around the objects and put the class name text on top of these boxes. Each class will have a different color bounding box to easily differentiate them. The final image that returns is the completely annotated image with bounding boxes and class texts. If the detected animal is of a particular class, then switch to the message passing and alarm producing module.

9. Message Passing

This system uses 1-way SMS, which refers to messaging that only moves in one direction. It uses the service of a bulk SMS provider, namely Twilio for message passing operation. Twilio's APIs (Application Programming Interfaces) make its platform able for communications. Behind these APIs is a software layer connecting and optimizing communication networks around the world to allow your users to call and message anyone, globally.

V. RESULTS AND DISCUSSION

In this section, we discuss the results obtained on the basis of the evaluation metric FPS.FPS (Frame Per Second) defines how fast your object detection model process your video and generates the desired output. It is the frequency (rate) at which consecutive images (frames) are captured or displayed. Higher frames per second, also known as frame rates, make the image appear smoother and more realistic The results obtained from the real-time implementation of the system detecting bears, elephants, cows, cats, and dogs are shown below.

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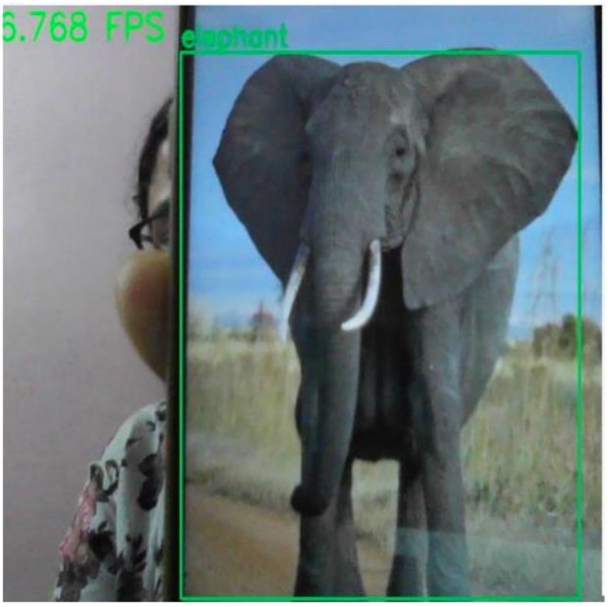
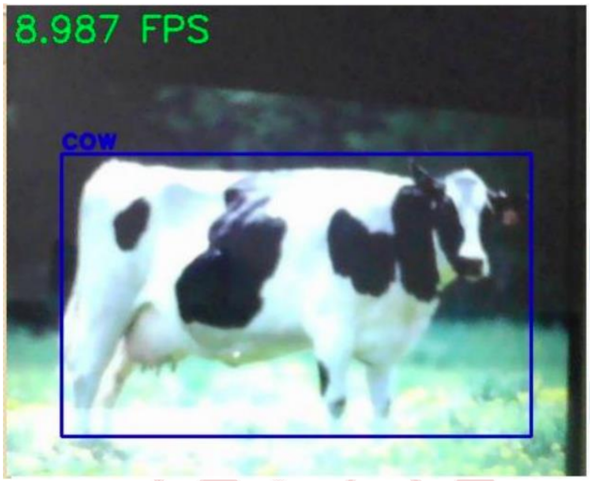
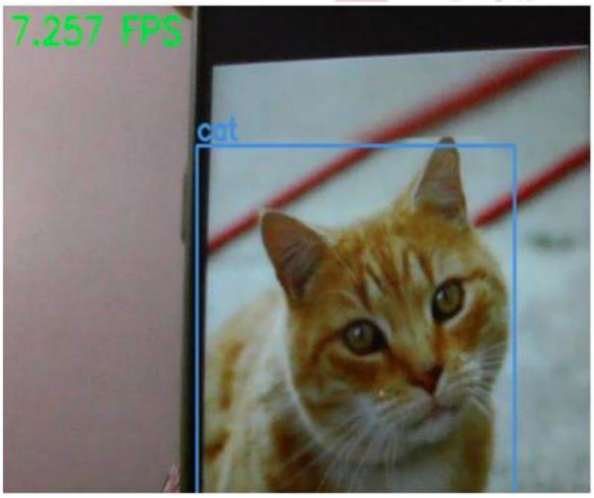
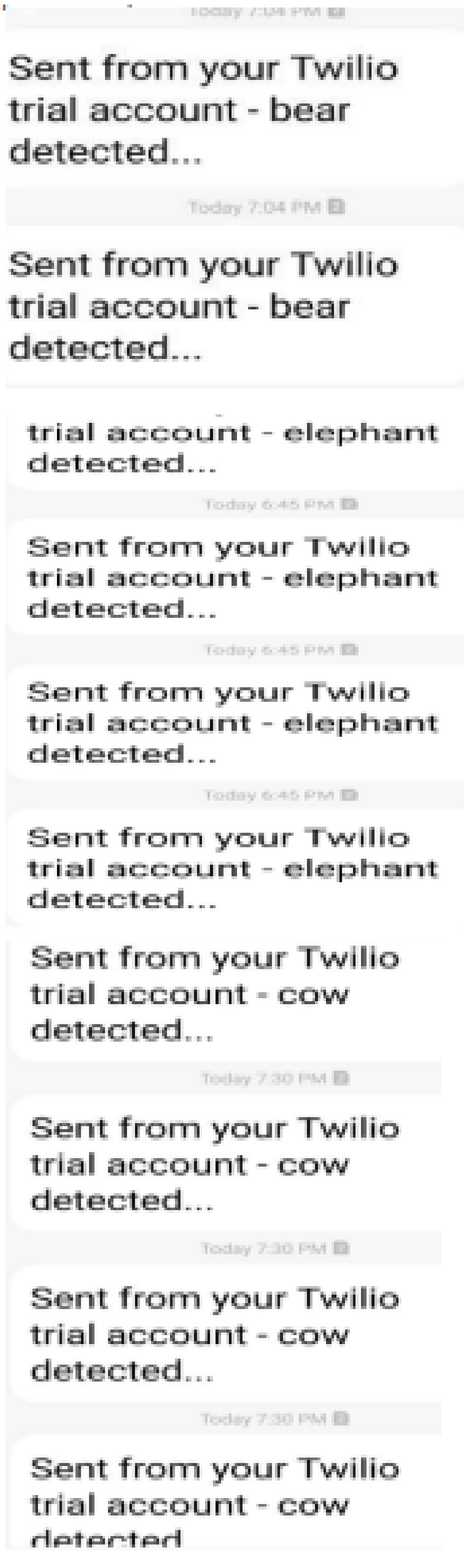




The results are obtained at varying FPS, under different conditions of lighting and brightness. The detection and recognition of cats and dogs do not make any response as they are considered harmless to agriculture.



On the other hand, the detection and recognition of bears, elephants, and cows make the system respond through alarm sounds and messages passing to the control room, as a repulsion technique.



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For real-time purposes, speed and accuracy are determining factors for smooth functioning MobileNet SSD, used in the proposed system strikes a better balance between speed and accuracy. It can be argued that Mobile Net-SSD offers somewhat similar speed to YOLOv5s, but it simply lacks the precision department. Considering the agricultural application, the system needs to be faster in detection to make alertness before the animal entered the crop field and makes any destruction, the technique used is a pretty decent model. Alarm sound used for repulsion makes less health impact than other systems using ultrasound emissions and other lethal techniques. This can also make an alert to the neighborhood. Although ultrasound cannot be heard by humans, at high decibels it can still cause direct damage to the human ears.

VI. CONCLUSION

Animal detection is useful in the prevention of human-animal accidents and will increase human and wildlife safety, it will detect large animals before they enter the human habitat and warn the locals through audio and visual signals. This also helps in saving crops on the farm from animals. Efficient and stable monitoring of wild animals in their natural habitat is essential. Since there are a large number of different animals manually identifying them can be a difficult task. This algorithm classifies animals based on their captured images so we can monitor them more accurately. This can be achieved by using effective deep learning algorithms.

Humans and Wildlife have become increasingly conflicting about living space and food, causing personal injury, loss of income from crop attacks and predation by livestock, and even loss of life. Wildlife can be killed in defense and retaliation, and support for protection can be diminished. Human-wildlife conflict is a global issue. Finding a safe way to live with the wildlife is important. Hence to avoid hampering both the safeties the proposed architecture promises a new platform to ensure the conservation of trespassed wild animals and also the human settlements.

The proposed system is an automated intelligent wild animal-intrusion detection and repulsion system that can repel them back to their habitat without any harm or threat. This is mainly used for crop protection as part of smart farming. It incorporates many techniques based on IoT and AI. This system can make a relevant impact on the agricultural sector by preventing animal attacks on crops without harming them.

For future work, this work will be primarily deployed to identify more customized items with better accuracy. And also this can be converted into an embedded kit by replacing the computation module with edge computing devices.

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