IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 7.39 ⁒ Vol. 11, Issue 4, April 2022

DOI: 10.17148/IJARCCE.2022.114159

Review of Real-time Animal Recognition to Detect Intrusions

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Abstract: Annually, the field harvest damaged by thewild animals is in sharp increase in India. It sometime poses hazards to humans and animals. Since then,more and more wild animals are causing damage to crops and farmland so that humans cannot tolerate it. Therefore, they require an vital and appropriate solution to overcome this situation. The goal of this research article is to recognize
animals before they are introduced in cultivation areasand implement appropriate real-time warning mechanisms. The presence of the animal will be sent to the farmer through application with an audible sound. In this study, two Convolutional Neural Networks (CNN) classification models have been developed using the machine learning YOLO algorithm as a pretrained model to detect elephants, wild boars. The two models have been merged and runon, which referred as the system processing unit for this, takes animal images, and predicts them.
The findings of this research indicate that theaccuracy rate of the classification model is 86 percentage. This system dramatically reduces human animal conflicts between human animals in crop fields by automatically setting up alert mechanism depending on the prediction.

Keywords: Animal Recognition, User Alert,Convolutional Neural Network, IOT, YOLO

I. INTRODUCTION

In India, farming is one of the important economic strengths. In 2021, the Gross Domestic Product (GDP) rate for agriculturewas 9.2 percentage and generated Rupees 179.15 lakh crores.
Every year, thousands of human-animal conflictscaused numerous deaths, physical injuries, and loss of properties. Mostly, human-animal disputes occur when animals search fields for food. In particular, greater deforestation contributed to reducing the size of animal habitat, and they are obliged to come out of theirrange to search for new habitats and food in farmlands. In fact, as stated by the agriculture ministry of India, it has been confirmed that 40 percentage of the annual crop is destroyed by wild animals. Commonly crops are damaged by elephants, wild boars, monkeys, peacocks,squirrels, and porcupines. Numerousincidents have taken place in the past where the human to animal conflict has caused significant damage to crops andanswered in the loss of the economy and agricultural and animals lives in India.
Mostly Farmers are depending and using various methods which are traditional, legal, and some incorrect methods to overcome wild animal's intrusion. For example, they used firecrackers to holdelephants at a distance. In India, 225 elephants have been killed by agricultural farmers every year since 2008 and elephants have killed approximately 60-80 people annually. Illegal methods uses like trap guns, snares, crackers, and explosives are again in practice and habit of killing theboar, which kills like many other animals and even humans. Electrified wires are placed on the way used by the animals,accidentally, humans injure themselveswhen they come into touch and contact withthese electrified wires sometimes. As an outcome, various preventive methods are used against various animals. Some may beefficient and others result in injury to both human being and animals. In addition, the preventive mechanism that has been used by farmers is very costly to implement and also detrimental to animals and humans' life, yet farmers often kill animals to securetheir crops and life. To solve the problem, the system was developed that can discoverwildlife entering the fields using CNN and also the implementation of an appropriate recognition mechanisms in real-time. It all will be done by alerting farmers through a mobile application about the presence of wildlife in their fields. The system will significantly reduce disputes betweenhuman, animals and crops. Briefly, this system has been developed to minimizedamages in the crop field, loss of human life, and destruction of animals. The scare- away mechanism helps to minimize the injury and death of wildlife in an eco-friendly manner. In addition, the animals protects the growing fields against damage.

II.LITERATURE SURVEY

We looked at various research papers to understand all the previous work done on the project we understand.
Zhang et al. [15] describe a system for segmentation of animals from images captured through camera traps. The procedure employed uses a multi-level iterative graph cut to generate object region proposals and accurately recognize

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regions of interest. This is especially useful when the animal blends together with the background and is difficult to identify. These proposals segmented into background and foreground in the second stage. Feature vectors are extracted from each image using Alex Net [4] architecture, and combined together with the system obtained an accuracy of 82.1% for animal and species detection.

Parham et al. [9] propose a multi-stage pipeline for animal detection and recognition. The fundamental steps include animal classification, animal localization and predicting animal characteristics, such as orientation. Animal localization is based on the YOLO [11] object detection model. The proposed system achieves an overall detection accuracy of 76.58% over 6 species.

Matuska et al. [5] propose a novel system for monitoring animals, consisting of a computing unit, for extracting features of animals, and a separate module to track movements. SIFT and SURF are used for feature extraction, and are classified using an SVM classifier . Use of SIFT descriptors achieved an accuracy of 94% for animal species classification.

Norouzzadeh et al. in [6] use the Snapshot Serengeti dataset and apply deep-neural networks to detect and identify animals in camera trap images. The system consists of multiple parts a) detection stage (whether there is an animal in the image), b) species identification stage, c) information stage, where the network reports additional data such as the count and attributes of the animals (standing, resting etc.). An ensemble of nine models is used, and obtains a top-1 accuracy of 99.4% for the species identification task, and the overall pipeline accuracy was around 93.8%.

It is not sufficient to detect the animal but also necessary to ascertain its intentions before creating alerts to ensure fewer false positives. All of this needs to be performed in real or near-real time. Since the solution also needs to be cost-effective.

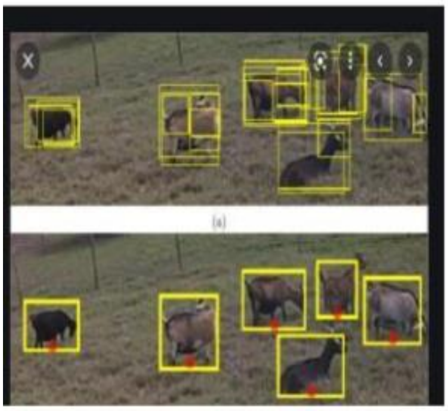
III. PROPOSED METHODOLOGY

The system idea proposed in this article uses a involvement of network of cameras, connected to PIR motion sensors, so that image capture is triggered only when some movement is detected. This enables power conservation. The images captured through these cameras are processed to detect presence and recognition of wild animals, and if an animal is found, identify the species. Once identified, the wild animals are tracked for a suitable time to determine their intent – such as to find whether they are moving across the village, or into it. In the upcoming case, alerts are generated and local authorities are notified through proper channels. Understanding the intent result a long road to reduce false positives, whether because of a false detection or when there is no real threat posed by the animal's presence.

Object Detection

YOLO object detection model is used to recognize the presence of wild animals in the captured images. YOLO is a DCNN (Deep Convolutional Neural Network) object recognition model which has good performance and outcome both in terms of accuracy as well as speed of inference. For the prototype version of the novel system proposed in this article, five different species of animals – elephant, zebra, giraffe, cheetah, lion are considered. Images of humans are also included, so their are a total of six different categories in the training data. The DCNN is fine tuned for better accuracy over these categories.

Training data is obtained from publicly available wild animal videos, including those from YouTube channels and National Geographic videos. Mostly frames extracted from these videos are manually annotated in the required format for training. The mean & average accuracy and precision over detecting five kinds of animals is 98.8%, and for human detection the accuracy obtained is around 99.8%.



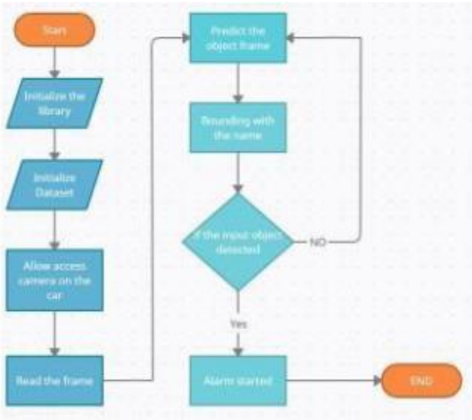


Figure 1,2 illustrates a chart of the animal detection module.

The YOLO object recognition model tiny weights and configuration is loaded and the image is loaded into the model.

The outcome of the object recognition and detection in neural network of system are tested in relation to a threshold value and subject to non-tax deletion**.** To reduce or remove low confidence and overlaying result of predictions. If animals are recognized and detected in the image frame then the object follow-up phase is triggered. As soon as the animals are detected, the object follow-up phase is triggered

, recognized, identified and find localized in the frame, object tracking is ready to used to determine intents or actions of the wild animal being monitored.

IV. CONCLUSION

The explained system depicts the attempts to reducehuman-animal conflicts by continuous and automatic monitoring of vulnerable areas usingcomputer vision to recognize and detect animal intrusions. The intrusion detection part consists of three stages – animal detection & recognition, wild animaltracking, user alerts and notifications. The system proposed is cost effective and highly efficient, withan average accuracy of 98.8% in detecting and identifying animals in images. While the prototype described in this research paper is formed to recognize five different species of animals, it is easily extendable to detect and track other type of species and types of wild animals with sufficient training data. The choice of species can also be region specific, thereby providing a unique edge overother existing solutions. Such a system if implemented on a big scale, has potential to largely reduce causalities due to animal intrusions.

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