



Real-time Animal Recognition To Detect Intrusions

Piyush Tiwari¹, Prajjwal Gupta², Dr. Ragani Karwayun³

^{1,2}Student, Department of Information Technology, Inderprastha Engineering College, Ghaziabad, India

³Professor, Department of Information Technology, Inderprastha Engineering College, Ghaziabad, India

Abstract: Annually, the field harvest damaged by the wild animals is in sharp increase in India. It sometimes 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 a vital and appropriate solution to overcome this situation. The goal of this research article is to recognize animals before they are introduced in cultivation areas and 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 run on , which referred as the system processing unit for this, takes animal images, and predicts them. The findings of this research indicate that the accuracy 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 agriculture was 9.2 percentage and generated Rupees 179.15 lakh crores.

Every year, thousands of human-animal conflicts caused 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 their range 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. Numerous incidents have taken place in the past where the human to animal conflict has caused significant damage to crops and answered 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 animals' intrusion.

For example, they used firecrackers to hold elephants 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 the boar, which kills like many other animals and even humans. Electrified wires are placed on the way used by the animals, accidentally, humans injure themselves when they come into touch and contact with these electrified wires sometimes. As an outcome, various preventive methods are used against various animals. Some may be efficient 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 secure their crops and life. To solve the problem, the system was developed that can discover wildlife 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 between human, animals and crops. Briefly, this system has been developed to minimize damages in the crop field, loss of human life, and destruction of animals. The scare-away mechanism helps to reduce the injury and death of wildlife in an eco-friendly manner. In addition, the animals protect the growing fields against damage.



II. BACKGROUND DESCRIPTIONS –

A. **Animal Recognition** - Mainly the animal detection systems developed based on deep learning is dominated by CNN. Deep learning refers a CNN neural network with many layers, thus the numbers of the layer in architecture are consulted to as the depth of the network. CNN represents feed-forward based neural networks which combination of three layers namely, the convolutional layer, the pooling layer, and the fully plugged-in layers. Convolutional neural network and machine layers act as an automatic feature extractor and it produce the feature map. Pooling layers act on the output of the convolutional neural network layer to down and sample them. Lastly, in the fully network connected layer, the neurons of the input characteristic cards are connected to their internal neurons. To develop a CNN with higher accuracy and less amount of resources transfer learning method is used widely. Transferrable Network Learning is a method of using previously learned weights in the base classification model as a initial point for current classification models. This results in a reduction in pretraining time and resources utilization, providing higher levels of accuracy and decreases the quantity of data required.

B. **Animal Prevention:-** Many animal prevention methods have been existing for different kinds of animals since this study mainly focuses on dataset contains elephants, wild boar, and buffalo. In India fencing, scream noises, drums and trees, the lashes used to frighten the elephant. Let the bees remain in their fields; when the elephants trying to cross the fence, the bees will disappear, disperse and scream. In addition, the uses of gunshots and firecrackers keeps the elephants at bay. Sometimes, fruit like pumpkins was packed with poison and explosives and stored them on the field for the elephants to eat. It explodes when it has bitten and blows the elephant's mouth. Throwing boiling oil or burnt polythene onto elephants is further used against the elephant. Buffalos normally move with many groups and the target on paddy, corn, mice, and some herbs. There are also some methods such as making barriers using magnet tapes, monofilament threads. Commonly buffalos are scared and feared of sudden lights and thunder sounds. Some of the traditional methods are used such as spraying local pigs' dung solution, burning of dried dung cakes, human hairs as a deterrent, erection of worn colored sarees, threads of net with dense vegetation, planting of furious bushes, xerophytes around the crop, creation of sound and light through birth fire, local dogs and the use of traps and poisoning to frighten the boars. Then some current and new approaches also applied nowadays, like ultrasound, air guns, and electric fences. There are usually a lot of traditional methods used currently. It is very easy to implement and maintain those traditional ways, also that are environmentally friendly. Such as bio fencing, stone fencing, trenches, watchtowers, throwing flame sticks and also rocks block, making noises, and unpalatable vegetables are some of them. The application and uses of the electric barrier is very efficient, but it harms the wild animals, and death may occur for animals and humans in this method.

III. LITERATURE REVIEW –

Animal Recognition :-

According to Yousif combination of deep learning classification with strong back-ground modelling to develop and build a fast and precise method for human and animal detection from a very congested camera to trap pictures. Background Modeling helps generate regional proposals for high-profile objects, which are then categorized using the DCNN, improving efficiency and increased accuracy.

The proposed idea system achieves a precision of 81% by segmenting the images in the classification of human, animal and background frames and patches.

Norouzzadeh et in use of the Snapshot dataset [6]. and apply deep-neural networks to detect and identify wild animals in camera trap images. The system involving multiple parts of a) detection stage (to check that if there is an animal in the picture or not), b) species identification stage, c) information stage, where the convolutional neural network reports additional data such as number and

attributes of animals (standing, at rest, in motion, etc.). It's a combination of nine designs and obtains a top-1 percent accuracy of 99.4% of the species or animals identification task, and the overall accuracy was around 93.7%. Propose a multi-stage channel for animal detection and recognition. The basic fundamental steps include animal classification, animal localization and predicting animal characteristics, such as their orientation. Animal localization is mostly depend on the YOLO object recognition model. The expressed system reach and achieves an overall and total detection accuracy of 76.58% over 6 species. Matuska propose a unique animal monitoring system, consisting of a calculation unit, to extract the characteristics of the animals, and a separate module to track the movements of animals.

Sharma et describe a vital system for animal detection that uses cross correlation filters for template matching. The training dataset is used as a base boundary for classification, and new images are matched with images in the database

to recognize the presence of animals. This system achieves an total accuracy of 86.25%.

Object Detection :-

YOLO object detection model is used to recognise 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 there 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 content like images, 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 model is trained by using images of dimensions 448 x 448. Learning rate was initialized at 0.001 along with a decrease rate of 0.995, and momentum is set at 0.9. The model converged it after running it for 135 epochs. The average accuracy and precision over detecting five kinds of animals is 98.8%, and for human detection the accuracy obtained is around 99.8%.

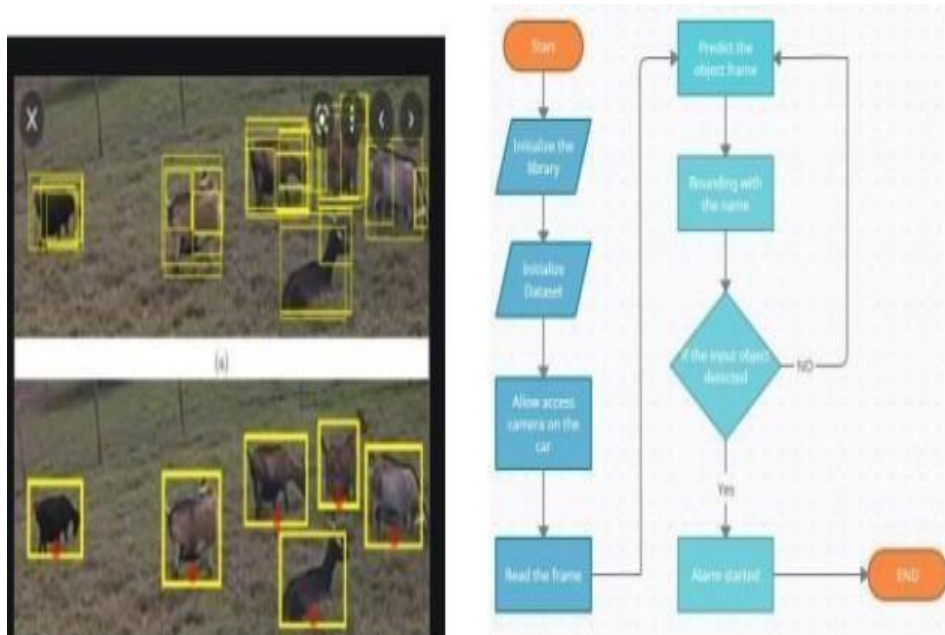


Figure 1,2 illustrates a chart of the animal detection module. The YOLO object recognition model tiny weights and configuration is loaded and the image is loaded into the model.

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.

V. SYSTEM AND SOFTWARE DESIGN :-

The proposed and suggested system contains software components; therefore, attention is given separately for those components. Along with that, the software component of this has two main parts : animal detection and alerting the user. The section has two main vital functions: of an implement an image capturing process and scare-away mechanism processes. The overall idea of this detection system will be implemented and follow the process using open cv for images and frames classification and YOLO v3 algorithm for object classification.

VI. RESULT

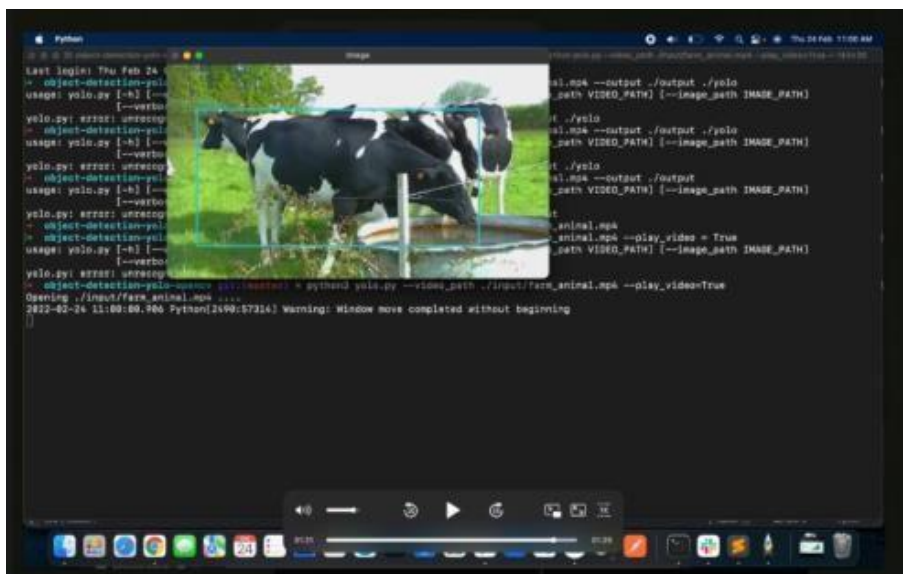
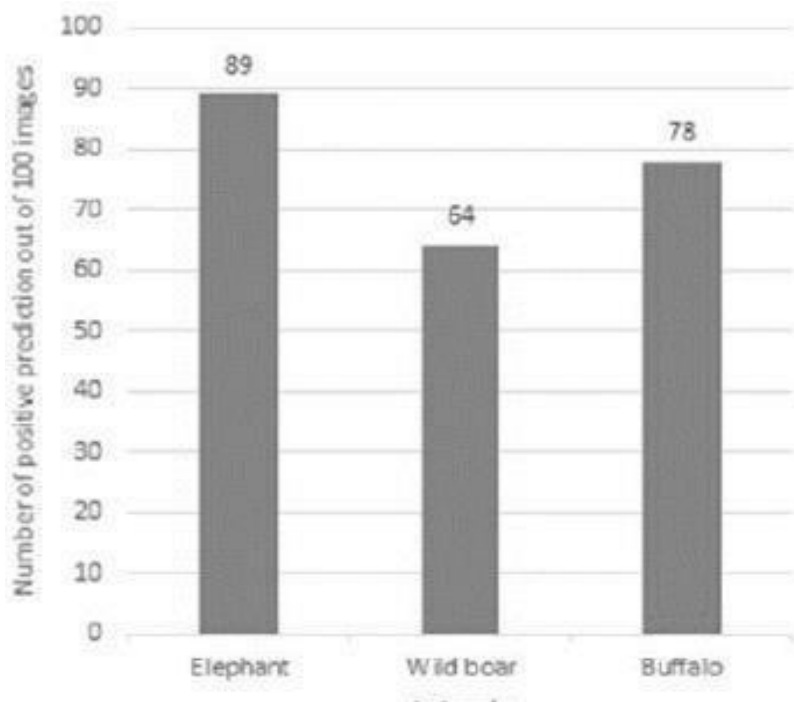
Animal Recognition and Detection using Computer Visions the performance calculated of the pre-trained model described in this article of research paper against most of the surveyed object detection models. The pre-trained model

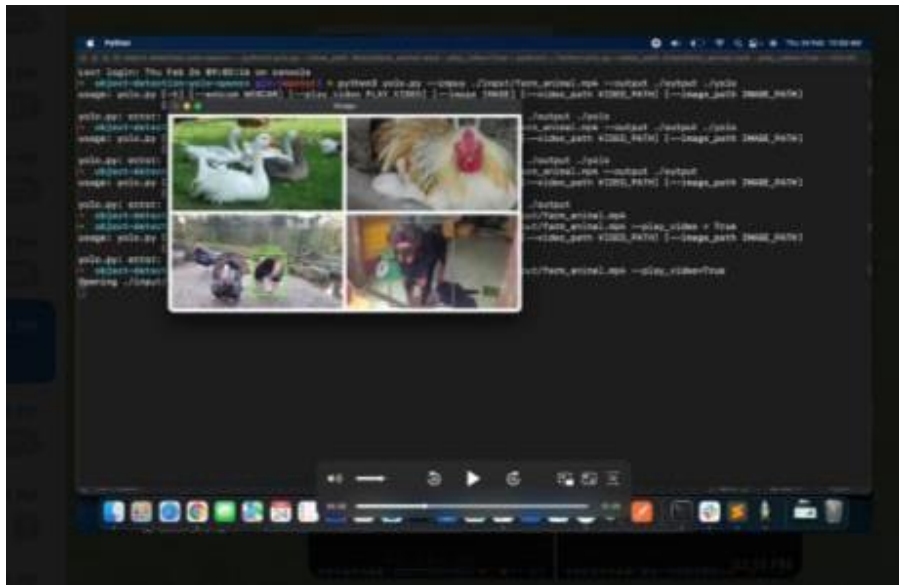


presented in this research paper achieves 98.8% accuracy for animal detection and 99.8% for humans. It contains the average of these two values. The time taken for processing an image for a few state of the art object detectors, when using a GPU.

Represents the qualitative results of the execution of the YOLO Object Detection Template for animal detection. The limiting boxes for the detection of wild animals in the frame are annotated with a confidence score and the type of animal as specified in the model. The figure shows results of running, moving inference on elephants, humans, giraffe and zebra.

Animal Recognition and Model # Species Accuracy (%) (2018) 48 99.4
(2018) 6 76.6
(2017) 2 82.0
(2017) - 60.0
(2016) 23 82.1
(2014) 5 94.0





VII. CONCLUSION

The proposed system depicts the attempts to reduce human-animal conflicts by continuous and automatic monitoring of vulnerable areas using computer vision to detect animal intrusions. The intrusion detection part consists of three stages – animal detection & recognition, wild animal tracking, user alerts and notifications. The system proposed is cost effective and highly efficient, with an 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 over other existing solutions. Such a system if implemented on a large scale, has potential to largely reduce casualties due to animal intrusions.

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