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An Intelligent Deep learning Based Animal Detection System

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***ABSTRACT* - Efficient and reliable monitoring of wild animals in their natural habitat is essential. We develop a system to detect animals with automatic alerts as part of the project. Since there is a large number of different animals, manually identifying them can be a difficult task. Our algorithm classifies animals based on a DarkNet deep learning model, which allows us to monitor them more efficiently. Animal detection and classification can help to prevent animal-vehicle accidents and animals from destroying agricultural lands. This can be achieved by applying effective deep learning algorithms. Furthermore, GSM and GPS devices are used to detect and alert the presence of animals using Arduino embedded systems.**

Keywords: Wild animals, DarkNet, Deep Learning, Animal Detection, Animal vehicle accidents, Arduino, GSM, GPS.

INTRODUCTION

Initially, the forest area was very large. By logging, the forest area was cleared and buildings were built. Forests are being destroyed as the population continues to grow. The human-animal conflict in society is primarily due to the lack of food for animals. This article describes animal intrusion detection methods based on deep learning. There are very expensive ways to detect and repel dangerous animals on farms and wildlife sanctuaries. Therefore, new methods and repellent systems for identifying dangerous animals will be introduced to distract animals cost-effectively. Previous automated systems included multiple vibration sensors to detect dangerous animals, a warning system to alert people in the area, and two repulsion systems to return animals to the forest. .. By changing the range of sensors and changing the defense system, you can use this system to protect the Wildlife Refuge from all dangerous animals such as elephants, bears, tigers, and leopards. Thousands of animals are injured or killed each year during agricultural reaping operations due to the increased work width and speed of agricultural machinery. Several methods and approaches have been used to reduce this wildlife mortality. The delayed mowing date, altered mowing patterns or strategies (e.g., leaving edge strips), longer mowing intervals, and the reduction of speed or higher cutting height have been suggested as ways to reduce wildlife mortality. Similarly, searching with trained dogs before mowing may enable the farmer to locate and relocate leverets and fawns to safety, while bird nests can be marked and avoided. Alternatively, various scaring devices, such as flushing bars or plastic sacks set out on poles before mowing, have been reported to reduce wildlife mortality. However, wildlife-friendly farming often results in lower efficiency. Attempts have been made to develop automated systems that can detect wildlife in crops to avoid unnecessary disruption to farm management. For example, infrared sensor-based detection systems have been reported to reduce German wildlife mortality. Due to its inefficiency, the maximum search area for the proposed system is about 3 ha / h on sunny days.

Overcrowding has resulted in deforestation and a lack of food, water, and shelter. The invasion of animals into residential areas is increasing, affecting human life and property and causing human-animal conflict. However, all living things on earth play an important role in the ecosystem according to the laws of nature. Agriculture is the backbone of the economy, but the invasion of animals into farmland causes huge crop losses. The effects of elephants and other animals in contact with humans are diverse. They destroy crops, damage granaries, water supplies, homes, and other assets, and injure or kill humans. In India, farmers suffer from pests, natural disasters, and animal damage, resulting in lower yields. Traditional farming methods are not very effective and you cannot hire security guards to monitor crops and stop wildlife. Human and animal safety is just as important. Therefore, farmland needs an animal detection system.

Reliable detection of large animals in images is a serious challenge for self-driving car computer vision systems. This is especially important as there are relatively many road accidents involving wildlife. Early approaches to solving this problem were detectors based on handmade features such as Haar features, HOG (Histogram of Orientation Gradient), and LBP (Local Binary Pattern). However, such an approach was not reliable enough. Modern research in the field of detecting large animals in images is primarily related to the use of deep convolutional neural networks. In addition, animal recognition is being studied as a solution to object classification, detection, and segmentation problems. Some works are dedicated to recognizing animals in images taken from unmanned aerial vehicles, for example on paper. The appearance of animals on the road is a relatively rare event, but at the same time, large enough and diverse datasets are needed to train neural network systems to detect them.

RELATED WORK

M. S. Nakandala, S. Namasivayam, and D. Chandima [4] proposed using Kinect-based sensors to enable programmed organism detection and to validate and assess animal development. Benefiting from 3D machine vision gadgets and rapid creation of strategies, point cloud information can be used to distinguish protests. As part of the exhibition work, a Kinect sensor will be written on the pig roof to receive 3D information. After determining the depth of each pixel as a threshold, a depth image is generated that extracts the objects in the depth curve. At this point, several shape-based instructions are combined to improve the identified protest area and accurately estimate measurements and weights for prediction. Testing confirmed the feasibility of the proposed approach.

Ouhongquam, Zheng Tong, Bi Fukun, and String Liping [2] argued that follow-up, question-finding, and show-building were all comparative exercises. Presents a fully programmed framework for building 2D audio models known as image structures from creature recordings. The taught show can be used to identify creatures in a unique video in this sense. You can think of a framework as a general tracker (one that can model an object while tracking it).

S.J.Sugumar and R.Jayaparvathyetal. [5] We have created a state-of-the-art in-vehicle night vision device for detecting creatures. This framework is currently used by Audi, BMW, and Daimler. Most of this white paper's commitment is productive based on the Cascade Boost concept, which significantly targets differences in global frameworks for tracking vehicles to deliver customer presentations, obstacles, attitudes, and sizes. Includes a classification approach.

Pankaj Verma, JS Bhatia [1] ensures that plantations are supplied by wildlife and feather organisms with ubiquitous sensory devices linked to plantations, in addition to traditional strategies to facilitate the implementation of protection. I proposed a strategy to do so. The receiver and camera module are included in the basic sensors of the USN hub. Camera images are analyzed for a variety of observations.

Saravana Kumar, Priscilla P., Germiya K. Jose, Balagopal G., et al. [3] Demonstrated a new framework for programming and classification of programmed creatures. The framework, called ASFAR (Programmed Framework For Creature Acknowledgment), is based on the common so-called "observation devices" in the allocated area and the basic processing unit (MCU) that acts as a server and framework monitor. Spotting devices are placed in wild nature and are responsible for distinguishing creatures and sending information to the MCU for evaluation.

PROPOSED SYSTEM

In this work we propose a deep learning framework to build automated animal recognition for detecting intrusion of dangerous animals at conserved areas, aiming at producing an automated wildlife monitoring system. In particular, a DarkNet-53 classifier, to train a computational system capable of filtering animal images and identifying them automatically. The proposed system includes an Arduino controller and a GSM module to alert the animal presence to the people.

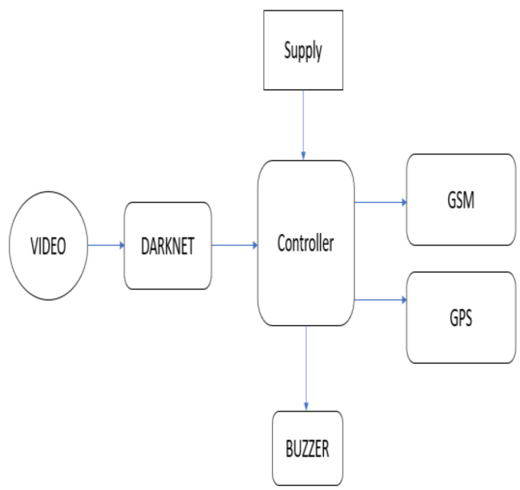

Figure 1: Block Diagram

YOLO V3

Yolo V3 is an improvement over the previous two YOLO versions where it is more robust but a little slower than its previous versions. This model features multiscale detection, a stronger feature extraction network, and a few changes in the loss function.

NETWORK ARCHITECTURE

For understanding the network architecture on a high level, let`s divide the entire architecture into two major components: Feature Extractor and Feature Detector (Multiscale Detector). The image is first given to the Feature extractor which extracts feature embeddings and then is passed on to the feature detector part of the network that spits out the processed image with bounding boxes around the detected classes.

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FEATURE EXTRACTOR

The previous YOLO versions have used Darknet19 (a custom neural network architecture written in C and CUDA) as a feature extractor which was of 19 layers. YOLO v2 added 11 more layers to Darknet19 making it a total 30layer architecture. Still, the algorithm faced a challenge while detecting small objects due to downsampling the input image and losing fine-grained features. YOLO V3 came up with a better architecture where the feature extractor used was a hybrid of YOLO v2, Darknet53 (a network trained on the ImageNet), and Residual networks(ResNet). The network uses 53 convolution layers where the network is built with consecutive 3x3 and 1x1 convolution layers followed by a skip connection (introduced by ResNet to help the activations propagate through deeper layers without gradient diminishing).

The 53 layers of the darknet are further stacked with 53 more layers for the detection head, making YOLO v3 a total of a 106 layer fully convolutional underlying architecture, thus leading to a large architecture, though making it a bit slower as compared to YOLO v2, but enhancing the accuracy at the same time.

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
	Convolutional	32	1 × 1	
1×	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
	Convolutional	64	1 × 1	
2×	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
	Convolutional	128	1 × 1	
8×	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
	Convolutional	256	1 × 1	
8×	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
	Convolutional	512	1 × 1	
4×	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Figure 2: Darknet-53 architecture

Astride is defined as the rate at which the input is downsampled. So the three scales in this case are 52 x 52, 26 x 26, and 13 x 13, and for large objects 13 x 13, 26 x 26, and 52 x 52. Used for medium and small objects.

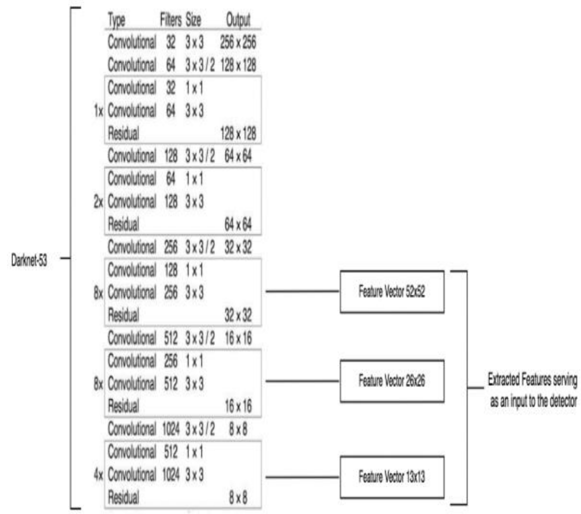

Figure 3: Multi-scale Feature Extractor for a 416x416 image

MULTI-SCALE DETECTOR

An important feature of the YOLO v3 model is the multiscale detector. That is, the final output detection of a fully collapsed network is done by applying the 1x1 detection kernel to three differently sized feature maps in three different locations. The shape of the kernel is 1x1x (B * (5 + C)).

COMPLETE NETWORK ARCHITECTURE

Ayush, Kathuria has created a very detailed diagram that beautifully illustrates the complete architecture of YOLO v3 (a combination of extractor and detector).

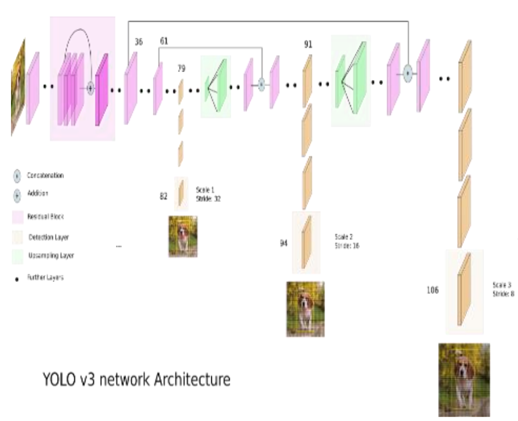

Figure 4: YOLO architecture

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For essential disclosure, the essential 81 layers are downsampled, the 81st layer contains the 32 gradients that occur in the initial order diagram (13x13), and the essential surface consists of (1x1) parts. And move to the 3D area. -Evaluation tensor (13x13x255).

At this time, 79 layers above the convolution layer (CL) have been dependent for some time and have recently been upsampled to measurements (26x26). This feature, including the outline, is now tightly integrated with the level 61 highlight outline, using the (1x1) level creases to generate an unused feature outline combined with the 61 levels. The moment detection layer is placed on the 94th layer using a 3D estimation tensor (26x26x255).

The last detection (third) applies the same strategy as the past detection. Here, the 91st layer is subordinate to the convolutional layer (CL) before representing the depth coordinates and is combined with the 36th layer. Finally, the discovery is delivered at the 16th level using the measure (52x52x52).

The multi-scale detector is used to ensure that small targets are detected as well as YOLO (version 2) if there is constant feedback on small targets. The upsampled layer integrated with the previous layer protects the fine-grained method that helps detect small targets.

WORKING OF YOLOV3

In this model, the input image is divided into (SxS) rasters, where each raster predicts the probability of a target B bounding box and C class whose center is inside a grid cell. This paper states that each bounding box can specialize in finding a particular species.

The "B" bounding box depends on the number of anchors used. Each bounding box contains a (5 + C) attribute. Where "5" defines five bounding box attributes and "C" indicates the number of classes used.

SOFTWARE AND HARDWARE SPECIFICATION

Hardware:

- **Arduino microcontroller**

Our project relies on the design of microcontroller boards to provide a set of digitized analog input pins that can be linked to numerous expansion boards and other circuits.

- **SIM800A Quad-Band GSM/GPRS Module with RS232 Interface**

This is a land grid array type quadband GSM / GPRS solution that can be installed in client applications and transmit voice and data information with less power consumption.

- **Single Power Supply:**

The power pack supplies all the components. Used to convert AC voltage to DC voltage. The transformer is used to convert 230V to 12VAC. 12VAC is given to the diode.

- **GPS**

A GPS navigator, GPS receiver, or simply GPS, is a device that can receive information from GPS satellites and calculate the geographic location of the device. Our system is connected to the GSM GPS module to locate animals.

Software:

- Arduino Software IDE
- Python IDE

RESULT & DISCUSSION

Figure 5: Herd of Elephants on a farming land

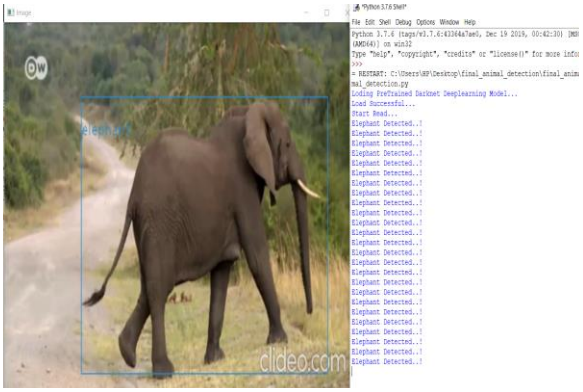

Figure 6: An elephant during road crossing

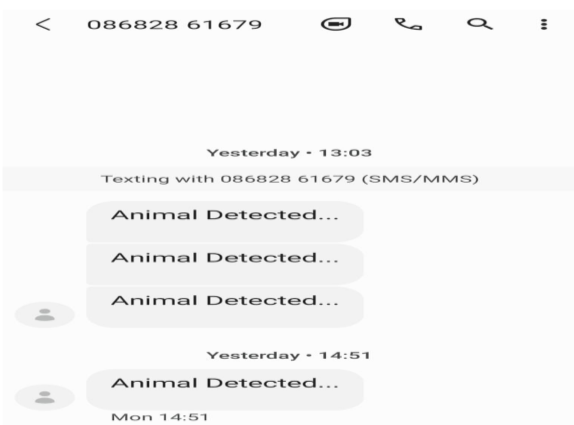

Figure 7: SMS sent to mobile

PERFORMANCE EVALUATION METRICS

- **Mean absolute error**

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}$$

MAE = mean absolute error
y_i = prediction
x_i = true value
n = total number of data points

- **Root mean squared error**

$$\mathrm{RMSD} = \sqrt{\frac{\sum_{i=1}^{N} \left(x_i - \hat{x}_i\right)^2}{N}}$$

RMSD = root-mean-square deviation
i = variable i
N = number of non-missing data points
x_i = actual observations time series
$\hat{x}_i$ = estimated time series

- **Normalized mean absolute error**

NMAE = MAE/Mean(actual values)

	MAE	NMAE	RMSE	ACCURACY
DT	2.5	0.92	3.6	92
ADABOOST	1.8	077	3.2	94.2
DARKNET	099	0.53	2.26	96.8

Table 1 : Comparision with base paper

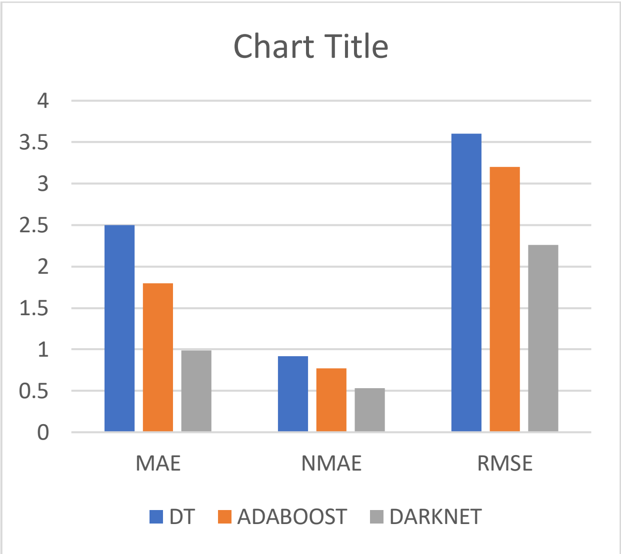

Figure 8 : Comparision using MAE,NMAE,RMSE

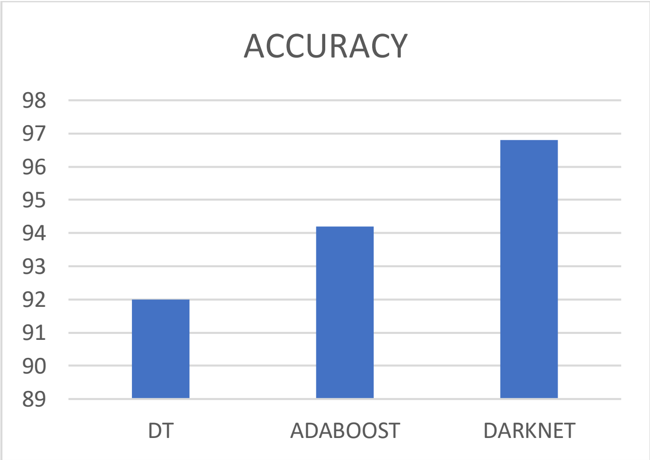

Figure 9 : Accuracy trend for 3 different Algorithms

CONCLUSIONS & FUTURE ENHANCEMENTS

By installing this system in all dangerous spots which can be done with the help of animal movement history, we can eradicate the animal intrusion near the forest borders and agricultural land. This system works automatically without human intervention and it will be active 24*7. This prevents the human confrontation with animals. GSM technology can also be implemented. By executing these ideas, we can prevent crop-raiding and the destruction of human lives.

In the future, we can improve this system to detect animals from a farther distance so that animals can be evacuated very much earlier leading to very less damage to farms and lands.

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