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Wildlife Detection Using Convolutional Neural Network

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Abstract- Protection of endangered species requires continuous detection and updated information about their existence. Remotely activated camera or "camera traps" is a reliable and effective method of photo documentation of local population size. However, manually analyzing a huge number of photos and collected footage is incredibly time-consuming, labor-intensive and expensive. Recent developments in deep learning techniques have showed promising results for the identification of objects and species in images. This paper proposes an automated wildlife detecting system that uses computer vision techniques to classify images and methods for machine learning. The objective is to validate and train a Convolutional Neural Network (CNN) namely MobileNet-SSD with detection capabilities wildlife captured on camera. Creating a flexible CNN architecture using labelled photos gathered from common benchmark datasets from several citizen science initiatives, deploying it in TensorFlow Lite format and measuring the Performance of the model. The model is updated to incorporate fresh camera-trap imaging data to better identify species. The effectiveness is assessed depending on how accurately the images are classified. Adding more training images of animals could also improve the performance of the detection model on the same task.

Keywords- detection; CNN; Computer Vision; TensorFlow.

I. INTRODUCTION

India is an agricultural country. Agriculture has always been India's most important economic sector. Human animal conflict is a major problem where enormous amount of resources is lost and human life is in danger. In recent times the numbers of these kinds of conflicts are increasing. So, this zone is to be monitored continuously to prevent entry of this kind of animals or any other unwanted intrusion.

Human-animal conflicts arises due to encroachment and poaching, humans move into the forest to satisfy their livelihood for claiming of land for agricultural practices rapid industrialization causes spreading of urban ground and animals enter the nearby villages and tramp the vegetation in farm land.

For monitoring wildlife, sensor cameras are placed on trees in a region creating a stationary camera-trap network.

The camera traps are activated; each time motion is sensed. For monitoring wildlife, sensor cameras are placed on trees in a region creating a stationary camera-trap network. The camera traps are activated; each time motion is sensed.

For these kinds of Existing methods frequently have low detection rates for videos because there is little contrast between the animals in the foreground and the background clutter, as well as high false positive rates because of the dynamic background.

II. LITERATURE SURVEY

The recognition of big animals on the images with road scenes has received little attention in modern research. There are very few specialized data sets for this task. Deep learning approaches to detect these objects are trained and modern neural network architectures YOLOv3, Retina Net R-50-FPN, Faster R-CNN R- 50-FPN, Cascade RCNN R-50-FPN are tested [1].In recent years, due to human destruction, the number of endangered species on the earth is increasing at an alarming rate, and it is urgent to protect the rare species. A new method for rare animal image recognition based on the basic model of Convolutional Neural Networks (CNNs) was proposed, which autonomously extract the image features in the training set and construct an image recognition system to identify rare animals [2].

A main hypothesis is that most of existing models trained for detecting animals does not have enough pictures of animals behind cage bars as in a training set. The M2Det is used as the main network together with the transfer learning approach and its pretrained weights [3].

Visual monitoring in scenes, for animal, is currently one of the most active research topics in computer vision (CV). Deep Convolutional Neural Network (CNN) is used to detect and classify the animals (vertebrate classes) in digital images [4].

III. FIELD RESEARCH

Human-animal conflicts are a problem in various parts of India. India has close to 30,000 Asian Elephants. Of this, around 6,000 elephants are in Karnataka. Around 60% of elephants of Karnataka live outside protected areas. Thus, contacting humans is inevitable. Loss of agricultural crops is a major source of conflict in the districts of Karnataka such as Hassan, Ramanagara, Chikkamagaluru, etc.

According to data from the Karnataka Forest Department, 79 people have died as a result of elephant encounters in Karnataka between 2019 and 2021. The Karnataka Forest department has taken various measures such as installing infrared sensors for movement detection, watch towers, alert systems, sign boards in man-elephant conflict zones. But there is a need for early warning SMS alert systems and regular broadcasting of herd locations for forest officials to keep vigil over their movements in certain conflict zones.

IV. PROBLEMS IDENTIFIED

This section introduces and identifies the problems which lead to the framing of this paper. Human-animal conflicts arises due to encroachment and poaching, humans move into the forest to satisfy their livelihood, for claiming of land for agricultural practices and rapid industrialization causes spreading of urban ground and animals enter the nearby villages and tramp the vegetation in farm land in need of nutritious food which puts the other in real danger, in this process resources are spoiled in sometimes, even the life is lost.

It is also common to see animals entering into highways leading to accidents and damage.

Usually, farms are protected with electrical fence, animal which tries to enter the field behave in abnormal manner. So, in order to overcome these problems, the proposed system can be installed in the required areas. Improving the accuracy of the CNN model with less computational complexity is needed. Also, the real time performance of the model should be comparable to the theoretical performance. There are many attempts on detecting animal using Convolutional neural network. However, efficiency is usually affected by the size and training time of a detection model [5].

The paper deals with development of animal detection and real time alert system that can be used to prevent wild animal assaults and other harmful consequences. Animal intrusions in the area are identified and an alert notification is sent.

1. Proposed Solution:

The solutions proposed are:

- To develop an animal detection and real time alert system that can be used to prevent wild animal assaults and other harm
- To capture the image of animals and categories it using image processing
- Alerting farm owners and forest officials about the animal intrusion

By following the above methods, it can be made sure to detect the animals, and hence reducing the risk of Human Animal conflicts and damage of crops.

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V. METHODOLOGY

1. Proposed Methodology:

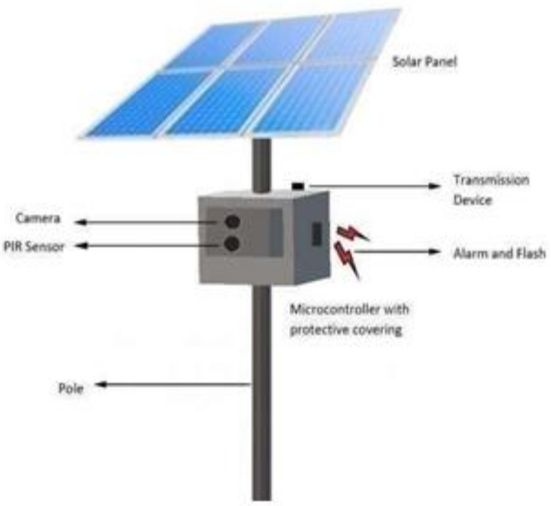

Fig 1. Working model setup.

The Fig 1 shows the working model setup in the area that needs to be monitored. The device is attached to a long stationary pole to which the camera is also attached. The PIR sensor, transmission device, alarm and flash are attached to the pole which functions independently. The Solar panel is used here in an attempt to use solar energy to power the Raspberry Pi via a battery for this paper. There is a protective covering used to safeguard the embedded Raspberry pi circuit and other sensitive components.

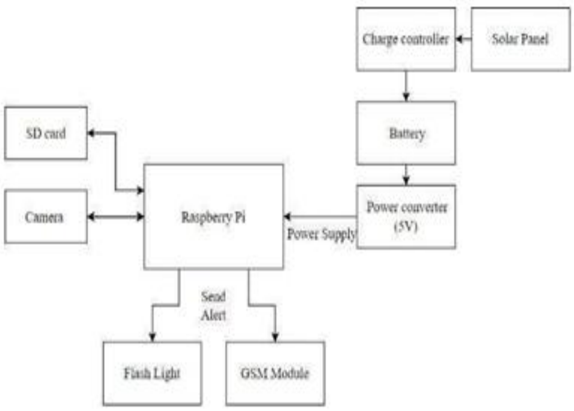

Fig 2. Block Diagram.

- The device is attached to a pole. A solar panel used here in an attempt to use solar energy to power the RaspberryPi via a battery and create a self-contained embedded solution for this paper.
- Camera module and SD card are attached to raspberry pi as shown in Fig. 2. The camera sends several images to Raspberry Pi. The images are stored in an SD card.
- Raspberry Pi uses trained neutral network model to detect if the specific animal is present in the images [6].
- Once the animal is detected, Raspberry Pi sends an alert to the forest officials using transmission device such as GSM.
- Additionally, flash light is used as an indicator for presence of the animal in the captured image.
- Data of animals can be stored in the SD card and deleted after it is sent to the computer, for efficient memory management.

2. Image Processing:

The image processing part of this paper is divided into four steps. Collection of Datasets, Labelling, Training Deployment of model on Raspberry Pi.

Fig 3. Collection of datasets

2.1 Collection of datasets:

Starting with the dataset, we first need to make the distinction between supervised and unsupervised learning. With the former our experience is a set of images with manually assigned labels. That is to say each image in the dataset has its relevant category assigned to it before the learning process starts. This allows us to calculate the performance and learn from the experience by comparing the predicted result (the task) with the known label of the image large data set of images of a particular animal in different background and directions is needed for training the model the elephant data is obtained from Asian vs African elephants' dataset as shown in Fig. 3 from kaggle.com website [7].

This dataset contains is created to practice various image processing techniques.

Dataset details
- Number of classes: 2(Asian elephants and African elephants)
- Number of images: 1028
- Image shape range: (100,100) to(4992,3328)

2.2 Labelling the images:

LabelImg tool is used for labeling the dataset. LabelImg is a straight forward and basic annotation tool to label a few hundred images to create dataset for computer vision model training. The annotations are saved as XML files in PASCAL. VOC format, the format used by ImageNet [8]. The Fig. 4 shows the process of creating boundary boxes and labelling for each elephant image in the data set using LabelImg tool.

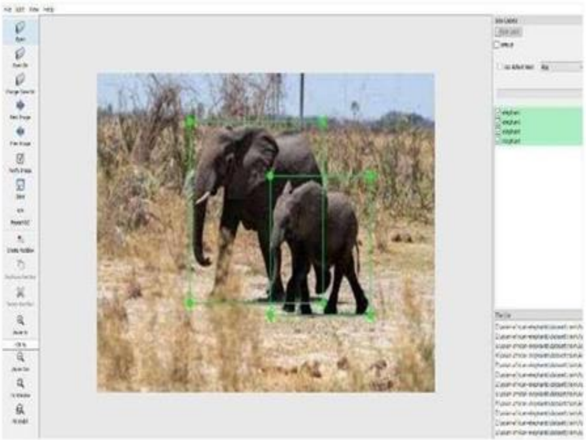

Fig 4. Labelling images.

2.3 Training the TensorFlow model:

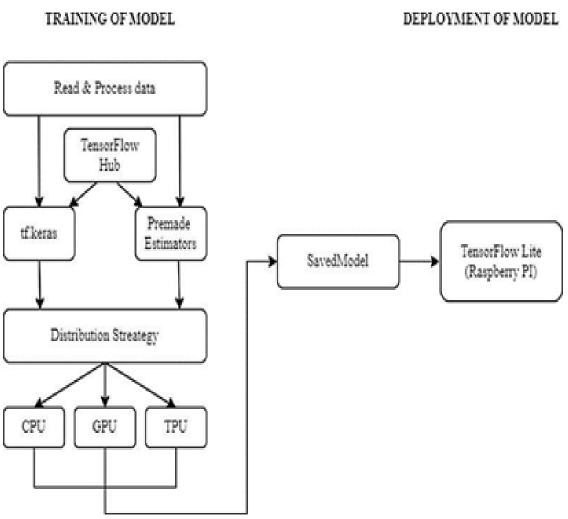

Fig 5. Training and Deployment of Model.

To train the TensorFlow model, the transfer learning process is used, where a pre-trained model is fine-tuned for the intended purpose. The dataset is loaded and the model is trained and tested for the images classified as test images. The accuracy of the model is measured using mean average precision (mAP).

2.4 Deploying the model:

The custom-trained TensorFlow model is deployed onto the Raspberry Pi and the program is run for animal detection.

3. Flowchart:

The steps involved in the animal detection system is shown in Fig. 6

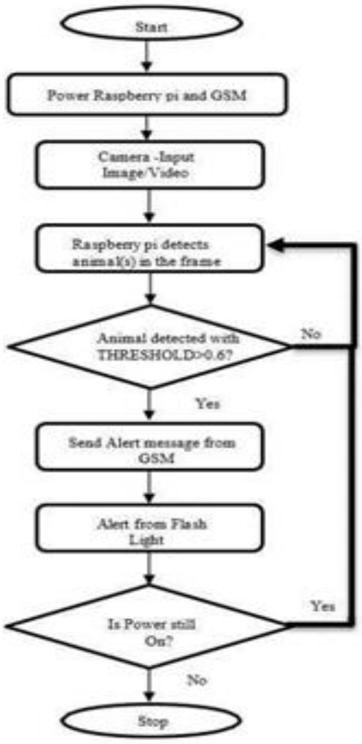

Fig 6. Flow chart depicting the working of the system.

The steps involved in the working system are as follows:
- Firstly, the system is initialized by the powering of the Raspberry Pi microcontroller and therefore the microcontroller powers on the camera module along with GSM module.
- The camera module captures a real-time video and feeds the frames into Raspberry Pi. The output of each frame depends on the threshold, which is set at 0.5.
- Any animal detected with a higher level of confidence is listed in part of the output, if

confidence is less than 0.6 then it is discarded [10]. The bounding box on the animal detected and the result can be displayed by the Raspberry pi desktop's camera display.

- The alert message is sent as SMS to the appropriate phone numbers of forest officers to assist them in safely stopping or capturing the wild animals [11].
- After this flash lights will be triggered that can be installed over certain distance to alert the villagers or farmers to protect themselves from conflicts with animals as such situations may result in loss of life.
- If the system is receiving required power, the steps 2-6 is repeated.

4. Model:

The model is shown in Fig. 7. The Raspberry Pi is connected to Li-ion battery which is powered by solar panel. The camera module is attached to the Raspberry Pi. The flash light is attached to the GPIO pins of Raspberry Pi. The GSM is connected via USB to serial converter.

The camera gives the input video to Raspberry Pi, the object detection model detects the animal present in the given video frame and displays the result on the Raspberry Pi window the results of the elephant detection system is displayed on the Raspberry Pi desktop.

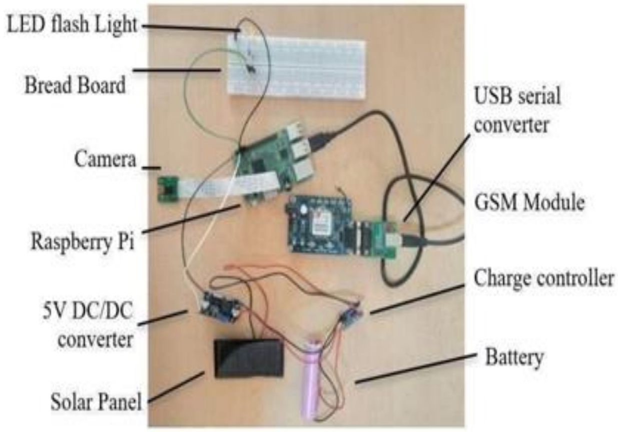

Fig 7. Project Model.

VI. RESULTS

The results are shown in Fig. 8. The proposed CNN model has been trained on 500 elephant images. The SSD MobileNet V2 model takes input images of sizes 320x320 [9]. The pixel values of the range 0-255 are converted into -1 to1 range during preprocessing. Fig. 8 shows the successful detection of one or more than one elephant using proposed model. The model shows high accuracy of 90 to 100% when elephant is in clear background.

Even when animal is partially hidden the accuracy is in the range 80 to 90%. The image is sent to MobileNet-SSD and is split into 3 layers and each layer is given as input to the model and the corresponding result is saved. If the probability of detected elephant is more than 60%, the image captured is successfully detected with higher accuracy and thus the model is verified. As soon as elephant is detected, a notification is sent to the intended receiver.

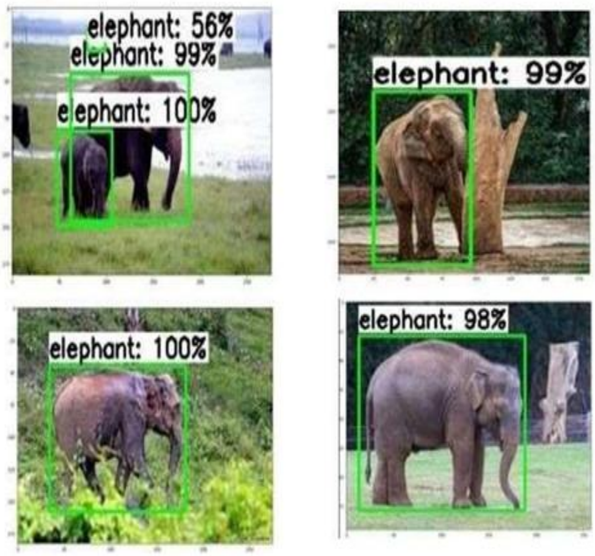

Fig 8. Results.

Single-Shot multibox Detector (SSD) has different types of models. SSD MobileNet v2 320*320 has a speed of 19Fps and of 43.5 mean average precision (mAP) and SSD MobileNet v2 coco has a speed of 31 Fps and 44.3 mean average precision (mAP).

The SSD MobileNet v2 320x320 is the latest MobileNet model configured for Single-Shot multibox Detection, which is optimized for speed at a very small cost in mean average precision (mAP), as compared to the model, SSD MobileNet v1 coco.

- SSD MobileNet V2 model is selected. The reason behind the selection of the SSD MobileNet V2 model has been the processing speed of detection and size of the model.
- The model takes inputs images of 320x320 and

takes only 19 milli seconds to detect objects and their locations in that image.

VII. CONCLUSION

The contribution of the paper is a reliable method for the detection and tracking of elephants applicable to real-life situation. As a consequence, we are able to detect and track elephants of different sizes and poses in their natural habitat. When the elephant intrudes, the field using the proposed CNN model, the camera senses and is detected, then a message is sent to the intended receiver e.g., farmer. The model is planned to be used in Cauvery Wildlife Sanctuary, Ramanagara.

The approach robustly handles occlusions and detects elephants even if most of their bodies are hidden, e.g., behind vegetation. This makes the approach a sound basis for higher-level analysis tasks, fromthe automated estimation of group sizes, to the identification of animals, and to the automated recognition of different activities and behaviors. This paper can help the forest officials to identify the elephant intrusion in the sensitive areas. By improving the camera resolution and quality, the efficiency and range of detection will be optimized.

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