MACHINE LEARNING BASED LIVESTOCK AND WILDLIFE ANIMAL DETECTION

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Abstract –

The use of science and technology to monitor wildlife enclosures in a specific region and to ensure animal security is known as wildlife monitoring using a raspberry pi. Animals escaping cages and hurting both people and other animals have been a frequent occurrence at zoo parks recently. people have also occasionally fallen into animal enclosures. Consequently, a system that can track these circumstances was devised. This technology is used for animal surveillance and security to identify intruders who enter the animal area as well as to determine whether any animals have fled or gone missing from their enclosure. Using machine learning, this system could identify the burglar who entered the container. The device is made up of raspberry pi camera and SD card circuitry interfaced to a raspberry pi B+ board, The raspberry pi camera takes the video of the cage and gives to the raspberry pi, then the obtainedvideo streaming data is analyzed using open cv platform.

The system comprises of a Raspberry Pi B+ board with interfaces for the camera and SD card. The raspberry pi camera records video of the cage and transfers it to the raspberry pi. The video streaming data is then processed using the open cv platform for analysis. In the open cv platform, machine learning techniques are used to classify the data. To determine if an intruder entered the cage or if the animal fled, the data is evaluated. IoT is used to send notifications to the caregiver if any of the aforementioned scenarios materialize.

Keywords –Web Camera, Raspbian, Twilio Smart phoneEdge impluse studio, Raspberry pi 3 model B+, Raspberry pi, Terminal App.

I. INTRODUCTION

Wildlife monitoring is essential to a wide range of medical and societal endeavors. Understanding animal behavior and activity patterns is helpful for comparing biodiversity and changes in habitats and land use, preventing harmful flora and fauna encounters with humans and habitat overlap, monitoring species health and population dynamics, and providing humans with overly educational tales with an adverse impact. Monitoring and regulating various operations is the main focus of technological developments. The necessity to meet human needs is becoming more and more important. The majority of this technology is primarily concerned with effectively regulating and monitoring various operations.

To keep an eye on their enclosures and to ensure the safety of wild animals at zoological parks, an effective surveillance system is needed. There have been a lot of recent zoo park accidents with animals escaping from cages and harming other animals and visitors, as well as occasionally visitors accidentally walking into animal enclosures and risking their lives.

II. **Literature Survey**

In many different disciplines, it is essential to accurately identify the target object and track it while managing occlusions and other added complexity. Numerous scholars have experimented with different ways to object tracking (Almeida and Guting 2004, Hsiao-Ping Tsai 2011, Nicolas Papadakis, and Aurelie Bugeau 2010). The application domain has a significant impact on the approaches' character. The following is a representation of some of the research projects that evolved into suggested work in the area of object tracking.Object detection is a crucial yet difficult visual skill. It is an essential component of many applications, including object tracking, scene comprehension, picture auto-annotation, and image search. One of the most crucial areas of computer vision was the tracking of moving objects in video picture sequences. Numerous computer vision sectors have already used it, including intelligent video surveillance (Arun Hampapur 2005), artificial intelligence, military guiding, safety detection and robot navigation, as well as medical and biological applications.

The background subtraction technique developed by Horprasert et al. (1999) was capable of handling variations in local lighting, including shadows, highlights, and even globe illumination. With this technique, each pixel's backdrop model was statistically modeled.The brightness distortion and the chromaticity distortion in computational color mode are used to distinguish between a backdrop with shading and a background with no shading or moving foreground objects.Finding tiny portions of a picture that match a template image is a method called "template matching." It compares for the best fit with the template by sliding it from the top left to the bottom right of the picture. It recognizes the segment with the highest correlation as the target and the template dimension should be equal to or less than the reference picture. Output if S has a subset image I where I and T are appropriately comparable in pattern given an image S and an image T, where the dimension of S was both greater than T, and if such an I exists, output the position of I in S as in Hager and Bellhumear (1998). (2011) Schweitzer et al.

Our suggested system is made up of three primary modules: GSM module (to send alarm messages to the appropriate person), Alarm (to turn on the buzzer to keep the animal away from the field), and Animal detection and identification (to detect the presence of the animal and identify them). The sensor recognizes an animal's presence as it enters the field. It begins measuring the distance before signaling the camera to begin taking photographs. The animal is then recognized by comparing this image to the previously stored information. The buzzer activates and an alarm message is sent to the appropriate people when the distance exceeds the threshold value.

The name of a DNN for computer vision is SqueezeNet. Researchers from Stanford University, DeepScale, and the University of California, Berkeley collaborate to build SqueezNet. The authors' aim in designing SqueezeNet is to produce a smaller neural network with fewer parameters that can more readily fit in computer memory and be transferred across a computer.

The Inception v3 image recognition model, which has demonstrated accuracy of better than 78.1% on the ImageNet dataset, is frequently utilized. The model is the result of several concepts that scholars have worked on for years. The book "Rethinking the Inception. Architecture Computer Vision" by Szegedy served as its inspiration. One of the newest neural networks for visual object detection is called DenseNet, which stands for densely connected convolutional networks. ResNet is comparable, however there are several key distinctions. One of the newest neural networks for visual object detection is called DenseNet, which stands for densely connected convolutional networks. ResNet is comparable, yet it differs in some key ways.

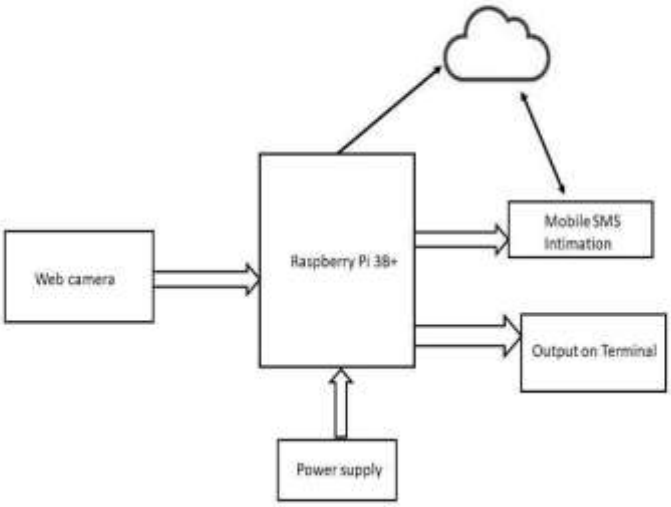

Fig: Block Diagram

III. **System Design**

Raspberry pi 3 model B+: The Raspberry Pi 3 Model B+ is the latest product in the Raspberry Pi 3 range, boasting a 64-bit quad core processor running at 1.4GHz, dual-band 2.4GHz and 5GHz wireless LAN, Bluetooth 4.2/BLE, faster Ethernet, and PoE capability via a separate PoE HAT. Webcam: HD webcams, or webcams that are described in terms of 720p or 1080p resolution, have an aspect ratio of 16:9, which is a widescreen view. When it comes to a webcam that has a 'normal' (3:4, like the sensor in a DSLR camera) aspect ratio, you are more likely to see the resolution listed in terms of megapixels. Edge impulse studio: Edge Impulse provides the ultimate development experience for ML on embedded devices for sensors, audio,at scale. It enables the deployment of highly-optimized ML on hardware ranging from MCUs to CPUs and custom AI accelerators.

Raspberry pi Raspbian: Raspberry Pi OS is highly optimized for the Raspberry Pi line of compact single- board computers with ARM CPUs. It runs on every Raspberry Pi except the Pico microcontroller.

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Twilio: Twilio is a cloud communications company which allows software developers to programmatically make and receive phone calls and send and receive text messages using its web service APIs. Twilio uses Amazon Web Services to host its communication infrastructure via APIs (Application Programming Interface) for SMS, MMS, and WhatsApp.

MobileNetv2 SSD: we are using the MobileNetV2 SSD FPN-Lite 320x320 pre-trained model. The model has been trained on the COCO 2017 dataset with images scaled to 320x320 resolution.In the MobileNetV2 SSD FPN-Lite, we have a base network (MobileNetV2), a detection network (Single Shot Detector or SSD)and a feature extractor (FPN-Lite).Terminal app: Terminal App is a program that acts as a wrapper and allows us to enter commands that the computer processes. In plain English again, it's the "window" in which you enter the actual commands your computer will process.

IV. **Proposd Method**

The following describes how the proposed system for "Livestock & Wildlife Animal Detection with Machine Learning" operates:

• Our project uses MobileNetv2 SSD and Twilio to recognize animals using machine learning.

• A sample image that we provide to the algorithm with the expectation that it would recognize and name the items in the image in accordance with the class to which they belong.

• As anticipated, our algorithm classifies the items and assigns each one a tag and a set of dimensions.

• For object detection jobs, ImageAI offers a ton more customizable options and production-ready installations.

Advantages :

- Deeply rooted in A successful design and demonstration of an animal detection and alarm system was made. In order to identify wild animals, this research use the MobileNet v2 SSD algorithm.
- These devices are specifically designed to protect people against huge animals (such as ungulates) that might harm, kill, or destroy property.
- Animal detection devices alert drivers when a big animal is on or near the road by seeing them before they join the road.
- These devices are specifically designed to protect people against huge animals (such as ungulates) that might harm, kill, or destroy property.
- Animal detection systems can identify huge animals before they cross a road and can alert drivers when one is present on or nearby.
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V. Results & Discussion:

Lives stock animal detection using machine learning algoritham.

Fig1 : Animal detection

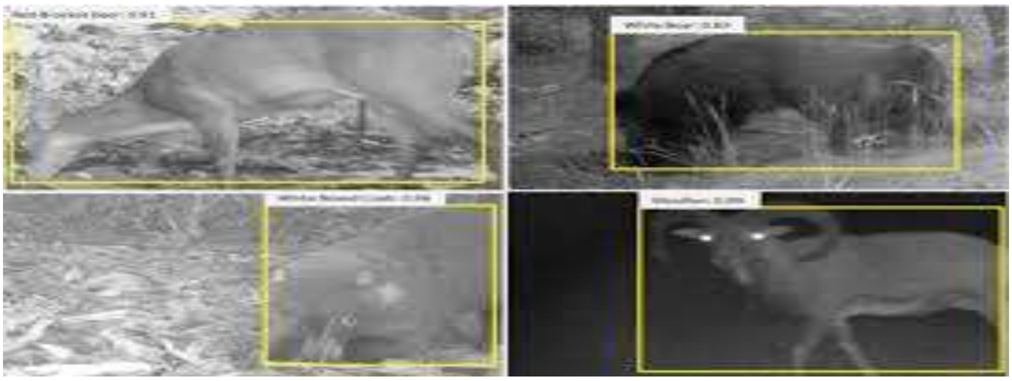

Fig 2 Animal detection

VI. Conclusion

Based on experimental results, we are able to detect obeject more precisely and identify the objects individually with exact location ofan obeject in the picture in x,y axis. This paper also provide experimental results on different methods for object detection and identification and compares each method for their efficiency. we tested the ability of state-of-the-art computer vision methods called DNNs to automatically extract information from images in the SS dataset, the largest existing labeled dataset of wild animals. our results show that using deep-learning technology can save a tremendous amount of time for biology researchers and the human volunteers that help them by labeling images. In particular, for animal identification, our system can save 99.5% of the manual labor (>18,000 h) while performing at the same 97.5% accuracy level of human volunteers. This substantial amount of human labor can be redirected to other important scientific purposes and also makes knowledge extraction feasible for camera-trap projects that cannot recruit large armies of human volunteers. Automating data extraction can thus dramatically reduce the cost to gather valuable information from wild habitats and will thus likely enable, catalyze, and improve many future studies of animal behavior, ecosystem dynamics, and wildlife conservation.

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