A Smart Farmland for Crop Prevention and Animal Intrusion Detection

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ABSTRACT

These days, object finding is applied encyclopaedically in a wide range of sectors, including appearance recognition, tone-driven buses, rambler displays, videotape surveillance, and vilification discovery. Decisions for management and conservation of wild animals must be based on accurate and efficient monitoring of these creatures in their natural environments. Because there are so many different kinds of animals, manually classifying them can be challenging. Thus, it's difficult to categorize animals based only on their pictures and provide them with more effective coverage. Additionally, it's critical to count the creatures because they are becoming extinct these days. In order to preserve them, we must properly record their numbers so that we may take decisive action to save them.. The sole manual counting in the system requires the presence of a mortal creature in order to maintain an animal count. This takes a long time to recognize the creatures. We're offering an automatic system that uses deep learning techniques to relate and count the animals in order to solve those issues. This method provides an accurate outcome for identifying and maintaining an accurate animal count.

Keyword: *Animal detection, Alert user, Yolov3 method.*

1. INTRODUCTION

These days, wildlife monitoring is crucial because many animal species some of which have already vanished are in danger of going extinct. Consequently, it is essential to record wild animal activities. However, without the aid of technology, maintaining these records becomes an overwhelming chore. Conventional techniques, like placing camera traps in the forest, taking pictures by hand, and then categorizing and labelling animals based only on the photos, take too much time and energy. Furthermore, it is not feasible for someone to snap images in the forest all day long. An whole new age of automated visual data analysis and interpretation has begun with the integration of deep learning techniques into computer vision applications. There has been a recent upsurge in interest in using similar approaches to identify animals in video feeds, with potentially revolutionary effects on a variety of industries, including agriculture and ecology. This paper provides a thorough and in-depth analysis of the most recent deep learning techniques used to identify animals in video footage. This work investigates deep learning approaches for animal detection in videos. This work investigates several deep learning techniques for the detection of numerous animals in diverse settings. Preparing the data, identifying salient aspects, and applying lessons learnt from one work to another are all closely considered in the analysis. This review not only highlights effective procedures but also discusses the drawbacks and restrictions that these approaches have. For example, there are substantial obstacles in adjusting to technological changes and limited data availability. It is essential to acknowledge and comprehend these obstacles in order to determine the future direction of research efforts. For those who are interested in using these powerful computer techniques for animal recognition in videos, this thorough review is a vital resource. It takes the newest concepts and illustrates areas that require more research to be improved.Moreover, this thorough analysis has shown that utilizing deep learning for animal detection can lead to a more sustainable and harmonious coexistence between humans and animals. In addition to advancing computer vision, this research has great potential to protect biodiversity and advance ethical land use, particularly in agricultural settings. The knowledge gained from this research will help us move toward a day where ecological harmony and cutting-edge technology coexist, to the mutual benefit of both humans and animals. By clarifying the significance of these techniques in improving the accuracy and efficiency of animal detection procedures, the survey seeks to provide a thorough review of the state-of-the-art developments in applying deep learning models for animal detection through cameras. One of the main uses of computer vision and deep learning is animal identification, which aims to automatically identify the presence of animals in films. Much deep learning architecture, each with advantages and disadvantages have been created over time to handle this task. Animal detection in video data has been accomplished using a variety of deep-learning architectures. The goal is to identify the animals in the movie so that you can tell normal Behavior from abnormal Behavior. Three main parts usually make up the system: tracking animals, analysing animal Behavior, and animal features.

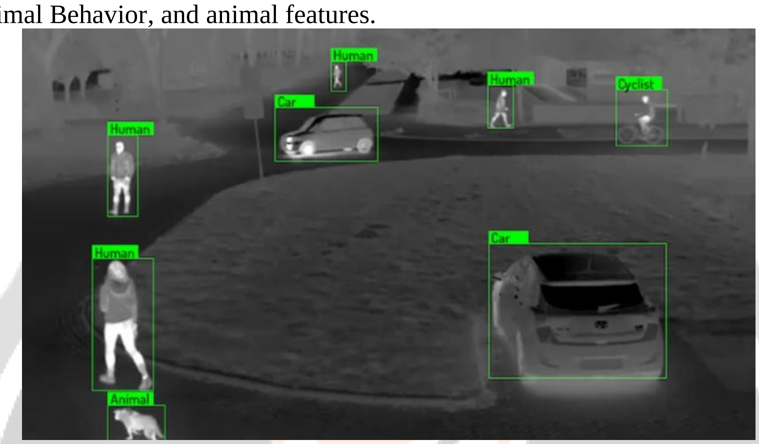

Figure 1: Animal Detection

2. ANIMAL DETECTION

In the first step, input is obtained from a video source, such as cameras positioned deliberately throughout wildlife areas. Video processing is applied to this input in order to improve quality and retrieve pertinent information. The yolov8 model, a cutting-edge object detection technique, is the system's main component for animal detection, which finds and locates creatures inside the processed video frames. After identification, the animals proceed to the hardware processing phase. In the event that an animal is detected positively, the system can notify specified recipients by phone, email, or text message. A light alert and a buzzer alert are also triggered to provide on-site signals of the animal that has been discovered. By combining AI algorithms with sophisticated video analytics, this integrated approach produces a potent intelligent animal detection system. Numerous animal species may be identified in the woodland using the YOLOV3 model. The YOLOV5 model can identify a variety of animals, including horses, sheep, cows, elephants, bears, zebras, and giraffes, from images, recorded movies, and real-time camera feeds. It is also capable of spotting birds. With a video feed connected via USB to the CPU, YOLOV5 can recognize objects in real time. Because YOLOv5 networks are lightweight, the identification model's deployment costs are lowered. In contrast to other techniques that reuse classifiers for detection, the paper presents YOLO, an inventive way to object detection. YOLO, on the other hand, approaches object recognition as a regression issue, wherein distinct bounding boxes and associated class probabilities are predicted. The detection pipeline functions as a single neural network, allowing for end-to-end optimization based directly on detection performance thanks to its unified architecture. Of particular note is YOLO's remarkable speed; its underlying model processes photos in real time at a remarkable 45 frames per second. Even the smaller version, Fast YOLO, outperforms existing real-time detectors in mean average precision (mAP), reaching an astounding speed of 155 frames per second. Compared to modern systems, YOLO could have more localization issues; yet,It exhibits a decreased propensity to produce false positives against the backdrop. Furthermore, demonstrating its broad generalization capabilities, YOLO learns extremely flexible object representations, surpassing competing detection techniques like DPM and R-CNN when used in a variety of domains including art work.

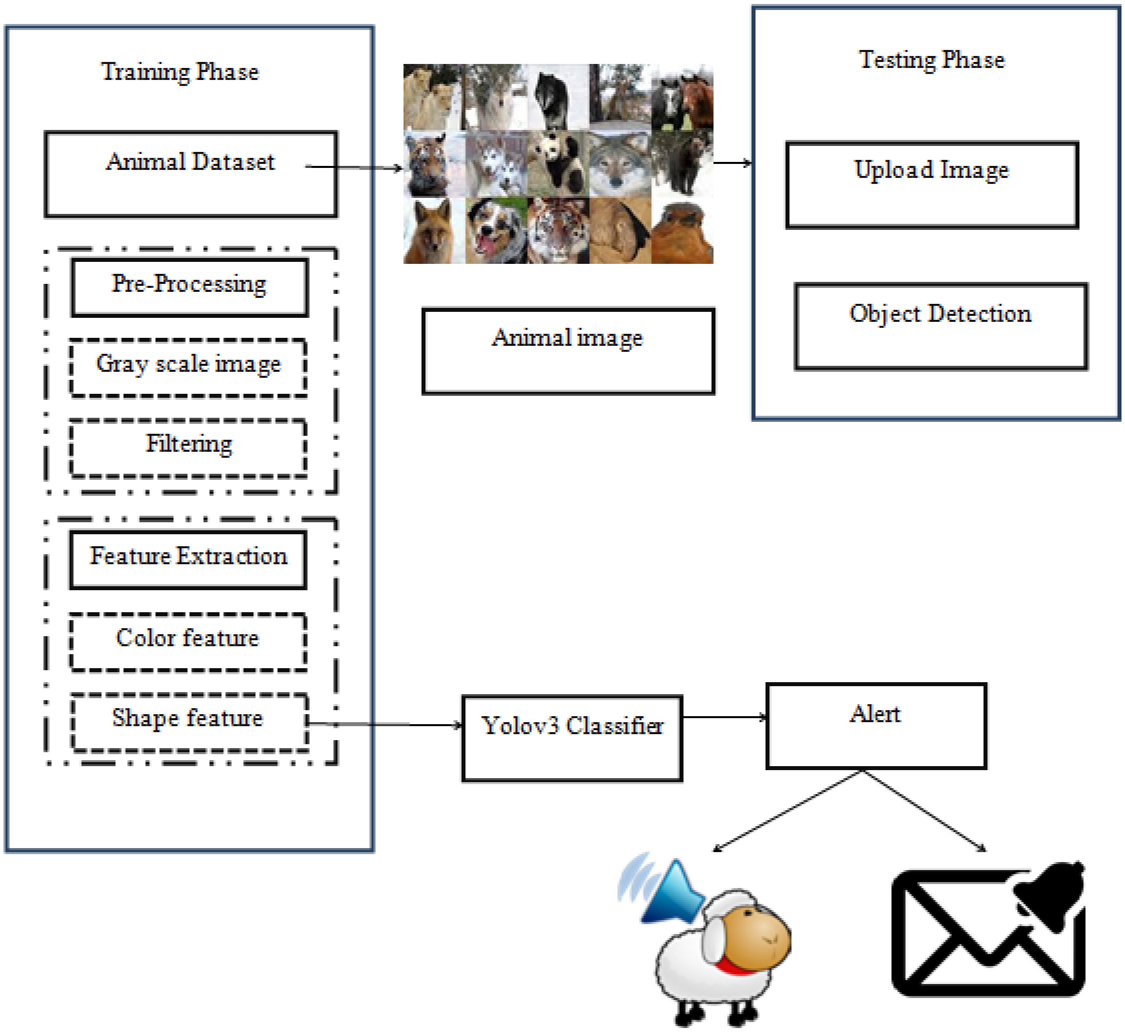

Figure 2: Proposed Architecture Diagram

3. RELATED WORKS

Mai Ibraheam [1] when compared to other object detection methods, deep learning techniques have produced the best results; yet, they come with a high computational cost and parameter requirements. A YOLOv2-based lightweight animal species detection model was put out. It was created as an initial step toward developing an embedded real-time mitigation system and as a proof of concept. To enhance the accuracy and feature extraction capability of YOLOv2, a new pass-through layer is added in order to perform multi-level features merging.

B. the Natarajan [2] The safety of both people and foresters can then be ensured by sending alert messages. Although methods based on computer vision and machine learning are widely employed to detect animals, their cost and complexity usually make it impossible to obtain adequate results.In order to recognize animals and provide alerts based on their activity, this research offers a Bidirectional Long Short-Term Memory (Bi-LSTM) network that is Hybrid Visual Geometry Group (VGG)−19+.

Panda Prabhat Kumar [3] This paper proposes a system that monitors the field and leverages the Internet of Things to help detect wild animal intrusions on agricultural farms in order to address this issue. At the corners of the field, ultrasonic sensors are used to detect intrusions. A camera mounted on the E-vehicle, which is equipped with a Node MCU Microcontroller to monitor the field, then takes a picture of the invader. Through an IoT application, the farmer receives an alert message. .. The efficacy of the suggested method has been examined in relation to the photos of the intruder that were taken and the alarm that was sent out.

In order to safeguard wild creatures, an algorithm is demonstrated by Gnaneshwar Bandari [4]. It could be difficult to manually recognize animals because they are so diverse. This technique classifies animals according to their

photos in order to monitor them more efficiently. Animal detection and classification can help with animal monitoring, theft prevention, and animal-vehicle accidents prevention. This is when effective deep learning algorithms come in handy. LoRa communication is used to transmit an alert when an animal is spotted to a different device because regular communications like WiFi and GSM technologies might not be available in the remote sensing area.
Image processing is done with computer vision using Python. The model is installed using a Raspberry Pi development board, and live streaming is processed to identify a wild animal that can tell the difference between humans and domestic animals.
Y A Roopashree [5] Our nation's roads are always growing and changing, and a large number of them are close to forests, which raises the risk of fatal collisions between humans and animals. This work presents an application that efficiently recognizes and classifies the animals in the photographs sent to it using the "YOLO" algorithm. It notifies the user via a map interface, along with the animal's location on Google Maps. Here, animal detection and classification are done using the deep learning method. A detection and alerting system is suggested that makes use of deep learning. Our program was trained using the tiger and elephant datasets.

4. METHODOLOGY

Taking pictures or videos of the monitored area is the initial stage in the animal detection and alert system. This can be accomplished by using a variety of tools, such security cameras, to capture an animal's movement within its surroundings. In order to guarantee the detection system's resilience, the video footage ought to encompass an extensive variety of viewpoints and illumination scenarios. In order to properly monitor places where animal intrusion is likely to happen, such as wildlife reserves, agricultural fields, or urban areas where wildlife encounters are common, the cameras or sensors must also be placed strategically. The imaging equipment must be properly calibrated and maintained in order to provide high-quality input data for further processing. After being obtained, the photos or video clips are pre-processed to improve their quality and analysis-friendliness. To normalize the input data, this entails performing operations like noise removal, scaling, and normalization. In order to separate moving objects from static backdrops and minimize processing overhead during analysis, background removal techniques might be used. Moreover, contrast and clarity can be increased through the use of picture enhancement techniques, leading to more precise animal detection. In order to guarantee optimal system performance, data pre-processing is essential for preparing the input data for the detection pipeline's later stages. In order to identify the presence of animals in the monitored area, the real-time monitoring module continuously evaluates incoming image or video streams. This module analyzes frames or video clips in real-time with the least amount of latency possible by utilizing effective algorithms and parallel processing approaches. To identify animals in the input data, sophisticated computer vision methods are used, such as deep learning-based object detection models. With real-time monitoring, animal incursions can be quickly detected, allowing for prompt alerting or intervention to reduce possible risks or damages. The identification and classification of found animals according to their species or traits is the responsibility of the classification module. This module makes use of machine learning algorithms that were trained using the Yolo technique using annotated datasets that include samples of several animal species. By giving labels to animals that are identified, the categorization module makes it possible for the system to distinguish between domestic animals, innocuous wildlife, and potentially dangerous species. Based on the identified animal activity, the detection result module creates alerts or notifications by combining the information from the categorization module. Relevant data, including species, location, and timestamp, are marked on detected animals to set the scene for further actions. The system can set off alerts, notify specific staff by email or SMS, or integrate with current security systems to provide automatic responses, all depending on the needs of the application. By acting as a conduit between the end-users and the detection system, the detection result module improves situational awareness in the monitored area and permits prompt response to animal incursions.

5. IMAGE PRE-PROCESSING AND IMAGE SETS

For training, all object identification techniques resize the input image to a predetermined resolution known as the "network resolution." Deep learning frameworks typically require a square input resolution for their feature extractors. In its initial setup, YOLO resizes the input image to 416 x 416 pixels while maintaining the same aspect ratio in the shorter dimensions of height or width. To accommodate larger input images (2048 × 2048 pixels), network resolution can be enhanced; however, this will result in higher memory and compute needs. Data augmentation was required prior to picture training in order to improve image representation by increasing image variety. To attain enhanced recognition precision and resilience through efficient data augmentation, pre-processing of the images using augmentation techniques like jitter, image rotation, flipping, cropping, multi-scale transformation, hue, saturation, Gaussian noise, and intensity was imperative. Labeled data, such as the class label and the coordinates of each ground truth bounding box in training images, are needed to train object detection models. The process of manually labeling images can be laborious, complex, and subject to user bias, particularly when there are many items and clusters in the image. Annotation, or the process of constructing ground truth bounding boxes, was, however, simpler when the images were tiles rather than entire images. The advent of free graphical annotation tools has made the work of naming items in photos easier. The YOLO Annotation tool5, a graphical picture annotation tool, was employed. The annotated data, which comprises the class of the annotated item and the coordinates of the rectangular box among other things, was saved in YOLO Darknet format. Processing of Images: Analyze camera footage and identify animals by their look using computer vision techniques. One can use methods such as item detection and CLASSIFICATION. Utilize machine learning techniques to analyze audio data in order to identify animal vocalizations and differentiate between various species. Combine information from several sensors to decrease false positives and increase animal detection accuracy. Put in place a rule-based system that uses sensor inputs to make decisions. For instance, activate repulsive mechanisms in response to the detection of a specific animal species or size. Develop machine learning models to anticipate patterns in animal behaviour and enhance the system's reaction. Provide consumers the option to remotely operate the system via a Smartphone app or web interface. Release fragrances that are repulsive to animals, such those of predators or potent spices. Notify users when repulsive measures are activated or when animals are spotted. Give users access to a dashboard where they may see previous activity logs, system status, and real-time sensor data. Save system events and sensor data for later study and optimization. Make sure you have dependable power sources for ongoing use, including solar panels that include a battery backup or mains power.

6. RESULT AND DISCUSSION

Additionally, experimental findings are shown to examine the legitimate reasoning outcomes and compare the suggested methodology with previous methods. The finer points of different development stages are elucidated with clarity and demonstrate the caliber of our output. Finding the expected outcomes in object recognition and classification models is quite complex. The model performance bottleneck causes low performance and deteriorates the development process as a whole in large-scale scenarios. A greater variety of techniques were employed in the earlier studies to tackle these problems. Using a real-time object detection technique requires complex computing processes, which call for strong hardware to run the algorithms. To get good outcomes in a shorter amount of time, this is crucial. However, gadget portability is crucial to achieving real-time animal detection because of the nature of our challenge and its surroundings. The extra limitations on memory footprint and power usage, which typically clash with the need for precision and latency, make this difficult. The usage of low form factor embedded devices will be encouraged by this research.

Table 1: Result **and Discussion**

Algorithm	Training	Performance	Testing
Yolov3	9.10	9.50	9.80
CNN	5.2	4.3	8.5
Xgboost	4.6	7.5	6.00

7. CONCLUSION

In summary, the creation of an animal detection and repellant system is a major step in resolving disputes between people and wildlife and fostering cooperation. By using cutting-edge technologies like sensors, machine learning algorithms, and compassionate repellents, this system provides a comprehensive strategy to minimize harm to animals and the environment while mitigating possible damages caused by wildlife infiltration. Through precise detection of animal presence in approved areas, the system notifies property owners or managers in a timely manner, allowing for preemptive measures to be taken to dissuade wildlife before disputes worsen. Furthermore, the inclusion of repellent mechanisms guarantees a humane and efficient way to deter animals from accessing prohibited regions, hence lowering the necessity of using deadly control techniques. Furthermore, a system of this kind can be applied in a variety of situations, including protected natural habitats, metropolitan areas, and agricultural regions, due to its versatility and scalability. Its ability to be tailored to certain wildlife species and their behavior patterns increases its efficacy in identifying and limiting pertinent threats while reducing false alarms.

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