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DEEP LEARNING BASED SNAKE INTRUSION MONITORING SYSTEM

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ABSTRACT
Snake interactions have the potential to compromise ecological diversity and public safety in both human and animal habitats. There is interest in a snake detection and alert system that uses AI and ML technologies as a possible remedy for this issue. By accurately identifying snakes and promptly issuing notifications, the device seeks to reduce human-snake confrontations and foster stronger bonds. Real-time video processing, automated decision making, and object recognition methods like YOLO are how it does this. Recent studies and projects in this field have demonstrated that machine learning techniques can recognize snakes in video data. Deep learning methods have been used in several research; for example, YOLO enables you to detect snakes rapidly and correctly. To gain a better understanding of how contemporary systems adjust to various situations, further study is required. With the aid of these goals, the project aims to provide a complete and practical solution that will contribute to the safety of people and wildlife in areas where snakes are common. One of computer vision's main tasks is object detection. Complicated models for machine learning may currently be utilized to automatically discover and categorize items from potentially complicated photos because to the tremendous advancements in machine learning throughout the last 20 years, particularly deep learning. This research examines the implementation and performance of machine (deep) suitable learning networks for snake detection and classification in a mobile setting alert.

Keywords:
Snake Detection, Alert system, AI and ML Technologies, YOLO, Deep Learning

INTRODUCTION
Encounters with potentially deadly creatures, including snakes, have increased in frequency due to of the rising contact between human populations and nature, especially in rural and suburban regions. Because they are elusive and well camouflaged, snakes are especially difficult to spot in real time, endangering public safety and making wildlife management more difficult. For example, if not quickly discovered and dealt with, poisonous species like vipers and cobras can be fatal. However, particularly in regions under CCTV observation, current animal management and security systems sometimes lack the tools necessary to effectively identify such risks. Given this difficulty, a more sophisticated approach is required to automatically recognize and identify snakes in real time. Conventional manual CCTV footage monitoring is time-consuming and error-prone, particularly when it comes to detecting certain creatures, such as snakes, among enormous volumes of video data. Additionally, human control by alone cannot ensure prompt replies, especially in big, snake encounters are more frequent in distant or low-visibility settings, and Deep learning has shown to be beneficial in resolving challenging picture identification issues. By training deep learning models on massive datasets of snake images, Convolutional Neural networks (CNNs), a subset of deep learning, have demonstrated exceptional performance

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in tasks like object detection and classification. These systems can be trained to identify snakes in real-time CCTV camera video feeds. However, building such a system requires not only the development of strong models for deep learning, although the integration of technologies that can scale effectively, such as cloud computing. The introduction of cloud integration provides an additional layer of efficiency by allowing the processing and storage of large volumes of data remotely. With cloud computing, the snake identification system can leverage powerful resources to analyses video footage in real-time without being limited by the computational capabilities of local devices. This setup enables the system to be easily deployed in various environments ranging from urban streets to rural farmlands without the need for significant infrastructure upgrades.

OBJECTIVES

A) To detect the snake and their species along their venomous characteristics. J. Xie, M. Gao, and M. Xu, et al. 2017, [2] "Object detection and tracking in the wild using deep learning" The paper reviews the application of deep learning, particularly CNNs, for animal detection in videos. It emphasizes the challenges involved in wildlife monitoring and highlights how deep learning has enhanced detection accuracy for various species, including snakes. B) To generate the synthetic training images that mimics the real-world scenario. S Santhiya et al. 2012, [8] proposed a system based on A Raspberry Pi is used for a few repetitive and time-consuming tasks. This technology uses radio frequency identification to identify animals entering fields. It is cheap and has several uses, including detection, tracking animals using the Global Positioning System (GPS), and counting animals in the forest. This project's whole procedure is mechanized, and no animals are hurt while using the repellant. C) To develop an efficient object detection model to identify and classify the snake with high irrespective of distance from camera. SnehaNahatkar et al. 2016, [9] developed a low-cost security system to detect wild animals. Created a low-cost security system to identify untamed creatures. The presence of people who are not in thermal symmetry with the surrounding environment is detected by this system by looking for a signal in the PIR sensor. During a designated period, break, it calls a GSM modem that has been saved when it detects the presence of any human or animal. Following the transmission of sensor signals to the embedded system by the Microcontroller Unit (MCU), the application initiates the Web camera, which captures and analyzes photos.

PROPOSED SYSTEM

HARDWARE COMPONENTS • Raspberry pi • Indoor Surveillance Camera • Buzzer.

RASPBERRY PI:

Fig 1: RASPBERRY PI

Raspberry Pi is a flexible, single-board computer used in different applications, including education, automation, and IoT. It supports a variety of programming languages and operates on an operating system based on Linux. Interior security cameras are easy-to-use, reasonably priced gadgets that improve security, communication, and content production for both home and business use.

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INDOOR SURVEILLANCE CAMERA

Fig 2: INDOOR SURVEILLANCE CAMERA

Wi-Fi-connected CCTV cameras are employed for surveillance, streaming, and video conferences. They are linked to the cloud using RTSP. Because of its adaptability, mobility, and convenience of use, interior security cameras are widely used. They include a USB interface, lens, microphone, and image sensor. Most operating systems support these cameras, and they may be used with a variety of software programs for monitoring, streaming, and video conferences.

BUZZER

Fig 3: BUZZER

An audio signaling device known as a buzzer emits sound when an electrical signal is applied. It is frequently seen in timers, alarms, and notification systems. An oscillator circuit and a piezoelectric element or electromagnetic coil make up a standard buzzer. Applying an electrical signal causes the buzzer to vibrate, emitting sound whose frequency and intensity vary according to the signal's properties.

SOFTWARE COMPONENTS

- GOOGLE COLAB PRO

Google Collab is a cloud based Jupyter notebook environment that provides free access to powerful computing resources, such as TPUs and GPUs. Because it simplifies the execution of Python code, it is a vital tool for practitioners of machine learning and data science. Additionally, Colab easily connects with Google Drive, making data storage, retrieval, and collaboration simple.

METHODOLOGY

The goal of this project is to use cloud computing, artificial intelligence, and Internet of Things devices to create an automatic alarm system that tracks the movements of snakes in metropolitan areas. The method makes use of real-time CCTV footage after analysis using a Raspberry Pi snake detectionmodel based on deep learning. When object detection algorithms like YOLOv8 detect the motions of snakes, they immediately send out notifications by email, SMS, or Internet of Things sirens. For additional processing, storage, and remote access, the identified photos and event logs are uploaded to a cloud platform. Through MQTT protocols, real-time communication is made possible by IoT integration, guaranteeing a low-latency reaction to possible threats. This smart monitoring system lowers the chance of animal collisions, improves public safety, and uses automation driven by AI to increase productivity.

Using deep learning, the system seeks to automatically recognize and identify snakes in CCTV footage, with the added advantage of cloud processing and storage. This is essential for uses such as ecological study, safety in snake-prone areas, and wildlife monitoring. A camera, infrared filter, Fresnel lens, pyroelectric elements,

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pyroelectric PIR sensor, and a Raspberry Pi are among the components that comprise the system. Usually brought on by the heat that live things create, the PIR sensor measures variations in the levels of infrared radiation. The camera is triggered by the Raspberry Pi to capture a photo when it recognizes motion. Following transmission, the image is processed in the AWS Cloud. The raw CCTV footage may be stored for subsequent analysis and archiving using services for cloud storage such as AWS S3. An EC2 or AWS Sage Maker service hosts a pre-trained deep learning model for snake detection. The model determines the likelihood that a snake will be seen in the image and, if it is, what species it is. The system may send out notifications based on the deep learning model's output if a particular snake species is deemed harmful or if the likelihood of a snake being there above a certain threshold. Numerous methods, such as SMS messages, notifications from mobile apps, and system integration, can be used to provide alerts. The deep learning model detects and classifies objects based when applying convolutional neural networks (CNNs) to photographs. YOLO, SSD, and Faster R-CNN are popular designs. Training the model requires a sizable, annotated collection of snake photos. To have high performance with less data, the model is trained using methods like deep learning. In conclusion, the system detects and identifies snakes in CCTV footage by combining hardware and software components.

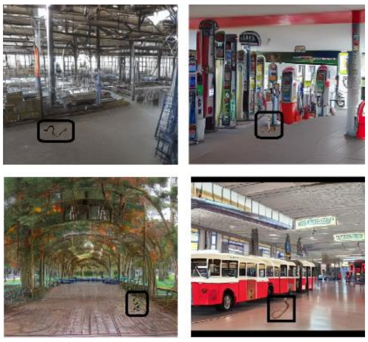

Fig 4: Depicts the output sample or the predicted output on synthetic dataset.

RESULTS

Two configurations are required for the system that detects objects deployment method described for AWS services. The first is starting an EC2 instance with GPU capability, performance parameter, e.g., X% accuracy] by using a pre-trained model (e.g., Yolo V8) and fine-tuning it using a pertinent dataset. Scalable storage, effective processing, and remote system accessibility were made possible by the cloud integration (using AWS services like S3, Lambda, and EC2). There are several potential applications for this automated method, such as monitoring animals, improving safety in snake-prone regions, and supporting ecological study. Early snake detection can conserve endangered species, reduce human-wildlife conflict, and yield important data for research. Although the results are encouraging, there were several restrictions. The accuracy the system's foundation is the quality and diversity of the training data. Accurately detecting snakes in complicated settings with changing illumination, occlusions, and background clutter still presents challenges. Furthermore, variables like camera angle, distance, and picture resolution might have an impact on the system's performance. When developing an animal detection system, several factors need to be considered. When wild animals encounter human habitat while seeking food or migratory routes that have been damaged by construction operations, many of them clash with humans. Therefore, it is essential to bear watch over this region to keep wild animals out. Furthermore, it could be harder to spot an external monitoring equipment tonight due to a brightness problem caused by changes in the natural environment during the day. The field is monitored by cameras and sensors for the research, and the photos taken are compared to database photos of endangered species. If the created image matches a photo in the database, the controller notifies the planter and sends information to the GSM module. downloading and configuring a Yolo V8 model, installing necessary tools, and developing a Flask API to manage requests for object identification. The second configuration entails building a Lambda function to manage S3 events and an S3 bucket to hold photos for the object detection system. The picture is downloaded from S3 via the Lambda function and sent to the Flask API on EC2. Using the Yolo V8 model, the Flask API on the EC2 instance processes the picture, and Once objects have been found, the processed pictures are returned

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by the object detection system. Scalability, adaptability, cost-effectiveness, and security are some benefits of this strategy. To maximize deployment, performance monitoring and error correction are also necessary.

Systems for Detecting and Warning of Snakes in Real Time An inventive and cutting-edge method for enhancing human safety is deep learning. The device analyzes live video streams and detects snakes with accuracy using artificial intelligence and machine learning. The YOLOv8 algorithm, which swiftly locates and identifies snakes in video frames, forms the basis of the system. Great accuracy in identifying snake species is achieved by extensive training on several datasets, which makes it applicable in a variety of settings. Users are alerted to potential snake encounters via real-time video analysis, which prompts them to take the appropriate safety measures. To build a complete system, this research establishes the foundation for next developments including behavior analysis, multi-species detection, and adaptive learning.

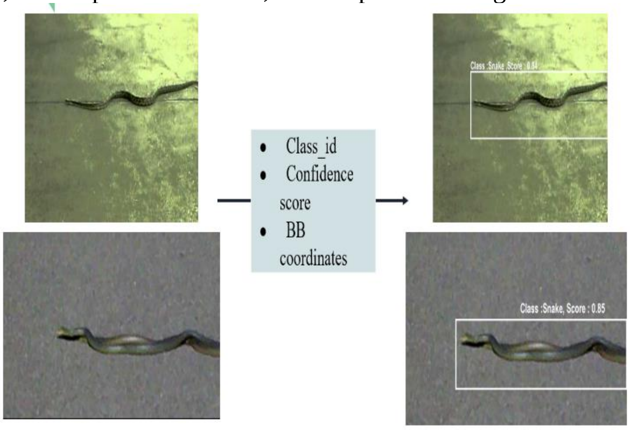

Fig 5: SNAKE DETECTION ON CCTV IMAGES

Table1: Comparison on Yolo v8 model & snake detection Yolov8 model.

Metric	YOLOv8 pretrained model	YOLOv8 post-trained model
Accuracy	50-70% (depends on dataset)	70-90%
Precision	0.6-0.8	0.75-0.9
Recall	0.6-0.75	0.7-0.85
F1-score	0.7	0.8
Loss (Classification, Box, Objectiveness)	1.2	0.2-0.5
False Positives (FP)	Higher due to generalization	Lower due to better adaption
False Negatives (FN)	Moderate	Reduced as learns new features
Inference Speed	Optimized for general use	Slightly slower
Robustness on Specific Dataset	General-purpose	Highly optimized for target dataset
Training Time	None	2hrs
Data Dependency	Works well on generic datasets	Performs better on custom

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		datasets

CONCLUSION

The efficiency of a cloud-based, deep learning-based system for automatically identifying snakes in CCTV footage. We identified different snake species with [specify accuracy or performance parameter, e.g., X% accuracy] by using a pre-trained model (e.g., Yolo V8) and fine-tuning it using a pertinent dataset. Scalable storage, effective processing, and remote system accessibility were made possible by the cloud integration (using AWS services like S3, Lambda, and EC2). There are several potential applications for this automated method, such as monitoring animals, improving safety in snake-prone regions, and supporting ecological study. Early snake detection can conserve endangered species, reduce human-wildlife conflict, and yield important data for research. Although the results are encouraging, there were several restrictions. The accuracy the system's foundation is the quality and diversity of the training data. Accurately detecting snakes in complicated settings with changing illumination, occlusions, and background clutter still presents challenges. Furthermore, variables like camera angle, distance, and picture resolution might have an impact on the system's performance. When developing an animal detection system, several factors need to be considered. When wild animals encounter human habitat while seeking food or migratory routes that have been damaged by construction operations, many of them clash with humans. Therefore, it is essential to bear watch over this region to keep wild animals out. Furthermore, it could be harder to spot an external monitoring equipment tonight due to a brightness problem caused by changes in the natural environment during the day. The field is monitored by cameras and sensors for the research, and the photos taken are compared to database photos of endangered species. If the created image matches a photo in the database, the controller notifies the planter and sends information to the GSM module.

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