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# AI Based Smart Animal Tracking and Detection with Multi-Faceted Alert System

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**Abstract: Recent developments in Internet of Things (IoT) combined with artificial intelligence (AI) have produced creative solutions in a number of fields, including animal conservation. This paper proposes a novel smart animal detection system that leverages the capabilities of the YOLOv8 AI model for real-time object detection and IoT integration for immediate response mechanisms. By training the YOLOv8 deep learning algorithm on a comprehensive dataset of wildlife images, the system can achieve accurate identification of animals in diverse environments. The integration of IoT devices further enhances functionality by enabling rapid response actions upon detection. These IoT devices include buzzers, automated phone calls and SMS alerts, which are triggered based on the severity of the detected event. For example, detecting a potential threat such as poaching or habitat destruction can trigger a loud buzzer to deter intruders and simultaneously notify authorities via phone calls and SMS, providing real-time information for quick intervention. This system presents significant advantages over traditional wildlife monitoring methods, including real-time threat detection, prompt alert delivery to relevant stakeholders, and adaptability for deployment in various environments. Thus, it represents a versatile and effective tool for wildlife conservation efforts.**

**Keywords: AI, Automated alert system, IoT, Real-time object detection, Wildlife econservation, YOLOv8.**

## I. Introduction

Image processing refers to the method of converting an image into digital form and performing various operations on it to enhance the image or extract valuable information. It is a type of signal processing where the input is an image, such as a video frame or photograph, and the output could be the processed image or specific characteristics associated with that image. Typically, image processing systems treat images as two-dimensional signals and apply established signal processing techniques to them. Many digital image processing techniques were developed in the 1960s at institutions like the Jet Propulsion Laboratory, Massachusetts Institute of Technology, Bell Laboratories, and the University of Maryland. These techniques were initially applied to satellite imagery, wire-photo standards conversion, medical imaging, videophone, character recognition, and photograph improvement. Due to the costly computing technology available at the time, processing expenses were considerable. However, due to increasingly accessible computers and increased demand for digital image processing, the 1970s witnessed real-time processing for certain applications, such as television standards conversion, is now possible because of the availability of specialized hardware [1]. Deep learning has completely changed the way objects are detected, affecting several sectors like autonomous cars, security, and medicine. Deep learning has significantly improved object recognition, a fundamental job in computer vision, especially using convolutional neural networks (CNNs). These networks improve object detection's precision and effectiveness. The concept of hierarchical feature learning, which uses CNNs to automatically learn hierarchical representations of input data, underpins deep learning for object recognition. CNNs extract more information by using many layers of convolution, pooling, and non-linear activation functions. assemble features from unprocessed pixels. Robust object detection is made possible by this approach, which enables computers to precisely locate and identify things in pictures or movies. The technique starts with standardizing the input photos through preprocessing and then feeds them into a CNN. CNN uses pooling and convolution to extract pertinent characteristics from a multi-layered network of interconnected nodes. Large amounts of labeled data are analyzed during training to teach CNN how to recognize things. Backpropagation is used to modify the CNN's internal parameters, which enhances object detection and localization [2]. The Region-based Convolutional Neural Network (R-CNN) and its variations, such as Fast R-CNN and Faster R-CNN, are popular designs for object detection because they identify and classify regions of interest within an image and use this information to precisely pinpoint objects. One more YOLO technique is a popular method that produces faster inference times than R-CNN variations by dividing the input image into a grid and simultaneously predicting bounding boxes and class probabilities for each grid cell. These models are essential to contemporary AI systems because, once trained, they can precisely recognize and locate things in fresh photos or videos. They can be used for autonomous navigation, medical diagnostics, and other purposes [3]. For object recognition, the

YOLO model offers a fresh and efficient method. Conventional systems use classifiers for detection, which means that they must classify at different spots in the image and then post-process to improve bounding boxes and remove duplicates. This procedure is frequently intricate and ineffective. Yolo, on the other hand, views object detection as a regression problem, accurately forecasting class probabilities and bounding boxes for the full image in a single pass.

## II. Literature Survey

Even while deep learning approaches are computationally demanding and require a large number of parameters, they have proven to be more effective than other object detection methods. A YOLOv2-based lightweight model for animal species detection has been offered as a solution to this problem. This model is a proof of concept and an initial step in creating an embedded real- time mitigation system. By adding a new pass-through layer to YOLOv2, multi-level feature merging is performed to improve feature extraction and accuracy. In addition, the two repeating 3×3 convolutional layers in the seventh block of the YOLOv2 architecture are eliminated to lower computational complexity and speed up detection without compromising accuracy. Although animal species detection has made extensive use of classic Convolutional Neural Networks (CNNs), these networks find it difficult to adjust to the geometric differences between images with animals. To overcome this limitation, a modified YOLOv2 incorporating deformable convolutional layers (DCLs) has been proposed, improving the model's adaptability to these variations [4]. The increasing concern of animal attacks poses significant risks for rural communities and forestry workers. Surveillance cameras and drones are commonly used to monitor the movement of wild animals, but an effective model is essential for identifying animal types, tracking their movement, and providing location information. By using this data, alarm messages can be sent, guaranteeing the security of both individuals and forestry workers. While animal detection is a prominent use of computer vision and machine learning techniques, these methods are often expensive and difficult, producing subpar results. To recognize animals and provide alerts based on their actions, this research presents a Bidirectional Long Short-Term Memory (Bi-LSTM) network that is Hybrid Visual Geometry Group (VGG)−19. Short Message Service (SMS) is used to send these notifications to the local forest office, allowing for quick action [5]. Wild animal invasions pose a significant threat, leading to substantial resource losses and endangering human lives. Consequently, people may lose crops, possessions, and potentially their lives. To identify wild animal incursions on agricultural farms, this study suggests an Internet of Things (IoT) based system that monitors the fields. Initially, incursions are detected using ultrasonic sensors positioned at the corners of the fields. A camera installed on an E-vehicle with a Node MCU Microcontroller detects the intrusion and takes a picture of the intruder. The farmer is then notified using an Internet of Things application. The photos of the intruders that are taken and the notifications that are sent out are used to assess how well the suggested system works. With the help of this model, any kind of incursion near the field can be effectively detected [6]. An algorithm designed to identify wild animals to aid in their protection. Given the vast variety of animal species, manual identification can be quite challenging. This method uses photos to classify animals to improve wildlife monitoring. Detecting and classifying animals can make a big difference in tracking initiatives, stopping theft, and lowering the number of incidents involving animals and vehicles. This process can be facilitated by putting effective deep-learning approaches into practice. Since normal connections like WiFi and GSM may not be dependable in distant sensing areas, an alert is delivered using LoRa communication when an animal is detected by another device. Python-based computer vision algorithms are used for image processing. The model is implemented on a Raspberry Pi development board, which processes live streaming to identify and differentiate between domestic animals and wild animals. An end-user who monitors the wildlife receives an alert via LoRa communication as soon as a wild animal is spotted [7]. 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 [8]. Several studies have explored the use of deep learning techniques for animal detection and classification. Convolutional Neural Networks (CNNs) have been particularly effective in this domain. For instance, YOLO (You Only Look Once) models have been employed for real-time object detection due to their speed and accuracy. A modified version of YOLOv2 has been proposed to improve feature extraction and detection speed by incorporating pass-through layers and removing redundant convolutional layers [9]. To improve detection accuracy and adaptability to various animal postures and movements, hybrid models combining CNNs with Recurrent Neural Networks (RNNs) like LSTM have been explored. For instance, animals have been detected and alarms have been generated depending on their activities using a hybrid VGG-19 and bidirectional LSTM network. This method makes use of VGG-19's spatial feature extraction power and Bi-LSTM's robust temporal sequence processing [10]. The integration of IoT devices in animal tracking systems allows for real-time monitoring and alerting. Ultrasonic sensors, cameras, and microcontrollers like Node MCU and Raspberry Pi are commonly used. These systems typically involve sensors detecting animal presence, followed by cameras capturing images, which are then processed using AI models deployed on microcontrollers. Alerts are sent via IoT applications or communication protocols such as LoRa, which is suitable for remote areas where conventional networks are unreliable [11].

## III. Background

Recent developments in Internet of Things (IoT) combined with artificial intelligence (AI) have produced creative solutions in a number of fields, including animal conservation. This paper proposes a smart animal detection system that leverages the YOLOv8 AI algorithm for real-time object detection, combined with IoT integration to enable immediate response mechanisms. The YOLOv8 algorithm is renowned for its high accuracy and efficiency in detecting objects in real-time scenarios. By training YOLOv8 on a comprehensive dataset of wildlife images, the system can accurately identify different animal species in their natural habitats. The integration of IoT devices significantly enhances the system's functionality, enabling rapid responses upon animal detection. These IoT components include buzzers, phone calls and SMS notifications, which can be activated based on the severity of the situation. For instance, if the system detects a potential threat to wildlife, such as poaching or habitat destruction, it can trigger a loud buzzer to deter intruders. Simultaneously, it can notify relevant authorities through phone calls and SMS messages, providing real-time information to facilitate prompt intervention. This system offers multiple advantages over traditional wildlife monitoring methods. Firstly, its real- time detection capabilities allow for immediate responses to potential threats, thereby reducing the risk to endangered species. Secondly, the integration of IoT gadgets make sure that notifications reach the appropriate parties on time, allowing for quick action. Last but not least, the system's versatility allows it to be implemented in a variety of settings, from dense woods to open plains, thus serving as a versatile tool in wildlife conservation efforts.

### *A. Problem Statement*

The rising incidents of wildlife conflicts, animal-related road accidents, and the need for effective wildlife monitoring necessitate a robust solution. Traditional methods are inadequate in providing real-time data and proactive measures to address these issues. Therefore, a Smart Animal Detection System that integrates advanced technologies like IoT and AI is essential to enhance wildlife monitoring and protection. The Smart Animal Detection System utilizes YOLOv8, a cutting-edge object detection algorithm, for real-time video analysis. The system incorporates IoT devices such as cameras and sensors strategically placed in wildlife habitats, along roadways, and in other critical areas. These devices continuously capture and stream video footage and environmental data to a centralized processing unit. The YOLOv8 algorithm processes the incoming video streams to accurately detect and classify animals. The AI model is trained to recognize various species, considering different sizes, shapes, and movement patterns. The system employs machine learning to continuously improve its detection accuracy over time. Upon detecting an animal, the system triggers an immediate response through IoT-enabled communication channels. SMS and/or call alerts are sent to relevant authorities, wildlife protection agencies, and nearby communities to ensure a swift and effective response. This approach aims to reduce wildlife-human conflicts, prevent road accidents involving animals, and enhance overall wildlife monitoring and conservation efforts.

## IV. Existing System

In existing systems, animal species detection is implemented using image processing and Convolutional Neural Networks (CNNs). The potential uses of this technique in wildlife management, conservation, and biodiversity monitoring have drawn a lot of interest lately. It entails using computer vision techniques to automatically identify various animal species by analyzing photos. CNNs are a kind of deep learning model that are useful tools in this situation since they are especially well-suited for image identification tasks. Usually, the procedure entails gathering sizable datasets of annotated photos, using these datasets to train a CNN to identify patterns and characteristics linked to various animal species, and then applying the trained model to identify the species in fresh photos. CNNs and image processing together provide an effective and non-intrusive way to track and study wildlife in a variety of environments. The purpose of the CNN model is to acquire hierarchical representations of features, allowing it to recognize complex patterns and traits unique to various animal species. Additionally, pre-trained models are leveraged using transfer learning techniques, which maximize training efficiency and improve generalization to novel species. The outcomes show how well the deep learning model works, even in difficult situations like changing lighting and a variety of environments, to correctly recognize and classify different animal species. The main disadvantages in the existing schemes are:

- Limited Dataset Diversity
- Lack of Interpretability
- Computationally Intensive
- Potential for Inaccuracies

## V. Proposed System

The initial stage of the system involves capturing input from video sources, such as cameras strategically placed in wildlife habitats. This video feed undergoes processing to enhance quality and extract relevant information. The core functionality of the system centers on animal detection, utilizing the YOLOv8 model, a cutting-edge object detection algorithm, to identify and locate animals within the processed video frames. Once identified, the information is transferred to the hardware processing stage. The animal classification results from YOLOv8 are fed into an Arduino microcontroller, a versatile and programmable platform. The Arduino processes this information and triggers various output alerts based on the identified animals. The system's IoT integration becomes evident as the Arduino microcontroller communicates with GSM modules. When an animal is detected, the system can send alerts via phone calls, email notifications, or SMS messages to designated recipients. Additionally, it activates a buzzer and a light alert to provide on-site indications of the detected animal. This integrated approach, combining advanced video analytics, AI algorithms, and robust hardware components, creates a powerful Smart Animal Detection System.

To further enhance the capabilities of the AI-based Smart Animal Detection and Tracking System, several additional features and improvements can be proposed.

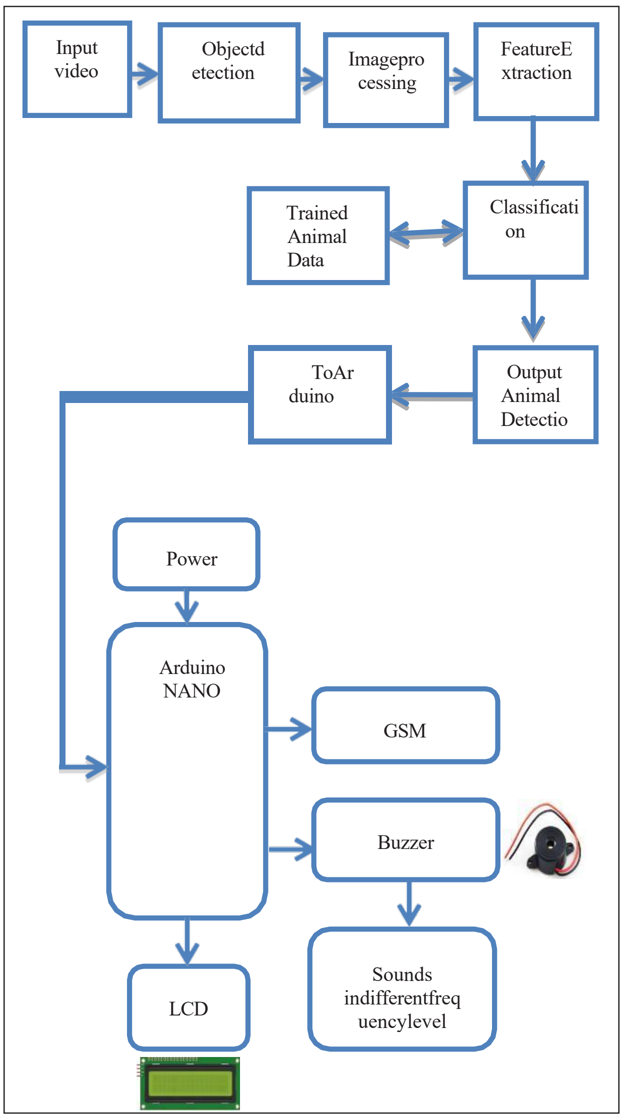


Fig. 1: Proposed Architecture

These enhancements aim to increase the system's accuracy, responsiveness, and versatility, providing even better support for wildlife conservation efforts. Incorporating additional sensors, such as thermal cameras and motion detectors, can significantly improve the detection accuracy, especially in low-light conditions or dense foliage. Implementing a cloud-based infrastructure can enhance data analysis and storage capabilities, facilitating advanced analytics and remote monitoring. Machine learning algorithms can be integrated to analyze animal behavior patterns, identifying unusual behavior that may indicate potential threats. Deploying drones equipped with cameras and sensors can extend the monitoring range and cover areas that are difficult to reach on foot, enhancing the system's ability to monitor larger areas and track animal movements more accurately. Developing a mobile application for community engagement and reporting can foster local involvement in wildlife conservation efforts. Incorporating renewable energy sources can ensure the system's sustainability in remote areas, while enhancing alert mechanisms and ensuring data privacy and security are crucial for effective and reliable operation. Overall, these proposed enhancements aim to create a more robust and comprehensive Smart Animal Detection and Tracking System, contributing to the protection and preservation of endangered species and their habitats.

### *A. Module Description*

#### *i) Input Video*

The system relies on input video streams obtained from surveillance cameras or similar sources, offering real-time footage of the monitored area. These video streams are crucial for analyzing animal behavior and movement patterns, forming the foundation for initiating appropriate responses to the detected events.

#### *ii) Preprocessing*

Before undergoing object detection and classification, the input video undergoes preprocessing to enhance its quality and optimize the performance of the AI algorithm. Preprocessing techniques, including noise reduction, image stabilization, and frame normalization, are applied to ensure that the AI algorithm receives clean and consistent input data. This ensures accurate animal detection and classification.

#### *iii) Object Detection*

YOLOv8, a state-of-the-art deep learning technique, is used in this module. It is well-known for its effectiveness and precision in real-time object recognition tasks. YOLOv8 uses convolutional neural network layers to quickly identify animals within frames based on the single-pass detection concept. It efficiently detects animals regardless of size, orientation, or occlusion, achieving robust performance with minimal computational overhead.

#### *iv) Training YOLOv8 Model*

The YOLOv8 model is trained using a labeled dataset, learning to predict bounding boxes and classify objects. Through bounding box regression, the model accurately localizes objects within images and identifies regions of interest. Object classification is performed to categorize detected animals into predefined categories based on learned features from training data.

*v) Classification*

This module further analyzes and categorizes detected animals using a classification mechanism. By leveraging machine learning techniques, the system learns from annotated data to accurately classify animals based on visual characteristics, behavior, or other distinguishing features. The classification output is then forwarded to the microcontroller, and classified animal images are sent to respective email addresses for further analysis.

*vi) Arduino Microcontroller*

The Arduino microcontroller serves as the central processing unit of the system, seamlessly integrating sensors, AI algorithms, and communication modules. With its versatile I/O pins and programmable logic, the Arduino enables efficient data acquisition, processing, and decision-making, ensuring precise detection and timely response to animal presence.

*vii) Buzzer Alert*

Upon detecting an animal, the system triggers a buzzer alert to notify nearby individuals with audible signals. This auditory alert system enhances situational awareness and aids in preventing unwanted animal interactions, with configurable parameters allowing adjustments for diverse environments.

*viii) SMS/Email Alert*

The system offers call and SMS alert functionalities to notify designated individuals or authorities of detected animal activity. Automated calls or SMS messages are initiated, providing real-time notifications and enabling prompt response to ensure the safety of both humans and animals.


Fig. 2: Animal Detection

## VI. Result

To reduce class imbalance, a dataset was carefully selected and split into train, test, and validation sets with splits of 15%, 15%, and 70%, respectively, taking into account Indian circumstances, specifically about the Asiatic lion. The dataset was trained on three YOLOv8 architectures (m, l, and x) utilizing Google Colab's Tesla-4 GPU to prevent bias and incorrect predictions. All of the photographs were resized to 640 x 640 during the training process before being fed through the models. With a patience threshold of 50 and 120 epochs, the training was designed to stop if there was no longer any discernible progress. To avoid making incorrect forecasts, an empirical confidence level of 0.75 was established. F1 Score, mean Average Precision (mAP), recall, precision, and precision were the evaluation parameters. While recall measures the percentage, precision measures how accurate forecasts are % true positives detected accurately, and mAP assesses the overall performance of the model while accounting for the trade-off between recall and accuracy. YOLOv8 uses mAP50 and takes a 0.5 Intersection over the Union (IoU) threshold into account. The overlap between ground truth and expected boundaries is measured by the IoU. F1 Score, a harmonic mean of precision and recall, offers robustness against outliers. Results analysis revealed the superiority of the YOLOv8x model in terms of accuracy. Validation accuracy plotted against epochs displayed logarithmic growth, with rapid initial improvement followed by gradual convergence. Similar trends were observed in precision, recall, and mAP50-95. Loss graphs (box, class, and distribution focus) demonstrated consistent reduction, indicating absence of overfitting. The mAP, precision, and recall values for each model were documented for further analysis. mAP, Precison and recall of YOLOV8 model:

| model | mAP | precision | recall |
|---|---|---|---|
| yolov8m | 93.2% | 89.6% | 90.2% |
| yolov8l | 93.0% | 90.2% | 85.7% |
| yolov8x | 94.3% | 91.0% | 89.9% |

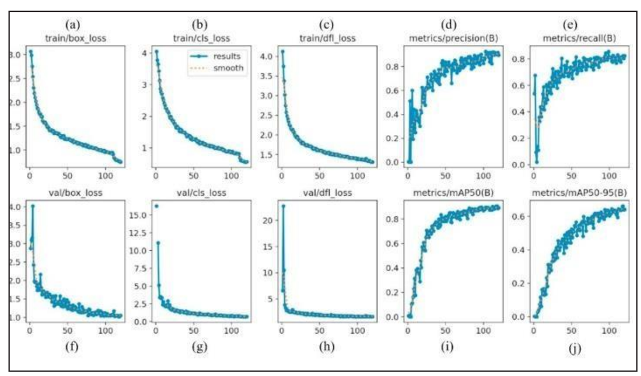


Fig. 3: Result analysis of YOLOv8

In particular, the precision-confidence, recall-confidence, F1-confidence, and precision-recall curves were examined for the top-performing model, YOLOv8x, as part of the model evaluation process. Plotting precision versus confidence scores yielded the precision-confidence curve, which showed that maximum precision (1) was reached at a confidence score of 0.947. The maximum recollection (0.96) was attained with a confidence score of 0, and the recall-confidence curve showed a declining tendency of memory with increasing confidence. The precision-recall curve represented mean average precision (mAP) as the area under the curve (AUC) showed precision as a function of recall. The model demonstrated a high detection effectiveness of 96%, demonstrating an effective balance between precision and recall. But there was a trade-off between recall and precision. noted, akin to the trade-off between bias and variance. It was common for attempts to increase precision to result in a decrease in recall, and vice versa, therefore a careful balance between the two was required. Last but not least, the F1-confidence curve showed the trend of the F1 score with rising confidence scores, peaking at 0.86 at 0.604 for confidence.

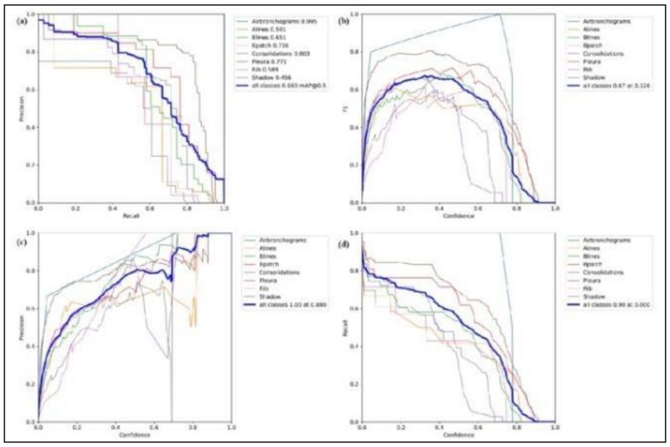

Fig. 4: YOLOv8 Architecture's Confidence, Recision-Recall, Recall-Confidence and Precision-Confidence Curves

## VII. Conclusion

To enhance early detection and reaction, this project combines Internet of Things and then artificial intelligence technology to wildlife presence across diverse environments. Through a network of strategically positioned IoT sensors deployed in wildlife-prone areas, the system continuously monitors and gathers data on animal movements. These sensors transmit real-time information to a central server, where sophisticated AI algorithms analyze the data for species identification and behavior analysis. Leveraging machine learning models, the AI component distinguishes between different animals, categorizes their activities, and evaluates potential threats. Advanced sensors deployed in agricultural fields, forested regions, and along roadways collect environmental data and animal movement information, which is then transmitted to a centralized platform via IoT protocols. In case of potential threats, the system automatically triggers notifications through email, SMS, and calls to designated stakeholders, such as farmers, forest rangers, and relevant authorities, enabling them to swiftly and effectively respond to the situation.

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