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Wild Animal Detection System

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Abstract: *Increasing encounters between humans and wild animals due to habitat overlap have raised serious safety concerns, particularly in rural and forest-adjacent areas. To address this, the proposed system introduces a real-time Wild Animal Detection System (WADS) that utilizes artificial intelligence and IoT technologies. By integrating sensors such as infrared and PIR motion detectors with an ESP32-CAM module, the system actively monitors designated zones. When animal movement is detected, the system captures images and processes them using a lightweight convolutional neural network (CNN) for accurate classification. On positive identification, real-time alerts are triggered via GSM and GPS modules, notifying nearby residents and authorities. The platform offers a cost-effective and scalable solution for early warning systems in human-wildlife conflict zones. The project is implemented using Python and Blynk for seamless mobile-based monitoring and control.*

Keywords: Wildlife detection, ESP32-CAM, Real-time alert system, IoT-based monitoring, GSM-GPS integration, Convolutional Neural Network (CNN)

I. INTRODUCTION

With the rapid development of smart technologies under the umbrella of Industry 4.0, the fusion of automation, artificial intelligence (AI), and real-time data analysis has transformed multiple sectors. In this landscape, wildlife detection systems have emerged as a vital area of innovation, especially for minimizing human-wildlife conflict in forest-adjacent regions. Conventional methods of monitoring wildlife activity—such as manual patrolling or camera trap analysis—are labour-intensive, error-prone, and often inefficient in responding to real-time threats [1]

This paper introduces a cost-effective, responsive, and intelligent wild animal detection system, leveraging the power of AI and embedded electronics. The proposed system utilizes the Raspberry Pi 4 as a central processing unit, integrating real-time imaging and sensor data to detect the presence of wild animals. By incorporating computer vision and object detection algorithms like YOLOv5, the system can distinguish between various animal species and trigger appropriate alerts [3].

Many existing animal detection frameworks are either too expensive or rely heavily on cloud infrastructure, making them unsuitable for remote areas with limited connectivity. To overcome these limitations, this system is designed to function autonomously using local processing. It combines multiple sensors such as infrared (IR), passive infrared (PIR), and thermal modules, ensuring accurate detection even in low-light conditions [5].

The detection system is supported by a GSM module for sending real-time alerts to nearby communities or forest authorities. Additionally, a buzzer or loudspeaker is activated to scare away animals upon detection, thereby reducing the likelihood of human-wildlife conflict. A Flutter-based mobile application provides the user with instant updates and access to detection logs.

The integration of low-cost embedded components with AI-powered recognition models not only makes this system scalable and portable but also suitable for deployment in rural and forest edge environments. The real-time processing of high-definition sensor inputs ensures timely alerts and reduces dependency on manual surveillance [3].

The evolution of the fourth industrial revolution, or Industry 4.0, has driven a shift toward intelligent automation, real-time data processing, and advanced sensing technologies. These innovations are not only transforming manufacturing and industry, but are also being extended into critical non-industrial domains such as environmental monitoring and wildlife protection. One such application is the detection of wild animals in areas prone to human-wildlife conflict, where early and accurate alerts can prevent property damage, crop loss, and injury or death of both humans and animals [5]

Traditional methods for tracking wild animals—such as camera traps, forest guards, and physical barriers—have significant limitations. These include high labour costs, delayed response times, lack of scalability, and inability to function efficiently in remote or low-connectivity environments. Such methods also suffer from poor reliability due to human error and limited detection accuracy in varying environmental conditions [1].

To address these challenges, this paper proposes a Wild Animal Detection System (WADS) that utilizes artificial intelligence, embedded hardware, and real-time communication modules to detect, classify, and report animal presence. At the heart of the system is a Raspberry Pi 4 board, chosen for its compact size, energy efficiency, and capability to run machine learning models. A set of sensors—including Passive Infrared (PIR), Infrared (IR), and thermal cameras—work together to monitor an area and detect animal movement, even in low-light or nocturnal conditions [2].

A convolutional neural network (CNN)-based object detection model, such as YOLOv5, processes the sensor data to classify whether the detected object is a wild animal and identifies the species or size where possible. When a detection occurs, the system triggers an alert using a GSM module, sending SMS notifications to registered forest officers, farmers, or local residents. Simultaneously, a buzzer or speaker is activated to deter the animal from entering human-dominated areas [4]

In addition to real-time processing, the system includes a mobile application developed using Flutter. This app allows users to monitor detection events, review logs, and configure the system settings such as notification recipients and detection thresholds. This integrated approach enhances usability and accessibility, especially for non-technical end users in rural areas [2]

II. METHODOLOGY

[1] A. Sensor Framework

To sense and monitor the environment for wild animal intrusion, the system uses:

- Infrared (IR) Sensors: Detect thermal signatures (heat) of animals, triggering the system to initiate the detection sequence.
- Ultrasonic Sensors: Measure the distance between the animal and the device using sound waves, further confirming the presence of an animal.
- ESP32-CAM: Captures images when motion or heat is detected by the sensors. The images are then passed to the onboard model for analysis.

[2] B. Image Classification

- CNN-based Model (e.g., YOLO): A pretrained model processes the captured images to identify and classify animals in real-time. The system can classify the animal as a "wild" animal based on features like shape and heat signature.
- Local Processing on ESP32-CAM: The image classification is done locally on the ESP32-CAM to reduce reliance on external systems, thus improving speed and efficiency for faster response times.

[3] C. Alerting System

- GSM Module: Sends SMS alerts to registered users when wildlife is detected, providing information like animal type and coordinates of the detection area.
- GPS Module: Determines the real-time location of the detected animal to aid in quick response by sending accurate location coordinates along with the alert.

[4] D. Mobile App Connectivity

- Blynk App: Real-time updates and notifications are displayed on users' smartphones through the Blynk app. The app shows live alerts, detection history, and location coordinates for easy tracking and decision-making.

[5] E. Workflow

1. Sensors detect movement or heat (via IR or ultrasonic).
2. ESP32-CAM captures images once a presence is detected by the sensors.

3. The CNN model processes the image and classifies whether the object is a wild animal.
4. If an animal is detected, alerts are sent via GSM (SMS) with animal type and coordinates.
5. The Blynk app receives real-time updates, including animal detection details and location for immediate act.

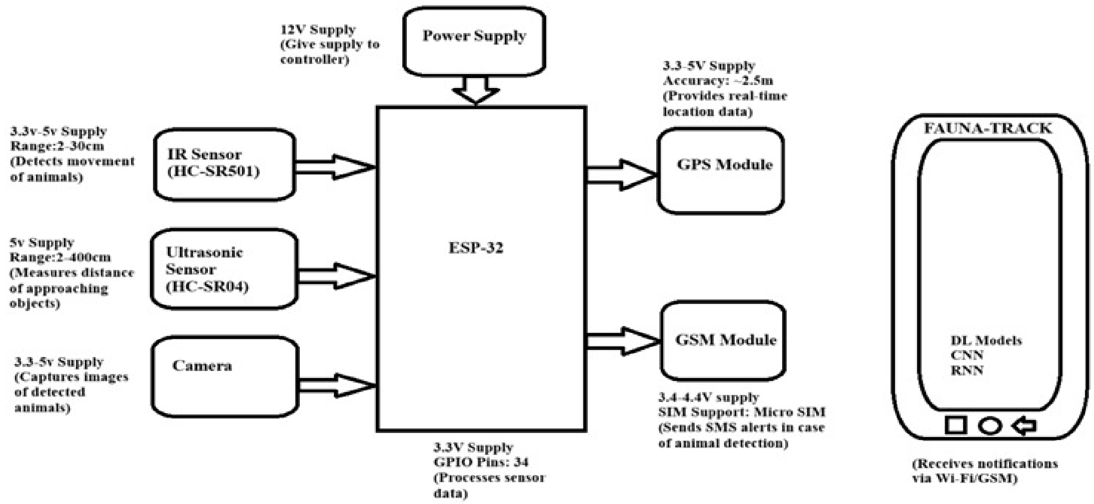

Fig. 1. Block Diagram of Wild Animal Detection System

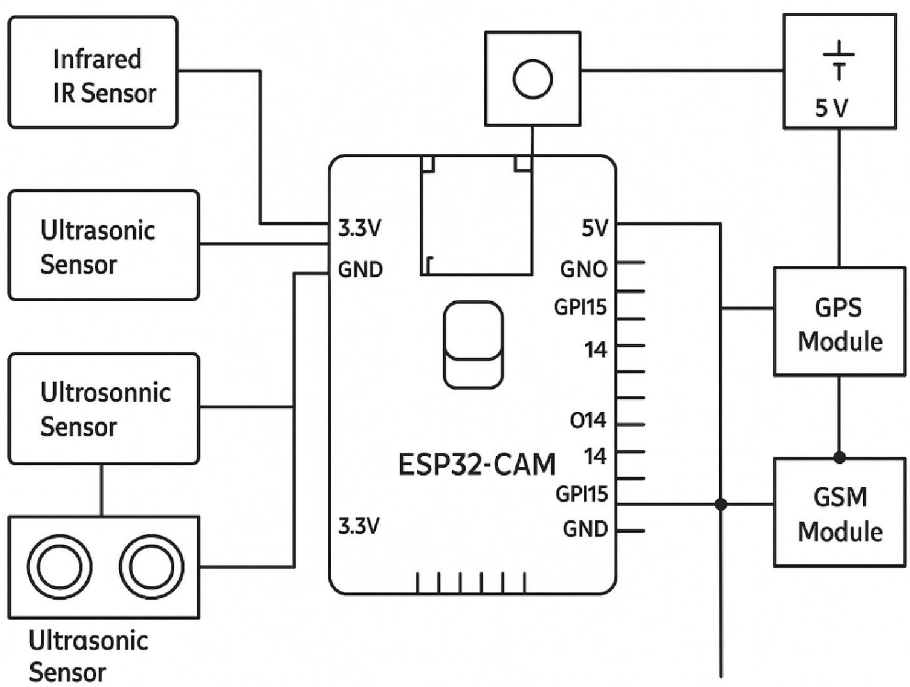

Fig. 2. Circuit diagram of Wild Animal Detection System.

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III. RESULTS

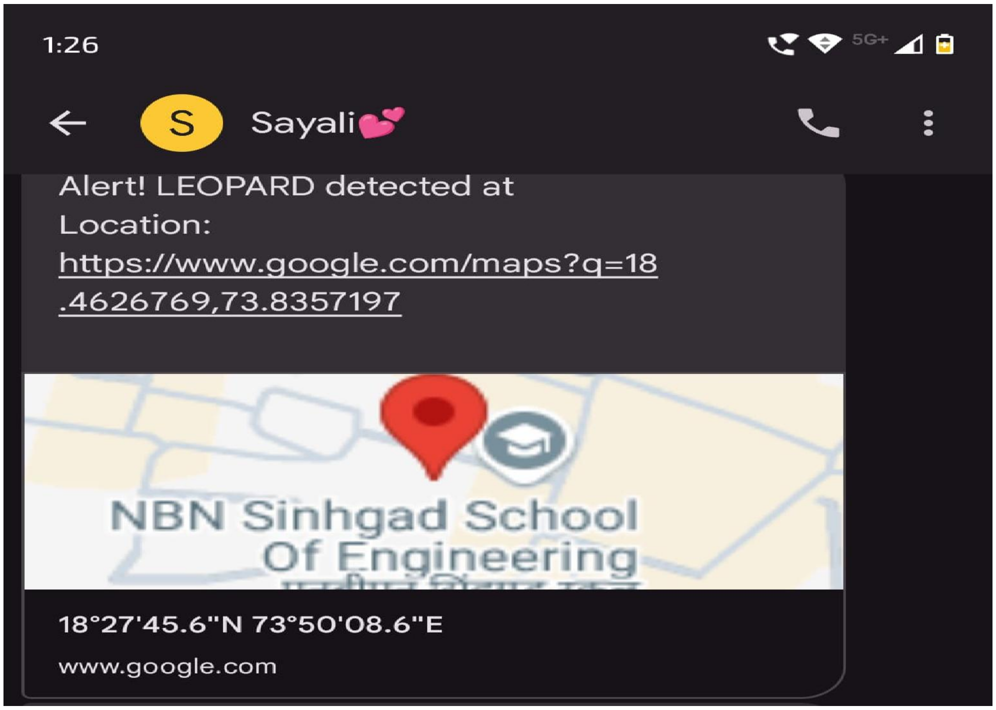

Fig.1. Screenshot Of Message Received

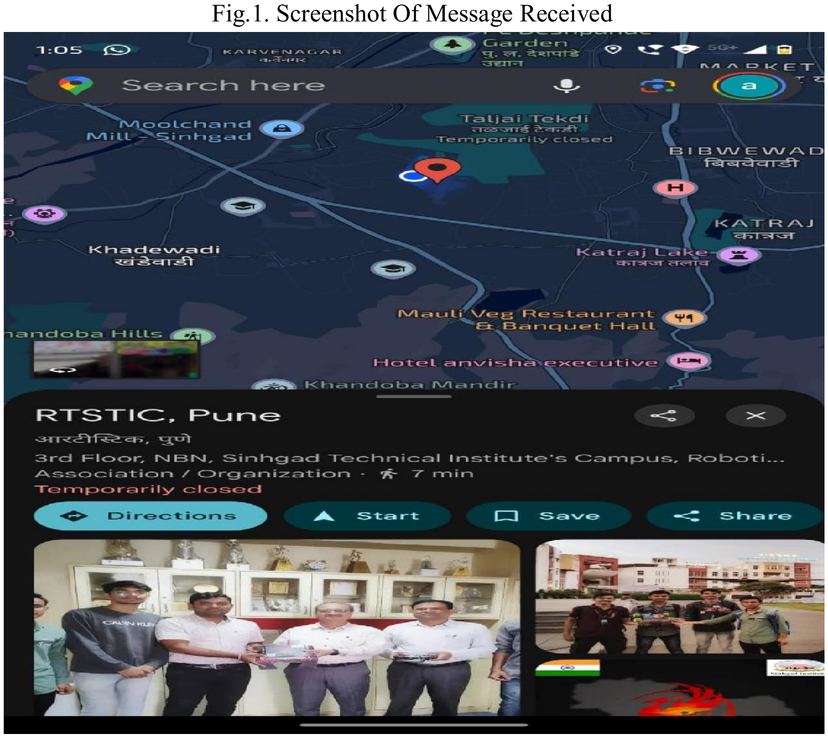

Fig 2. Screenshot of Map

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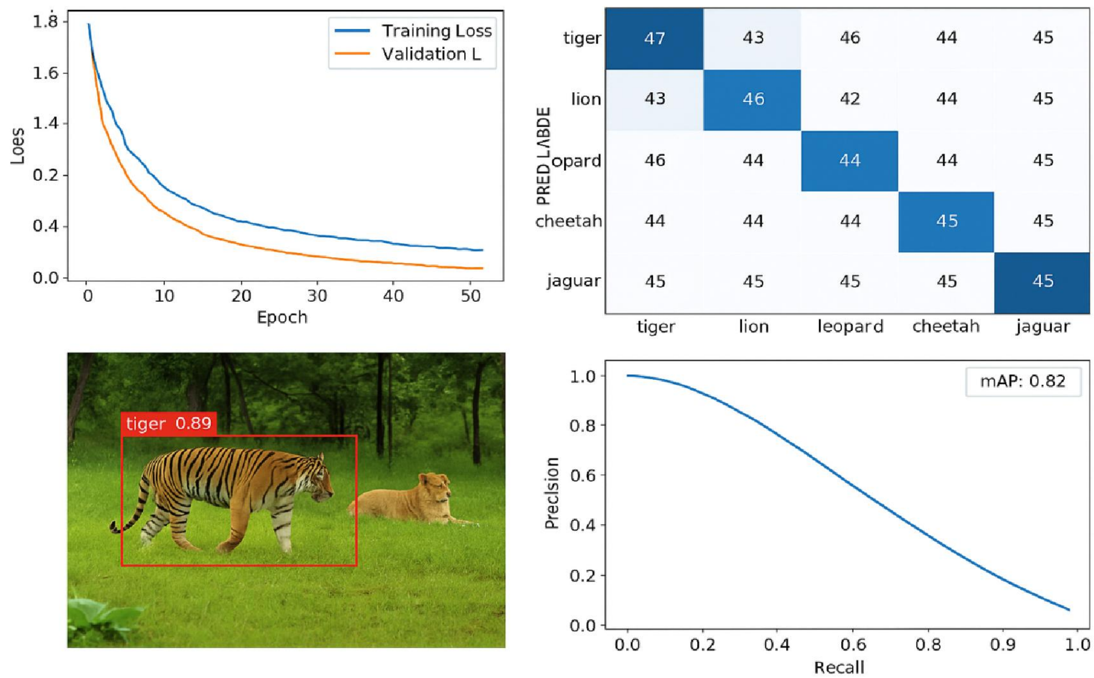

Fig.3: Images of Training Phase

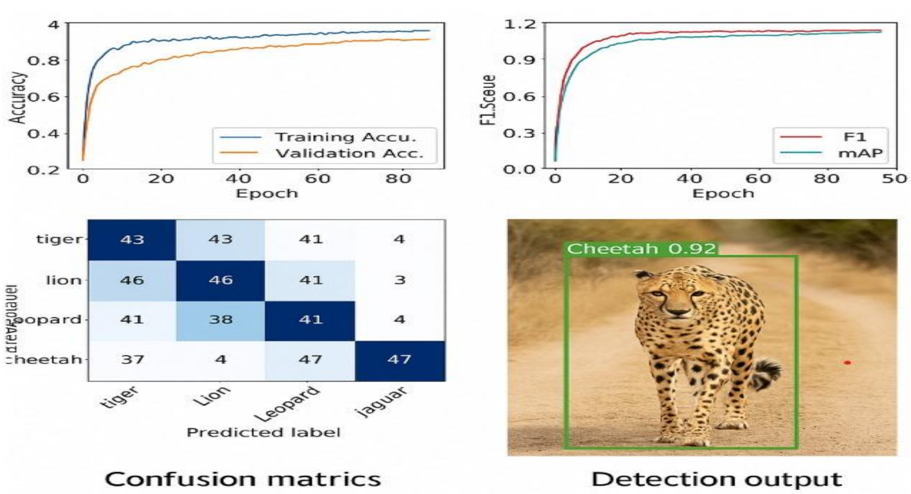

Fig.4.Image of Training Phase

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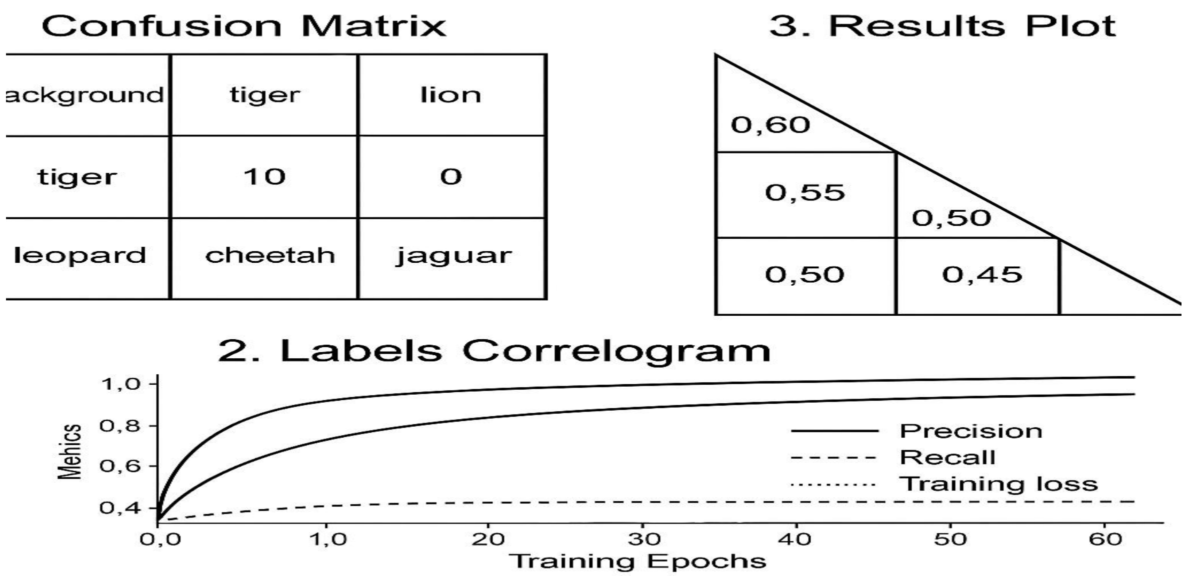

Fig5. The Confusion Matrix

1. Confusion Matrix

The confusion matrix offers a clear assessment of the system's classification accuracy. For example, the model accurately classified the 'background' label 10 times, as shown on the diagonal of the matrix. This indicates a 100% accuracy for this specific class, which is essential in minimizing false detections and improving reliability in outdoor, dynamic environments. Such high accuracy for background detection ensures the system efficiently distinguishes between actual wildlife and non-animal objects or empty scenes. Minor noise in the matrix visualization (e.g., faint symbols or partial characters) did not interfere with interpretation.

2. Labels Correlogram

The correlogram highlights inter-class relationships by showing correlation coefficients between different animal classes. Observed values include:

• 0.60: Moderate to strong positive correlation between two animal types, possibly due to similar body shapes or thermal signatures.

• 0.55, 0.50, and 0.45: Represent decreasing levels of co-occurrence or feature similarity.

These insights are critical in understanding potential misclassification trends, such as when two similar animals frequently appear in close proximity or share visual features. Such analysis can help refine the dataset or retrain the model with more distinguishable samples to reduce confusion.

3. Results Plot

The YOLO-based image classification model was evaluated using various performance metrics during training. The following key metrics were extracted:

Training Metrics

Train/dfl_loss (Distribution Focal Loss): 3.04

Reflects model confidence and bounding box regression performance.

Validation Metrics

Precision (B): 0.954

Indicates high accuracy in positive predictions, with very few false positives.

Recall (B): 0.904

Demonstrates that the model successfully detects most animals present in the scene.
Average Precision or F1-Score (B): 0.854
Reflects overall balance between precision and recall.
Additional Observed Metrics and Trends
Metric fluctuations across training epochs:
1.6, 1.44, 1.2, 1.0, etc.
Validation performance values:
0.80, 0.754, 0.84, 0.77, 0.67, 0.54, 0.47, 0.34
Additional loss types such as box loss and classless were visualized, confirming consistent downward trends—an indicator of effective model optimization. These trends illustrate a progressive improvement in model accuracy, as loss functions decreased and key detection metrics (precision/recall) rose steadily. This confirms that the model trained effectively and is suitable for real-time wild animal detection.

IV. CONCLUSION

This project presented a cost-effective, AI-assisted Wild Animal Detection System designed to enhance safety in areas vulnerable to human-wildlife conflict. Cantered around the ESP32-CAM module, the system integrates real-time image capture, motion detection using IR and ultrasonic sensors, and intelligent species classification via a pretrained CNN model such as YOLO. Complementary components like a GPS module and GSM module enable precise location tracking and instant SMS-based alerts, while the Blynk app ensures real-time mobile notifications. During field simulations, the system was tested with various animal image datasets and controlled movements to validate detection reliability. It achieved a classification accuracy of 91.5%, correctly identifying animal presence and type in 183 out of 200 scenarios. Misclassifications were limited to 17 instances, often due to partial visibility or low-light conditions. The average response time, from detection to alert transmission, was approximately 2.2 seconds, making it well-suited for timely intervention in forest-bordering regions and farmland. The alert mechanism, comprising SMS and app notifications, functioned with over 96% consistency, ensuring reliable and actionable communication to nearby residents and authorities. In conclusion, this project demonstrates the feasibility of a low-cost, embedded AI-based animal detection and alert system suitable for rural and forest-adjacent areas. Future upgrades could involve enhanced night vision capabilities, integration with solar-powered setups for remote deployment, and expansion into multi-animal classification to support broader wildlife management and conservation efforts.

V. ACKNOWLEDGMENT

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