

Agro Guard Edge AI - Development of Sustainable IoT Framework for Wildlife Intrusion Detection

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Abstract

The rising global population and increasing food demand have placed immense pressure on agriculture, particularly in regions like the Marudhamalai foothills in Coimbatore district, where farmers face frequent crop damage caused by wildlife intrusions, such as wild boars and deer. To address these challenges, a wildlife intrusion detection system has been developed to safeguard crops, enhance agricultural productivity, and enable coexistence with wildlife. The system combines a laser detection setup with an AI-CAM that employs lightweight deep learning algorithms for real-time animal detection and classification. This system also ensures efficient animal deterrence and real-time monitoring for farmers, enabling them to assess the situation with the assistance of an intelligent rover built using IoT. The detection system consists of a processor, Light Dependent Resistor module, laser diode, and buzzer are used to detect intrusions with precision and provide an immediate response. The system includes an ESP32-CAM to monitor and deter animals effectively. It features live image processing through an OLED display and a USB-to-TTL adapter, ensuring reliable performance with minimal power consumption. By integrating IoT technology and advanced monitoring systems, farmers receive real-time updates and can remotely control a rover for necessary interventions. The system achieves 96.3% accuracy in real-time animal detection

using an ESP32-CAM and a YOLO v8 model, with results displayed on an OLED screen and bounding boxes for classification.

Keywords: Edge AI, Animal Intrusion Detection, Internet of Things, TinyML, YOLOv8 Model, ESP32 Microcontroller, Edge Impulse and Machine learning.

1 Introduction

Agricultural farms worldwide face increasing security challenges, including wildlife intrusions, theft, and unauthorized access. These threats not only lead to significant economic losses but also compromise food security and farm sustainability. Traditional security measures such as physical barriers, manual surveillance, and chemical deterrents are often ineffective, labor-intensive, and environmentally harmful. The need for an intelligent, efficient, and cost-effective solution is more pressing than ever [6,7].

The advent of the Internet of Things (IoT) has enabled the development of advanced monitoring and security systems that can transform farm protection. This research presents an IoT-driven smart protection system designed to enhance agro-farm security through real-time monitoring, adaptive surveillance, and automated threat detection. The proposed system integrates low-power IoT devices, AI-driven analytics, and cloud-based automation to provide a multi-layered security framework capable of detecting, analyzing, and responding to threats with high accuracy [8,9].

Unlike conventional methods, the proposed system utilizes smart sensors, surveillance cameras, and AI-driven decision-making algorithms to enhance security operations. The cloud-based architecture ensures scalability, broader coverage, and seamless remote access, enabling farmers to manage security challenges effectively. Moreover, the system is designed to function reliably in diverse farming environments, overcoming operational constraints such as limited connectivity and energy availability[10-14].

Field trials of the proposed system have demonstrated significant improvements in threat detection accuracy, response time, and overall farm security, making it a viable solution for modern agricultural challenges. Additionally, by reducing human-wildlife conflicts and safeguarding agricultural resources, the system contributes to sustainable farming practices and long-term food security. This research underscores the transformative potential of IoT in

agricultural security, offering an innovative approach to protecting crops and livestock while ensuring a safer and more resilient farming ecosystem.

2 Related Work

Recent advancements in technology have led to significant progress in wildlife intrusion detection systems and smart farming. Various studies have explored the integration of IoT, AI, and machine learning for the protection of agricultural assets and livestock management.

Venkateswarlu et al. [1] proposed an Edge AI-based IoT framework designed to enhance crop protection from wildlife threats. The study focused on integrating real-time data processing capabilities at the edge to minimize detection delays, utilizing deep learning algorithms for intelligent decision-making. The framework incorporated IoT sensors for monitoring environmental conditions and wildlife activities, addressing challenges such as detection accuracy, scalability, and energy efficiency. This research laid the groundwork for using AI in precision farming for sustainable agricultural practices.

Drexel et al. [2] explored the application of digital passive infrared motion detectors for non-invasive monitoring of piglet behavior. This study highlighted the use of smart agricultural technology to track animal activity patterns without disturbing the animals. The research demonstrated how passive infrared sensors can collect continuous data to assess animal welfare and optimize livestock management, enhancing productivity while ensuring animal well-being.

Chappidi and Sundaram [3] introduced an innovative animal detection system utilizing a cascaded YOLOv8 architecture, integrated with adaptive preprocessing and feature extraction techniques. The system aimed to improve object detection accuracy in challenging environments. Their approach demonstrated the potential for real-time wildlife monitoring, particularly in agricultural settings, where accurate detection of animal species is essential for mitigating risks to crops and livestock.

Sayem et al. [4] developed an IoT-based smart protection system for agro-farm security in Bangladesh, addressing threats like theft and wildlife intrusion. The system integrated smart sensors, real-time data processing, and automated alert mechanisms to enhance security and reduce human intervention. This research demonstrated the effectiveness of IoT technologies in improving farm management and safeguarding agricultural assets in developing regions.

The proposed wildlife intrusion detection system combines the YOLOv8 algorithm with laser diode-based detection, offering a non-intrusive method for precise monitoring of animal activity. This system's real-time data processing and machine learning capabilities ensure quick and accurate detection of wildlife threats, providing a more scalable and energy-efficient solution compared to traditional PIR sensors[2]. This approach contributes to the growing body of work in sustainable farming practices and intelligent wildlife management.

A recent article published in the Indian Express news research highlights the incidents of elephant intrusions in the Chinnathadagam and Maruthamalai areas of Coimbatore, Tamil Nadu. These events disrupted human habitats, keeping forest officials on alert during the early hours of Friday. Such incidents underline the growing human-wildlife conflict, often triggered by shrinking forests and urban expansion into wildlife territories. To address this issue (Figure 1), an innovative solution like the animal intrusion detection system has been developed.



Figure 1. The New Indian Express, "Elephants Enter Two Localities in Coimbatore," New Indian Express, Sep -1, 2024. [Online]. [15,16]

3 Proposed Work

The Agro Guard Edge AI framework aims to enhance wildlife monitoring and prevent human-animal conflicts by utilizing advanced IoT[5] and AI technologies. Animal detection serves as a cornerstone in EdgeAI-based Agro Guard systems[1], ensuring the security and sustainability of agricultural fields. The system operates through real-time monitoring, continuously scanning for the presence of animals within the designated area. This allows for

the timely detection of any intrusion, acting as a proactive measure to address potential threats. By identifying animal activity early, the system triggers alerts, ensuring immediate response to potential threats. The detection process also facilitates preventive actions, enabling quick and targeted responses to mitigate risks effectively.

Animal classification plays a pivotal role in EdgeAI-based Agro Guard systems by providing a deeper understanding of the animals detected within agricultural areas. Once the presence of an animal is confirmed, classification identifies the specific species or type based on its unique characteristics. Through advanced machine learning models powered by platforms like Edge Impulse, the classification system continuously improves its accuracy and adaptability. It can analyze animal behavior patterns, predict potential threats, and enhance long-term agricultural safety strategies. For instance, recognizing the behavior of a predator can help anticipate its next action, allowing proactive measures to be taken. Together, the animal detection and classification features of the Agro Guard Edge AI framework provide a comprehensive solution for wildlife intrusion monitoring. By combining reliable hardware with cutting-edge AI models, this system offers a sustainable, real-time method to detect and classify wildlife, enabling timely interventions to mitigate the impact of wildlife on human activities and contributing to better wildlife management practices.

3.1 Block Diagram

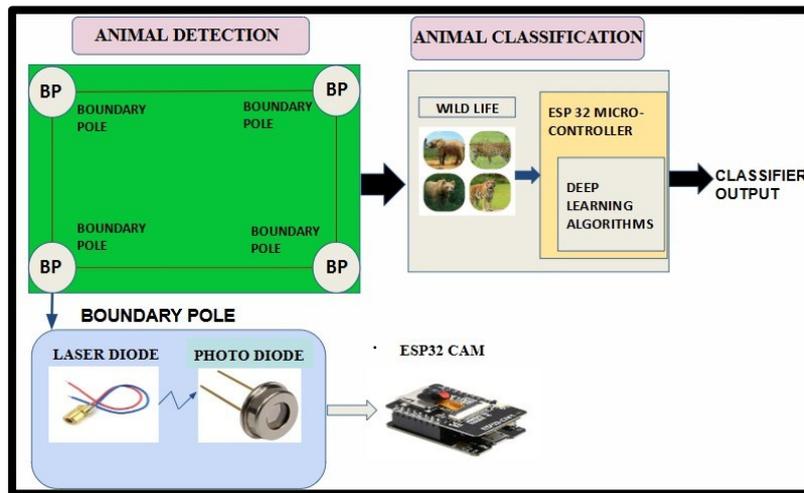


Figure 2. Block Diagram of Animal Detection and Animal Classification

Figure 2 illustrates an animal detection and classification system for safeguarding crops from wildlife threats. The system comprises boundary poles equipped with

laser diodes and photodiodes for detecting animal crossings. Detected signals are processed through an ESP32 CAM module, which captures the image of the approaching wildlife. The image is then sent to an ESP32 Microcontroller [1], where deep-learning algorithms classify the animal species. The classifier's output enables appropriate actions to prevent wildlife intrusion, ensuring crop safety.

3.2 Deep Learning Algorithm

3.2.1 YOLOv8 Model Selection and Training

YOLOv8[3] is a state-of-the-art deep learning model for real-time object detection, utilizing advanced computer vision and machine learning algorithms. It enables accurate and efficient object localization in images and videos, which is essential for applications like self-driving cars, robotics, and surveillance. The model focuses on identifying and localizing objects within images or videos, allowing machines to understand and interact with the visual world. To achieve this, YOLOv8 uses Convolutional Neural Networks (CNNs)[3] to extract features and make predictions for object detection, ensuring high accuracy and performance.

YOLOv8 [17-19] offers pre-trained models on large datasets like COCO for general object detection tasks and supports creating custom models using labeled datasets for specific domain purposes. The performance of these models is highly dependent on proper data preparation, including effective dataset collection and labelling. Additionally, YOLOv8 can be seamlessly integrated into web browsers for real-time detection, enhancing its usability in web applications. YOLOv8 supports various detection methods, including classification, object detection, and image segmentation. Classification assigns class labels to images, object detection locates multiple objects with bounding boxes, and image segmentation provides pixel-level object boundaries for detailed content analysis.

3.2.2 YOLOv8 Integration in the System Workflow

In this research, YOLOv8 serves as the primary deep-learning model for real-time animal detection and classification. Known for its efficiency in object detection, YOLOv8 has been integrated into the wildlife intrusion detection system to accurately identify and classify animals that threaten agricultural fields. Initially pre-trained on the COCO dataset, the model was fine-tuned using a custom dataset of wildlife images from the Marudhamalai foothills, annotated with bounding boxes for improved precision. The training process involved image augmentation and transfer learning to enhance adaptability to real-world conditions. Once

optimized, the model was deployed on the ESP32-CAM in a lightweight format. The system workflow begins with image capture triggered by intrusion detection using laser diodes and LDRs. The captured images undergo preprocessing before being processed by the YOLOv8 model for classification. The results, including the detected species name and confidence score, are displayed on an OLED screen.

3.2.3 Performance and Efficiency

YOLOv8's efficient architecture ensures high-speed inference while maintaining high accuracy, making it an ideal choice for real-time animal detection. The model achieves 96.3% accuracy in identifying wildlife intrusions, ensuring precise classification and minimal false detections. With a low latency of approximately 20ms per inference cycle, YOLOv8 enables rapid decision-making, which is essential for real-time applications. Additionally, its optimized resource utilization allows for smooth execution on the ESP32-CAM, even with limited processing power and low energy consumption. The integration of YOLOv8 in this research significantly enhances the reliability, speed, and scalability of the intrusion detection system, providing an effective solution for real-time monitoring, automated interventions, and improved agricultural security.

3.3 Circuit Diagram

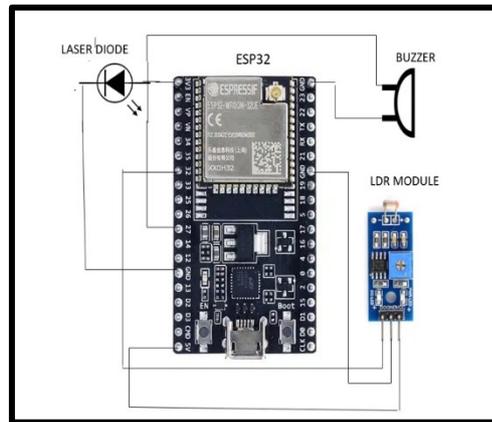


Figure 3. Circuit Diagram of Animal Detection System

Figure 3 illustrates a system designed for automated notification to farmers using the ESP32 microcontroller. The core components of the system include a laser diode, an LDR module, a buzzer, and an ESP32 board. The laser diode generates a consistent light beam, which is detected by the LDR module. Any interruption in the light beam is identified as a

signal by the ESP32, triggering appropriate actions such as activating the buzzer to alert the user. This mechanism ensures reliable detection and quick responses, making it suitable for applications like intrusion detection or monitoring systems in agricultural fields.

The ESP32 acts as the central processing unit, interfacing with peripheral components to execute programmed instructions. The buzzer provides an audio alert, while additional outputs, like a speaker, may be included for multi-channel notifications. This setup is highly adaptable and can be further integrated with wireless communication modules for remote monitoring, enhancing its functionality in diverse real-world scenarios like farm management or industrial safety systems.

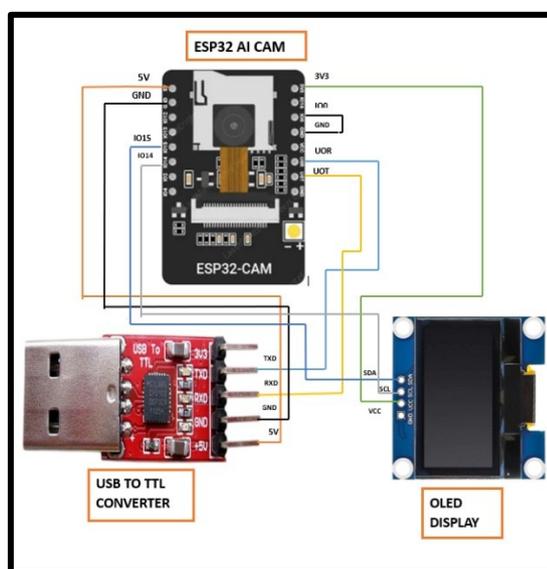


Figure 4. Circuit Diagram of Animal Classification System

Figure 4 illustrates a setup using an ESP32-CAM module integrated with an OLED display and a USB-to-TTL converter for interfacing and communication. The ESP32-CAM serves as the central module, featuring a camera for image or video capture and processing capabilities. It is powered through a 5V and GND connection, with its communication facilitated through TX and RX pins linked to the USB-to-TTL converter. This converter enables programming and data exchange between the ESP32-CAM and a computer, simplifying the deployment of custom applications.

The OLED display is connected to the ESP32-CAM using the I2C protocol, with the SDA and SCL pins facilitating data transfer. This display is utilized for visual output, such as displaying status information, sensor readings, or real-time data processed by the ESP32-CAM.

The circuit configuration is compact and efficient, making it ideal for applications like remote surveillance, smart home devices, or IoT applications where visual monitoring and system feedback are essential. The algorithm 1 and 2 depicts the steps in animal detection and classification respectively.

Algorithm 1. Algorithm for Animal Detection

STEP1: Start the process.

STEP2: Set up the LDR pin on the pin 32 of ESP32

STEP3: Define a threshold value of 500 to detect interruptions.

STEP4: Begin Serial communication for debugging.

STEP5: Capture the LDR value using analog Read ().

STEP6: Check if the LDR value is below the threshold.

STEP7: Print "Animal is detected" if the LDR value is below the threshold.

STEP8: Print "Animal is not detected" if the value is above the threshold.

STEP9: Continuously check every 2 seconds using a delay().

Algorithm 2. Algorithm for Animal Classification System

STEP1: Import libraries and define constants for camera, OLED, and Edge Impulse.

STEP2: Configure ESP32-CAM settings, including pins and camera parameters.

STEP3: Set up I2C communication and initialize the OLED display.

STEP4: Initialize the serial monitor and ESP32-CAM camera module.

STEP5: Allocate memory and capture an image using the camera.

STEP6: Convert, resize, and crop the image to match model input requirements.

STEP7: Create a signal object and run the Edge Impulse inference model.

STEP8: Display detected object labels and confidence scores on the OLED screen.

STEP9: Free allocated memory and prepare for the next frame.

STEP10: Repeat the process in a continuous loop for real-time inference.

3.4 Flowchart of The Proposed System

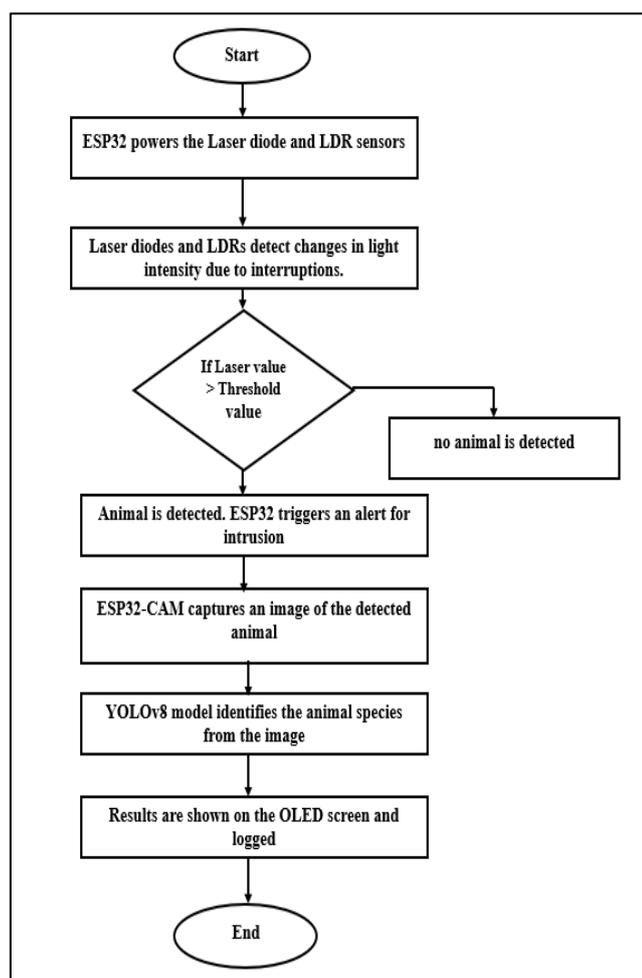


Figure 5. Flowchart of the Proposed Wild Animal Detection System

Figure 5 depicts the workflow of the proposed wild animal detection and classification system

4 Results and Discussion

The proposed system is an animal intrusion detection and classification setup that utilizes an ESP32-CAM module for real-time monitoring and animal detection. The system operates with a laser beam trigger that is interrupted when an animal crosses its path, activating a buzzer to alert the presence of an animal. The ESP32-CAM, integrated with an OLED display and a USB-to-serial converter, enables wireless transmission of captured images and displays real-time data. The system employs an object detection framework to capture and classify animal images, such as elephants and leopards, for wildlife monitoring and classification tasks.

A trained machine learning model, based on the YOLOv8 architecture, is deployed on the ESP32 using Edge Impulse [20], ensuring high accuracy in object detection. The setup also offers a user-friendly interface for collecting, testing, and downloading datasets, facilitating the deployment of efficient animal detection and classification systems for IoT-based wildlife monitoring applications.

4.1 Animal Detection System

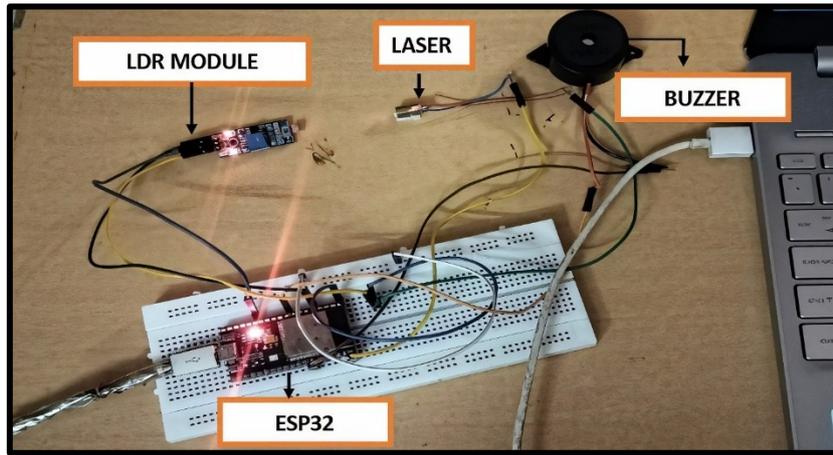


Figure 6. Hardware Module of Animal Detection System

Figure 6 demonstrates an animal detection system using a microcontroller-based prototype. A laser beam serves as a trigger if it is interrupted caused by an animal crossing the path. The microcontroller detects the signal change and activates the buzzer. Once the laser beam is restored, the buzzer automatically turns off.

4.2 Alert System

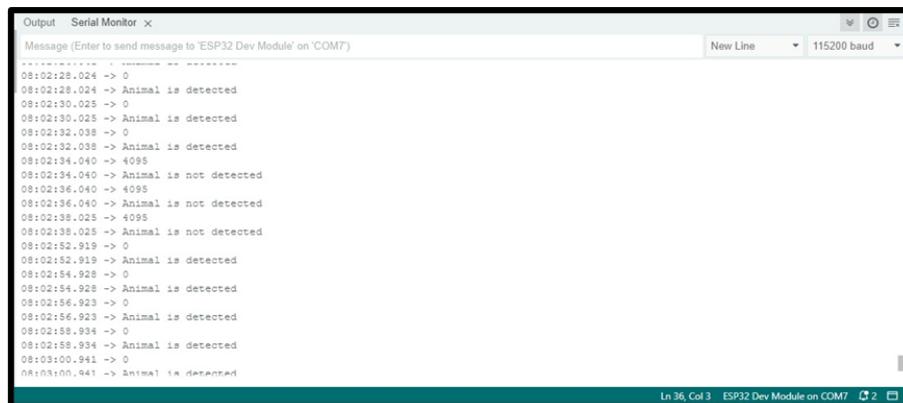


Figure 7. Real Time Output of Animal Detection

Figure 7 shows the serial monitor displaying real-time output from the ESP32, alternating between "Animal is detected" and "Animal is not detected," along with sensor readings such as "0" and "4095," indicating changes in light intensity for intrusion detection.

4.3 Animal Classification System

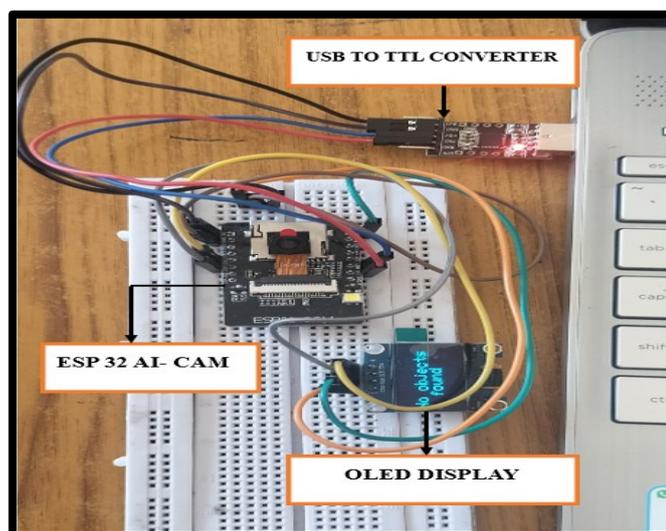


Figure 8. Hardware Module of Animal Classification Circuit

Figure 8 shows the circuit that integrates the ESP32-CAM module, an OLED display, and a USB-to-serial converter on a breadboard for prototyping. The USB-to-serial converter is used to program and debug the ESP32-CAM, with the TX and RX pins connected to the U0R and U0T pins of the ESP32-CAM, respectively, while providing power through its 5V and GND pins. During programming, GPIO0 is grounded to enable boot mode. The OLED display is connected to the ESP32-CAM through the I2C interface, with the SDA and SCL pins linked to GPIO21 and GPIO22, and powered through the ESP32-CAM's VCC and GND pins. This setup enables the ESP32-CAM to display real-time data on the OLED and transmit captured images wirelessly, making it ideal for IoT applications like remote monitoring and automation.

4.4 Collection of Data Sets

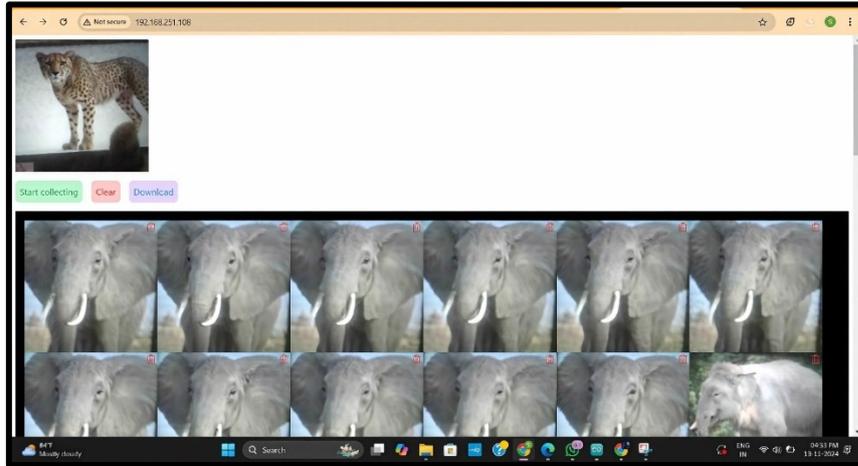


Figure 9. ESP32 Cam Image Collection

Figure 9 shows an interface for collecting image data using an object detection system. It displays a captured image of a leopard at the top and multiple images of elephants below, likely used for training or testing a machine learning model. The interface includes options to start collecting, clear data, and download the dataset, indicating its purpose for data acquisition in wildlife monitoring or classification.

4.5 Trained Data Sets

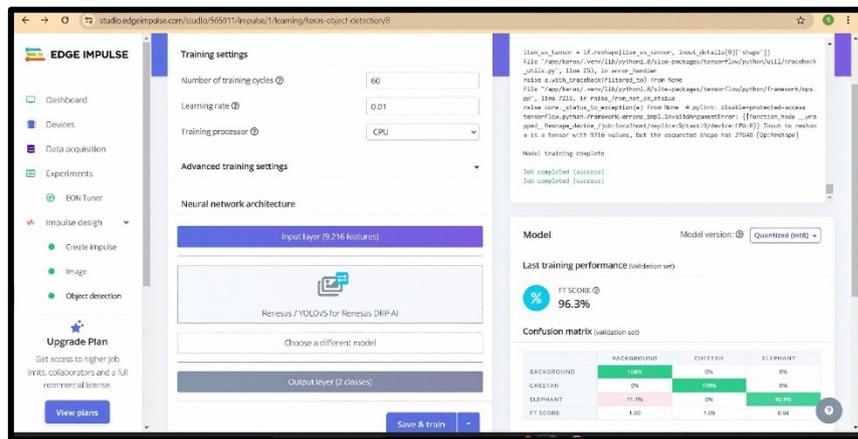


Figure 10. Confusion Matrix

Figure 10 illustrates the training configuration and results for an object detection model in Edge Impulse. Key details include 60 training cycles, a learning rate of 0.01, and the CPU as the training processor, with data augmentation enabled. The neural network architecture used is YOLOv8 model. The model achieved 96.3% accuracy on the validation set, as indicated

in the training performance, with a confusion matrix displaying its performance across different object classes.

4.6 Building and Integrating

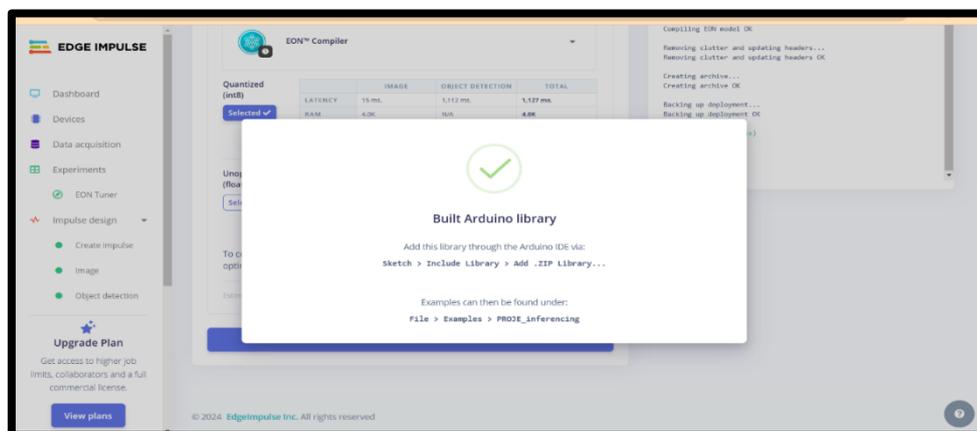


Figure 11. Edge Impulse Library Built for Arduino Integration

Figure 11 illustrates the process of creating an Arduino-compatible library from a trained model on the Edge Impulse platform. The generated library is optimized for image processing and object detection tasks, utilizing the EON Compiler for efficient deployment. The compilation process includes quantization and generates examples for inference using the PROJE_inferencing module. This integration facilitates the seamless deployment of machine learning models on microcontroller-based systems such as the ESP32, with provided example code for testing and implementation. The Arduino Library generated in Edge Impulse allows seamless deployment of trained AI models on microcontrollers like the ESP32-CAM. It includes model parameters, feature extraction, and inference code for real-time classification. The library can be added to Arduino IDE through Sketch > Include Library > Add .ZIP Library..., with example codes available under File > Examples > PROJE_inferencing. This enables efficient on-device processing without cloud dependency, making it ideal for wildlife intrusion detection.

remote farming areas. Additionally, expanding the system's scalability to support larger agricultural operations without sacrificing efficiency is key. Future iterations may also explore the use of drones and robotic systems for active threat intervention, such as deterring wildlife or identifying intruders. By integrating emerging technologies like blockchain for better connectivity, reliability, and data security, the system could evolve into a transformative tool for modern agriculture, offering robust protection and contributing to sustainable farming practices.

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