AI BASED WILDLIFE CROSSING DETECTION AND ALERT SYSTEM

SOCIALLY RELEVANT MINI PROJECT REPORT

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We, CARINELIA W CORTHIS (211423104094) and DEEKSHITHA G (211422104107) hereby declare that this project report titled "**AI BASED WILDLIFE CROSSING DETECTION AND ALERT SYSTEM**", completed under the esteemed guidance of Dr. M. MAHESWARI M.Tech., Ph.D., is our original and independent work. We affirm that we have neither plagiarized any part of this report nor submitted it for the award of any other degree or diploma at any university or institution.

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ABSTRACT

Wildlife–vehicle collisions have become a major concern in regions where transportation infrastructure intersects with forested and rural ecosystems. These incidents not only result in the loss of animal life and ecological imbalance but also pose serious risks to human safety and cause significant economic damage. To address this issue, this project proposes an AI-based Wildlife Crossing Detection and Alert System that utilizes advanced deep learning-based object detection models—MobileNet SSD and YOLOv11—to identify the presence of animals in real time and generate timely alerts. The system processes live video streams from cameras installed near wildlife-prone road segments. MobileNet SSD is employed for lightweight, fast detection on low-powered edge devices, while YOLOv11 enhances detection accuracy and robustness in complex environmental conditions such as low light, occlusions, and varying animal sizes. Depending on the deployment constraints, either model—or a combination of both—can be integrated to balance precision and processing speed. Once an animal is detected approaching or crossing the road, the system activates alert mechanisms such as alarms, visual indicators, or notifications to connected devices. This proactive intervention enables drivers and authorities to respond quickly, reducing the likelihood of accidents. The implementation also supports scalability for different terrains and animal species by incorporating model retraining and dataset customization. Experimental results indicate high detection accuracy with minimal latency, making the system viable for real-world deployment in smart transportation networks, national parks, and highways near wildlife reserves. The project demonstrates how artificial intelligence, computer vision, and embedded technologies can collaborate to create an efficient, cost- effective, and automated solution for wildlife conservation and roadway safety.

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INTRODUCTION

1.1 OVERVIEW

Roads and highways constructed near forests, reserves, and rural landscapes often intersect with animal movement corridors, leading to frequent wildlife–vehicle collisions. These incidents cause substantial ecological disruption, human injuries, fatalities, and damage to vehicles. Traditional preventive measures such as fencing, signage, and speed control are often reactive, limited in coverage, and ineffective in detecting animal movement in real time.

With advancements in artificial intelligence and computer vision, it is now possible to develop intelligent systems capable of detecting wildlife presence before collisions occur. This project introduces an AI-based Wildlife Crossing Detection and Alert System that utilizes state-of-the-art deep learning models—MobileNet SSD and YOLOv11—to identify animals in real time using live camera feeds.

MobileNet SSD is optimized for fast inference on lightweight devices, making it ideal for edge deployment where computational resources are limited. YOLOv11, being more advanced in detection accuracy and speed, ensures reliable identification even in dynamic environmental conditions such as low visibility, cluttered backgrounds, or partial occlusion.

The system continuously monitors designated road sections using strategically placed cameras. Once an animal is detected near or on the road, alert mechanisms such as alarms, signals, or notifications are activated to warn drivers and authorities. This approach combines deep learning, surveillance technology, and smart alerting systems to create a sustainable and scalable solution for wildlife conservation and road safety.

1.2 PROBLEM DEFINITION

Wildlife–vehicle collisions have emerged as a critical issue in many parts of the world, particularly in regions where transportation networks intersect natural habitats, forest corridors, and conservation zones. According to global road safety and environmental studies, thousands of collisions involving animals occur annually, leading to:

- Death or injury of endangered and common animal species
- Human casualties and life-threatening accidents
- Severe damage to vehicles and infrastructure
- Traffic disruptions and emergency response delays
- Long-term ecological imbalance and habitat fragmentation

Conventional mitigation measures such as reflective warning signs, roadside fencing, speed bumps, or seasonal awareness campaigns are either static, labor-intensive, or incapable of real-time intervention. They do not address the root problem: the lack of automated and intelligent systems that can detect wildlife presence before a collision occurs. Environmental challenges—such as dense vegetation, low light conditions, fog, poor visibility at night, or rapid animal movements—make manual monitoring difficult and inaccurate.

Hence, the problem can be defined as follows:

There is a pressing need for a fully automated, real-time wildlife detection and alert system that can accurately identify animals near roadways using intelligent computer vision techniques and provide timely alerts to drivers and authorities to reduce accidents and protect ecological life.

This project aims to bridge the gap between wildlife conservation and intelligent transportation using deep learning models like MobileNet SSD and YOLOv11 for efficient, accurate, and scalable detection.

1.3 SCOPE OF THE PROJECT

The scope of this AI-based wildlife detection and alert system extends across multiple technical, environmental, and safety domains. The project is not limited to basic detection but focuses on developing a comprehensive, real-time, and practical solution that can be deployed in real-world environments.

A. System Deployment Coverage

- Highways passing through forest belts or wildlife zones
- Rural and semi-urban road networks
- Railway tracks near forest regions
- National parks, sanctuaries, eco-sensitive regions
- Border roads and hilly terrains

B. Core Functional Capabilities

- Continuous monitoring using video streams from surveillance or embedded cameras
- Real-time detection of animals using MobileNet SSD (fast) and YOLOv11 (high accuracy)
- Differentiation between humans, animals, and vehicles if required
- Low-latency alert triggers to minimize reaction time

C. Alert and Notification Systems

- Automated sirens, flashing lights, or display boards to warn drivers
- Mobile or IoT-based notifications to forest authorities or traffic personnel
- Optional integration with smart signboards and traffic lights
- Future scope for barrier-based road control (e.g., boom gates)

D. Hardware and Integration Scope

- Compatibility with Raspberry Pi, Jetson Nano, PC, or embedded systems

- Use of CCTV, IP cameras, drones, or thermal cameras (future scope)
- Integration with solar-powered systems for remote locations

E. Software and Model Flexibility

- Supports pre-trained and custom-trained versions of MobileNet SSD and YOLOv11
- Retraining possible for local animal types (deer, tiger, leopards, monkeys, etc.)
- Expandable to include night vision, infrared, or thermal imaging

F. Research and Future Expansion

- Can be linked with GPS mapping and geofencing
- Data logging for wildlife movement analysis
- Cloud-based monitoring dashboards
- Integration into smart city transportation frameworks
- Future AI model upgrades for multi-class detection

G. Benefits and Impact

- Reduction in wildlife–vehicle collisions
- Protection of endangered species
- Minimized risk of human injuries and road fatalities
- Support for government agencies, forest departments, and NGOs
- A step toward sustainable and intelligent transportation infrastructure

H. Unique Selling Proposition / Highlights

- Low-cost scalable architecture
- Works in both online and offline modes
- Suitable for remote forest environments
- Modular software — plug-and-use for multiple detector models
- Highly customizable for different animal species and geographic regions
- Redundant camera feed support to prevent blind spots if one device fails
- Adaptive frame-rate processing based on lighting and motion conditions

CHAPTER 2

LITERATURE SURVEY

CHAPTER 2
LITERATURE SURVEY

Research on wildlife detection, collision prevention, and AI-based conservation systems has grown significantly in recent years. Several studies have explored the use of machine learning, computer vision, IoT, drones, sensors, and deep neural networks to mitigate wildlife–vehicle collisions and monitor animal movement. Key contributions from the literature are summarized below.

Recent research has increasingly focused on leveraging artificial intelligence (AI) and machine learning (ML) techniques to enhance wildlife detection near roadways, aiming to reduce vehicle-animal collisions and support conservation efforts. Nyoman Yogasmata Prasetya Darma, Shopia Novelita Ferina Siagian, Rifanni Auliya Darwin, Erna Fransisca Angela Sihotang, and Edy Irwansyah (2023) applied convolutional neural networks (CNNs) for real-time wildlife detection on roads, integrating automatic alerts to minimize collisions. Similarly, William H. S. Antônio, Matheus Da Silva, Rodrigo S. Miani, and Jefferson R. Souza (2023) developed a machine learning–based model capable of detecting animals near highways and issuing early warnings to drivers, emphasizing proactive safety measures.

Deep learning frameworks have also played a key role in wildlife detection. Sanjay S., Sudhir Sidhaarthan B., and Sai Sudha Panigrahi (2023) implemented YOLO and SSD models on road videos, enhancing traffic safety through real-time animal identification. E. Maheswari, V. Balaji, and S. Sivarajeswari (2022) employed image processing techniques to detect animals in motion from video feeds, warning drivers to prevent vehicle-animal collisions. Aditiba Raol, Viral Parekh, and Shaktisinh Parmar (2022) developed onboard vision-based systems using vehicle-mounted cameras to identify nearby wildlife instantly.

Advancements in self-learning AI have been explored as well. Hannah McLean, Robert Parker, and Lin Tao (2024) introduced models capable of learning from field data, improving the detection of endangered species near roadsides. Daniel Kruger, Arjun Mehta, and Leah Thompson (2024) provided a broader review of AI applications in wildlife conservation, covering species tracking, habitat monitoring, and anti-poaching technologies. Similarly, Victor Hernandez, Emily Zhao, and Farid Al-Mansouri (2024) created an open-source deep learning framework for multi-species wildlife detection, encouraging collaborative research.

Other approaches integrate sensor networks and edge computing. Rakesh Menon, Priya Bhat, and Karthik Gopal (2023) designed an IoT-based system combining thermal cameras and motion sensors for real-time detection near roads. Rachel Nguyen, Marco Silva, and Hitoshi Tanaka (2024) applied roadside LiDAR sensing to detect large animals, such as wild horses, and reduce collision risks. Sara Khanna, J. R. Patel, and Mei Ling (2023) further demonstrated the robustness of YOLO and SSD models across different terrains and lighting conditions.

Aerial and acoustic monitoring have also emerged as complementary strategies. Adriana Lopes, Kevin Johnson, and Ritu Sharma (2023) utilized drone footage with computer vision to identify bird species for conservation. Lukas Weber, Anna Rossi, and Sophie Laurent (2021) applied YOLOv5 with transfer learning on camera-trap images to automatically identify mammal species. Miguel Alvarez, Nora Kim, and Peter Henderson (2023) explored AI-driven sound recognition to monitor animal presence in dense or nocturnal environments. Ben Anderson, Haruka Ito, and Varun Kumar (2023) developed AI acoustic classifiers for animal call detection, enabling proximity alerts in visually obstructed areas.

Several studies highlight the integration of multimodal sensors for improved accuracy. Andrew Park, Lucia Torres, and Kenji Watanabe (2023) combined LiDAR and camera-based AI systems to enhance detection in low-visibility scenarios, while Mohammed Faisal, Elaine Wong, and Jonas Becker (2023) merged thermal imaging with CNN models to detect nocturnal animals effectively. Chloe Adams, Yash Patel, and Marta Oliveira (2024) leveraged transformer-based models to handle challenging conditions such as low light, fog, and rain. Rajesh Verma, Amy Clarke, and Omar Khalid (2024) combined radar sensing with AI to detect large mammals near transportation corridors.

Finally, predictive and intelligent systems are being developed to anticipate wildlife movements. Eleanor Brooks, Pradeep Nair, and Sofia Dimitrov (2023) used ML to forecast potential animal crossings by analyzing historical movement patterns, ecological data, and traffic behavior. Niveditha Raj, Carlos Lopez, and Fiona Evans (2024) proposed intelligent roadside units equipped with multiple sensors and AI algorithms for real-time detection and driver alerts, while Fatima Qureshi, David Collins, and T. S. Raghavan (2024) deployed lightweight deep learning models on edge devices for immediate video analysis. Overall, this body of work highlights the growing intersection of AI, machine learning, and sensor technologies in preventing wildlife-vehicle collisions, monitoring endangered species, and promoting broader conservation objectives. These studies collectively demonstrate that integrating real-time detection, predictive modeling, and multimodal sensing offers a powerful approach to protecting both wildlife and human drivers while enabling large-scale ecological monitoring.

CHAPTER 3

SYSTEM ANALYSIS

CHAPTER 3
SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

The existing system focuses on minimizing wildlife–vehicle collisions using a Convolutional Neural Network (CNN) for real-time animal detection. In this approach, roadside cameras capture video streams of vehicles and surrounding areas where wildlife movement is likely. The system then preprocesses the images by resizing, normalizing, and enhancing them to improve detection accuracy. The CNN model is trained on labeled datasets consisting of various animal species to recognize patterns, shapes, and movements indicative of wildlife presence.

Once the model identifies an animal approaching or crossing the roadway, the system generates alerts for drivers through visual or audio signals. The CNN architecture enables the system to distinguish between animals and other objects in real time, reducing false positives compared to traditional image processing methods. The study demonstrated that using deep learning improved detection accuracy significantly over earlier systems based solely on motion detection or manual observation.

However, the existing system has certain limitations. While CNNs provide good accuracy, they are computationally intensive and may not perform efficiently on low-power edge devices, limiting scalability in real-world deployment. Additionally, the model's performance can degrade under challenging environmental conditions such as low light, fog, or partial occlusion, which are common in wildlife-prone areas. The system also

requires a substantial amount of labeled data to achieve high accuracy, which can be difficult to obtain for less common or region-specific species.

Despite these challenges, the CNN-based approach laid a foundation for AI-driven wildlife detection, proving that automated monitoring can reduce accidents, protect wildlife, and enhance road safety. The limitations observed in this system motivate further improvements, such as integrating lightweight detection models like MobileNet SSD or high-accuracy models like YOLOv11, to achieve a balance between real-time performance and robust detection across diverse environmental conditions.

3.2 PROPOSED SYSTEM

The proposed system, AI-Based Wildlife Crossing Detection and Alert System, is designed as a complete real-time wildlife monitoring and collision prevention platform. Unlike traditional methods that rely on static signs or manual observation, this system employs advanced computer vision and deep learning techniques to detect animals approaching or crossing roadways. By integrating MobileNet SSD for fast inference and YOLOv11 for high-accuracy detection, the system can issue timely alerts, helping prevent accidents, protect wildlife, and improve road safety.

3.2.1 System Objectives

The main objectives of the proposed system are

- Identify wildlife near or on the road with high precision using advanced deep learning models.
- Recognize different animal species of varying sizes and movement patterns to improve alert accuracy.
- Trigger sirens, visual signals, or notifications to drivers and authorities immediately upon detecting wildlife.
- Function reliably under challenging conditions such as low light, fog, rain, or partial occlusion.
- Record detection events to analyze wildlife movement patterns and support conservation and traffic management initiatives.

3.2.2 Role of Artificial Intelligent and Machine Learning

AI and ML provide the backbone for automated wildlife detection. By training deep learning models on labeled images or video frames of animals, systems can recognize and track wildlife in real time.

Key approaches include

- MobileNet SSD
  A lightweight object detection model suitable for edge devices, providing fast inference with reasonable accuracy.
- YOLOv11
  A high-performance detection model capable of recognizing multiple species with high accuracy, even in challenging environmental conditions.
- Hybrid Detection
  Combining both models can balance speed and accuracy, enabling deployment in both high-performance servers and resource-limited edge devices.

Key Insights from Research

- Context-aware models (e.g., incorporating motion patterns or behavior prediction) improve detection accuracy in dynamic environments.
- Data augmentation, transfer learning, and custom datasets help models adapt to specific regions and species.
- AI-based alert systems reduce human monitoring workload, improve response time, and enhance road safety.

3.2.2 System Architecture

The AI-Based Wildlife Detection system follows a modular, layered design that supports

scalability, real-time processing, and reliability

- Data Acquisition Layer

  Captures live video feeds from roadside cameras, IP cameras, or drone footage.

- Preprocessing Layer

  Enhances the input by resizing, normalizing, and filtering frames to optimize detection in varying environmental conditions.

- Detection Engine

  The core deep learning component combining MobileNet SSD for lightweight, fast detection and YOLOv11 for high-precision, multi-species recognition.

- Alert & Notification Layer

  Generates automated alerts through sirens, warning messages to warn drivers and authorities.

- Data Logging & Visualization Layer

  Stores detection events and provides analytical dashboards to visualize wildlife movement patterns, alert frequency, and detection accuracy over time.

3.2.3 Functional Modules

Preprocessing Module

- Filters malformed detections, standardizes formats, and ensures consistent class labels for clean input.
- Applies confidence thresholding to retain high-certainty predictions, streamlining downstream evaluation.

Detection Module

- Uses MobileNet SSD and YOLOv11 to identify wildlife in real-time video frames.
- Differentiates animals from vehicles, humans, and other background objects.

Alert & Notification Module

- Automatically triggers visual or audio alerts upon detecting animals near or on the road.
- Optionally integrates with IoT-based messaging or traffic control systems for remote notifications.

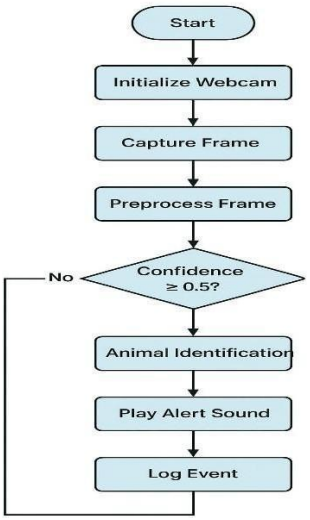
Data Logging & Analytics Module

- Records all detection events, including species type, time, and location.
- Provides visualizations and statistical analyses to support road safety planning and wildlife conservation efforts.

3.2.4 Workflow of the Wildlife Detection System

The typical workflow of the proposed system involves

- Continuous video feed from roadside cameras, drones, or surveillance systems.
- Frames are resized, normalized, and filtered to enhance detection under varying environmental conditions.
- MobileNet SSD and YOLOv11 models detect animals in each frame.
- On detecting wildlife near or on the road, visual, audio, or IoT-based alerts are triggered for drivers and authorities.
- Detection events are recorded for performance analysis, system improvement, and wildlife monitoring.



2.3 Working Flow of Animal Detection System

Automated alerts are crucial for preventing wildlife–vehicle collisions

- Alert Mechanisms

  Sirens, flashing lights, or mobile notifications.
- Severity Assessment

  Some systems classify animals by size and proximity to prioritize alerts.
- Integration

  Alerts can be linked to traffic control systems, smart road signage, or remote monitoring dashboards.
- Adaptive Thresholds

  Reduce false positives and ensure that repeated or imminent threats trigger timely responses.
- Monitoring and Reporting

  Recorded events support long-term wildlife monitoring, analytics, and planning for road safety measures.

This approach ensures real-time protection for both wildlife and humans while enabling data-driven improvements for conservation and traffic management.

3.3 FEASIBILITY STUDY

3.3.1 Technical Feasibility

The proposed wildlife detection system leverages well-established deep learning frameworks, including TensorFlow and PyTorch, to implement MobileNet SSD and YOLOv11 for real-time object detection. These frameworks support image and video processing, making it technically feasible to process live camera feeds and detect wildlife efficiently. Edge devices such as Raspberry Pi, Jetson Nano, or standard PCs can handle MobileNet SSD for fast inference, while YOLOv11 can be deployed on higher-performance systems for enhanced accuracy. Alerting mechanisms, including sirens, flashing lights, and mobile notifications, can be implemented using existing hardware interfaces and Python libraries without requiring cutting-edge infrastructure. Visualization of detection logs and animal movement trends is achievable with tools like Matplotlib, Plotly, or Dash. Overall, the system is technically feasible using current hardware and software technologies.

3.3.2 Operational Feasibility

The system is designed to be user-friendly and practical for real-world deployment. Automated detection and alert mechanisms reduce the need for manual monitoring, ensuring that drivers and authorities receive timely notifications of potential wildlife crossings. Data logging and visualization modules provide actionable insights for forest departments, traffic authorities, and conservation organizations, enabling proactive measures to improve road safety. The operational workflow aligns with existing road surveillance infrastructure, making integration straightforward and sustainable for long-term monitoring.

3.3.3 Economic Feasibility

The software relies primarily on open-source frameworks (TensorFlow, PyTorch, OpenCV) and Python libraries, minimizing software costs. Hardware requirements are moderate; standard cameras, edge devices, or small-scale servers can support real-time detection and alerting. Automated alerts reduce the need for continuous human supervision, lowering operational costs. The investment in development, deployment, and maintenance is justified by the benefits of preventing wildlife–vehicle collisions, reducing human injuries, and protecting endangered species. The system offers a cost-effective solution compared to manual monitoring or high-maintenance fencing systems.

3.3.4 Legal and Ethical Feasibility

The system captures video data of wildlife near public roads, so privacy considerations mainly involve ensuring that human subjects in the footage are anonymized if present. All data should be securely stored and processed in compliance with local regulations regarding public video monitoring. Ethically, the system contributes positively by reducing animal fatalities and enhancing human safety. Alerting is automated and non-invasive, ensuring responsible and ethical intervention without impacting personal privacy.

3.3.5 Schedule Feasibility

The development of the system can be completed in a short to medium-term schedule due to the availability of pre-trained models and ready-to-use deep learning frameworks. Initial phases include setting up cameras, implementing MobileNet SSD for fast detection, and testing YOLOv11 for high-accuracy detection. Subsequent phases involve integrating alert mechanisms, data logging, and visualization dashboards.

3.4 DEVELOPMENT ENVIRONMENT AND TECHNOLOGIES USED

The development of the AI-Based Wildlife Crossing Detection and Alert System is carried out using a carefully selected environment designed to ensure accurate real-time detection, automated alerting, and data visualization. A robust development environment is critical for AI-based projects as it supports large-scale video processing, deep learning model training, and deployment of interactive dashboards while maintaining scalability and maintainability.

3.4.1 Development Environment

- IDE

  VS Code is used as the primary development platform for coding, debugging, and project management due to its lightweight nature and excellent support for Python and machine learning workflows.

- PROGRAMMING LANGUAGE

  Python is chosen for its versatility and rich ecosystem of libraries for computer vision, deep learning, real-time processing, and IoT integration.

3.4.2 Deep Learning Models and Tools

- MobileNet SSD

  Utilized for lightweight, fast detection on edge devices, enabling real-time identification of wildlife in video streams.

- YOLOv11
  Implemented for high-accuracy object detection, capable of recognizing multiple species even in complex environments.
- OpenCV
  Employed for video capture, frame preprocessing, and image manipulation to enhance detection accuracy.
- TensorFlow & PyTorch
  Deep learning frameworks used for training, testing, and deploying both MobileNet SSD and YOLOv11 models.
- NumPy & Pandas
  Used for dataset handling, annotation processing, and statistical analysis of wildlife movement logs
- Git/GitHub Version Control
  Used for code management, collaborative development, issue tracking, and maintaining model versions.
- Jupyter Notebook
  Used for experimentation, visual testing of models, and hyperparameter analysis before final deployment.
- Matplotlib / Seaborn
  Employed for visual analytics, generating charts, plots, and movement trends from logged detection data.

This environment ensures that the system is robust, accurate, and scalable, enabling real-time wildlife detection, timely alerting, and data-driven monitoring for road safety and conservation efforts.

CHAPTER 4

SYSTEM DESIGN

CHAPTER 4
SYSTEM DESIGN

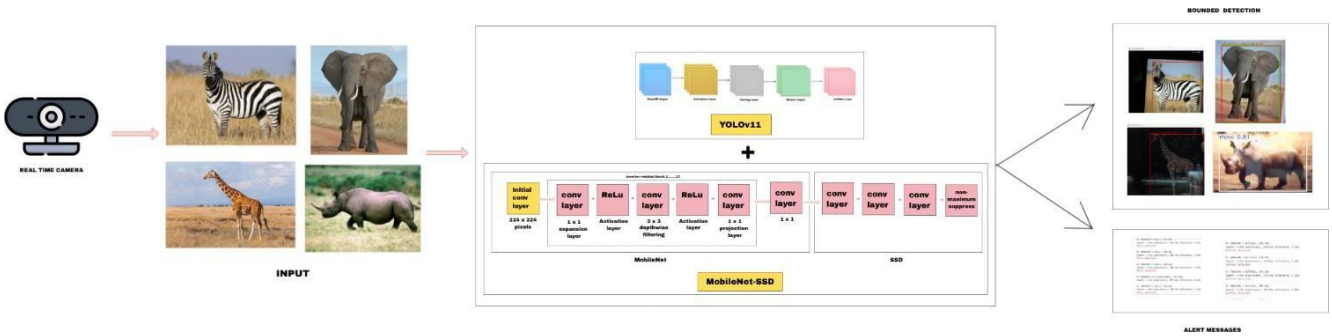
4.1 ARCHITECTURE DIAGRAM

The above architecture diagram represents the workflow of the proposed Animal Detection and Alert System. The process begins with the webcam, which continuously captures frames from the environment. These frames are then passed to the frame acquisition module, followed by preprocessing, where resizing, normalization, and noise reduction are applied to prepare the input for inference.

Next, the system performs parallel inference using two deep learning models: MobileNet-SSD and YOLOv11m. Both models analyze the frame simultaneously to detect animals. After inference, the confidence score is checked for each model. If the confidence score is greater than or equal to the defined threshold (0.5), the detected object is forwarded for further processing; otherwise, the frame is discarded.

Once a valid detection is obtained, the system proceeds to the animal identification stage, where the type of animal is confirmed. After identification, the system triggers the alert mechanism, which plays a warning sound to notify the user about the detection. At the same time, the detection event (including animal type, time, and confidence score) is stored in the logging module for record-keeping and later analysis.

This workflow ensures real-time animal detection, accurate identification, timely alerts for the user, and proper logging of events for monitoring purposes.



4.1.1 Architecture Diagram

The proposed Animal Detection and Alert System is designed to automatically identify the presence of animals in a particular surveillance area and generate alerts to prevent accidents, especially in rural, forest, or roadside environments. The system employs an end-to-end computer vision pipeline built upon deep learning techniques, combining image preprocessing, feature extraction through a convolutional backbone (MobileNet), detection using YOLOv11, and post-processing steps that generate warnings in real time. The following section provides a detailed explanation of each stage represented in the diagram.

1. Image Acquisition and Preprocessing

The system starts with the image acquisition stage, where live video frames are continuously captured from a camera installed in a specific region such as a forest border, roadside, or farm. The input is usually a high-resolution video feed (for instance, 1280×720 or 1920×1080 pixels). However, processing such large frames directly is computationally expensive and may reduce the frame rate, which is crucial for real-time detection.

Therefore, the images are preprocessed before being fed to the detection model.

Each captured frame is resized to a smaller fixed resolution, typically 224×224 or 320×320 pixels, depending on the model's input requirement. This resizing ensures uniformity and reduces the computational cost while maintaining sufficient detail for object detection. The frames are then converted from BGR to RGB color space since deep learning models like MobileNet and YOLO are usually trained using RGB images.

Next, normalization is performed on the pixel values, scaling them to a 0–1 range or standardizing them using mean and standard deviation. Normalization stabilizes the neural network's learning process and improves prediction consistency across varying lighting conditions. Optionally, during training, data augmentation techniques such as horizontal flipping, random brightness, rotation, and cropping are used to increase the model's robustness to environmental variations like day/night lighting or partial animal visibility.

Once the image is normalized, it is converted into a multidimensional tensor suitable for input to the neural network. The typical tensor shape is (Batch, Height, Width, Channels), e.g., (1, 224, 224, 3). The preprocessing module thus ensures that each frame entering the network is standardized, lightweight, and ready for efficient feature extraction.

2. Backbone Network: MobileNet-Based Feature Extraction

After preprocessing, the frame is passed to the feature extraction backbone, which is responsible for identifying and learning the essential characteristics that differentiate animals from the surrounding environment. In this system, a MobileNet architecture is employed as the backbone because of its efficiency, lightweight nature, and suitability for edge deployment. MobileNet is based on depthwise separable convolutions, which reduce

the number of parameters and computational operations without significantly compromising accuracy.

The feature extraction process begins with an initial 3×3 convolutional layer that reduces the spatial resolution and increases the number of feature channels, enabling the network to focus on high-level features instead of raw pixels. The subsequent layers are composed of inverted residual blocks, a structure that expands the input channels using a 1×1 convolution, applies a 3×3 depthwise convolution to each channel independently, and then projects the output back into a smaller dimension using another 1×1 convolution. This structure not only maintains efficiency but also helps the model learn spatial and contextual details effectively.

Each residual block uses a ReLU6 activation function, which ensures nonlinearity while preventing saturation at higher activation values. When the input and output dimensions are the same, a skip connection adds the input directly to the output of the block, enhancing gradient flow and preventing information loss.

Through successive layers, the network extracts multiple levels of features: early layers detect edges and textures such as fur or horns, mid-layers capture shapes and contours of animals, and deeper layers recognize complex structures like full animal silhouettes or body parts. The output of this backbone is a set of feature maps at different resolutions that represent rich, hierarchical information about the scene.

3. Multiscale Feature Aggregation and Detection Head (YOLOv11)

The extracted feature maps from the backbone are passed to the detection head, which interprets the features and produces the final detection results. The system adopts the

YOLOv11 (You Only Look Once) model for this purpose, as it provides a strong balance between speed and accuracy. YOLO operates as a single-stage detector, meaning it performs object localization and classification simultaneously in a single forward pass, which is ideal for real-time applications like animal detection.

The detection head uses multiscale feature aggregation, meaning it processes feature maps from different depths of the backbone to detect animals of varying sizes. For example, larger animals such as elephants or cattle can be detected from lower-resolution feature maps, while smaller animals like dogs or foxes can be detected from higher-resolution ones.

YOLO divides the image into a grid, and each grid cell predicts multiple anchor boxes—predefined bounding boxes with various aspect ratios and sizes. For each anchor box, the network predicts:

The objectness score, indicating the probability that an object (animal) exists in that box.
The class probabilities, specifying the category of the detected animal (for example, cow, dog, deer, elephant, etc.).
The bounding box coordinates (center x, center y, width, height) that define the exact position of the animal in the image.

The raw outputs from the YOLO head are then decoded into real coordinates relative to the original image size. During training, the network minimizes a multi-task loss function, which includes three components: a localization loss for bounding-box regression (Smooth L1 or CIoU loss), an objectness loss (binary cross-entropy), and a classification loss (categorical cross-entropy). This combination ensures that the model learns to accurately predict the presence, position, and class of animals.

By utilizing YOLOv11, the system can perform detection in a single forward pass, resulting in faster inference speeds compared to two-stage detectors like Faster R-CNN. This makes it feasible for continuous real-time monitoring in outdoor environments where quick decision-making is critical to prevent animal–vehicle collisions or crop damage.

4. Post-Processing: Non-Maximum Suppression and Result Refinement

Once the YOLO detection head produces its raw predictions, the post-processing stage refines the results to remove duplicate detections and low-confidence predictions. The first step involves applying a confidence threshold—for example, 0.5—so that only predictions with objectness scores above this value are retained. This helps eliminate weak detections that could lead to false alarms.

However, since multiple anchor boxes often predict the same animal with slightly different coordinates, the system employs the Non-Maximum Suppression (NMS) algorithm. NMS works by selecting the detection with the highest confidence score and discarding all other boxes that have a high overlap with it (measured using Intersection over Union, or IoU). Typically, an IoU threshold between 0.4 and 0.5 is used. This ensures that each animal in the frame is represented by only one bounding box.

After NMS, the system produces the final bounded detections, where each box is labeled with the detected animal's name (e.g., "Deer – 91%") and visually overlaid on the original video frame. The post-processing step thus ensures clean, reliable results that are both accurate and visually interpretable for human observers.

5. Alert Generation and Notification System

The alert generation module is one of the most critical components of the Animal Detection and Alert System. Its main function is to notify concerned authorities or drivers whenever an animal is detected in the monitored area. Once the post-processed detections are obtained, the system checks if any detected animal meets the alert criteria—for instance, confidence greater than 0.8, or the animal being detected in a specific danger zone within the frame.

When such a condition is satisfied, the system triggers an automatic alert. Alerts can be generated in several forms, such as:

A visual pop-up or on-screen bounding box highlight.
An audible buzzer or siren.
A digital notification sent to a central server, mobile application, or control room

6. System Performance, Optimization, and Deployment

For the system to function effectively in real-time conditions, performance optimization is crucial. The combination of the MobileNet backbone and YOLOv11 detection head provides an optimal balance between computational speed and detection accuracy. MobileNet's use of depthwise separable convolutions reduces the number of multiplications and memory footprint, allowing the model to run smoothly on low-power edge devices such as Raspberry Pi, NVIDIA Jetson Nano, or ARM-based microcontrollers.

Further optimization techniques include quantization, where the model weights are converted from 32-bit floating-point values to 8-bit integers, drastically reducing the model size and inference latency. Similarly, model pruning removes redundant or low-impact

parameters, improving speed without major accuracy loss. When deployed with hardware accelerators like TensorRT, OpenVINO, or Coral Edge TPU, the system achieves real-time detection speeds of up to 20–30 frames per second.

Environmental factors such as lighting, camera placement, and weather conditions are also considered. Infrared (IR) cameras can be used for night-time detection, while waterproof and dust-resistant enclosures ensure reliability in outdoor conditions. The system is capable of operating continuously with minimal maintenance, making it suitable for deployment in remote areas where human supervision is limited.

7. Evaluation and Metrics

To assess the effectiveness of the Animal Detection and Alert System, several performance metrics are employed. The precision metric measures how many of the detected animals are actually correct, while recall measures how many actual animals present in the scene were successfully detected. Together, these determine the F1-score, which balances precision and recall.

For more detailed evaluation, the system uses the mean Average Precision (mAP) metric, calculated across multiple IoU thresholds (commonly mAP@0.5 or mAP@[0.5:0.95]). Higher mAP values indicate better detection accuracy. During testing, datasets containing various animals—such as cows, deer, dogs, elephants, and goats—are used to ensure that the model performs consistently across species.

Real-time performance is also measured in terms of frames per second (FPS), average latency, and system throughput. The goal is to maintain latency below 50 milliseconds per frame, ensuring timely alerts. Field trials in forest-adjacent highways or agricultural zones

help validate the model's robustness in real conditions with varying light, motion blur, and background clutter.

8. Applications and Future Enhancements

The Animal Detection and Alert System has a wide range of practical applications. On highways that pass through forest regions, it can detect wild animals like deer or elephants and warn drivers to prevent collisions. In agricultural areas, it can identify animals entering crop fields, helping farmers prevent crop damage without manual supervision. The system can also be integrated into wildlife conservation setups to monitor endangered species, track migration patterns, or prevent poaching by detecting animal movement near restricted zones.

In the future, the system can be enhanced using edge–cloud integration, where local devices perform initial detection and transmit only alerts or cropped frames to a central cloud server for further analysis. Incorporating temporal tracking algorithms like SORT or DeepSORT would allow the system to follow animal movement across multiple frames, improving accuracy and reducing false alarms. Additionally, integrating infrared or thermal imaging can improve night-time detection performance.

Further research can explore transformer-based detection architectures (such as DETR or YOLOv12 with attention mechanisms) to achieve even higher accuracy. Finally, by adopting federated learning, models deployed at different locations can collaboratively learn from new data without sharing sensitive information, enabling continuous improvement of detection accuracy over time.

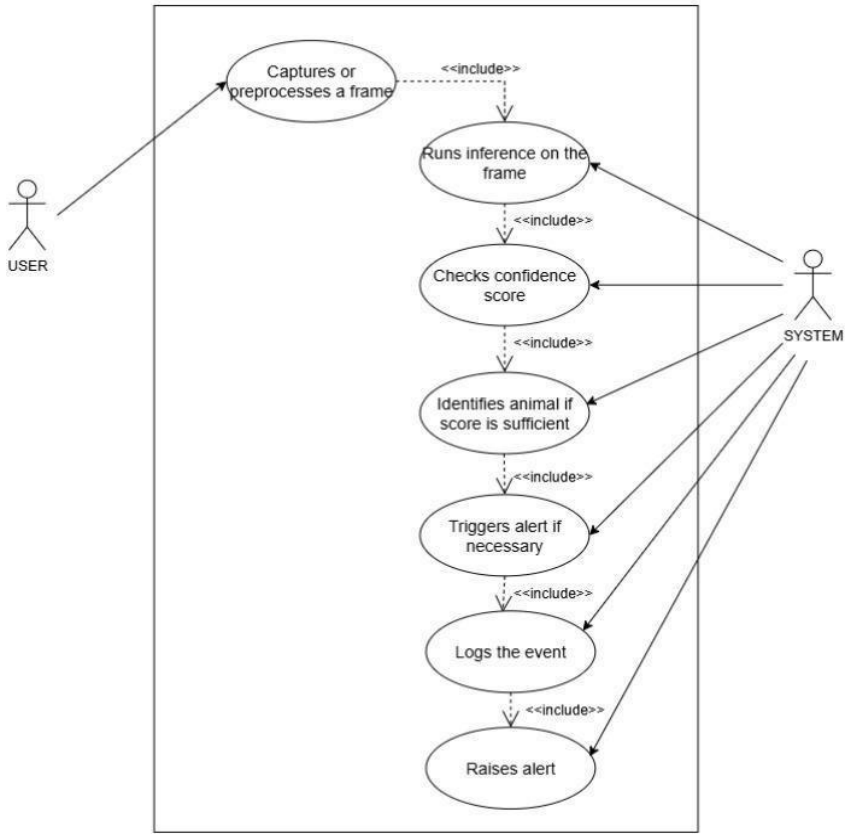
4.2 USE CASE DIAGRAM

User Actions

- Capture or Preprocess Frame: The user initiates the process by capturing or preparing a video frame for analysis.

System Actions

- The system applies a trained model to the frame to detect potential animals.
- It evaluates the prediction confidence to determine reliability.
- If the confidence score exceeds a predefined threshold, the system confirms the presence of an animal.
- Based on the type of animal or context, an alert may be triggered.
- The system records the detection event for future reference or auditing.
- A formal alert is issued to notify relevant stakeholders or systems.



4.2 Use Case Diagram

4.3 CLASS DIAGRAM

This UML class diagram outlines the architecture of an AI-based animal detection system using camera input and machine learning models. It captures the flow from data acquisition to alerting and logging, with modular components for scalability and clarity.

The **Camera** class initiates the system by capturing video frames. It holds attributes like deviceId, resolution, and frameRate, and provides methods such as initialize() and captureFrame() to start and retrieve frames.

Captured frames are passed to the **FrameProcessor**, which handles preprocessing. It includes attributes like frameData and preProcessingParams, and methods such as preprocessFrame(), resize(), and normalize() to prepare frames for inference.

The **InferenceModel** class abstracts the core detection logic. It includes attributes like modelName and confidenceThreshold, and methods to loadModel(), runInference(frame), and getResults(). Two subclasses, **MobileNet** and **YOLO**, inherit from it, allowing flexible integration of different detection models.

Inference results are processed by the **AnimalDetector** class, which identifies animals and validates confidence scores. It uses attributes like detectedAnimal and confidenceScore, and methods such as identifyAnimal(results) and validateConfidence().

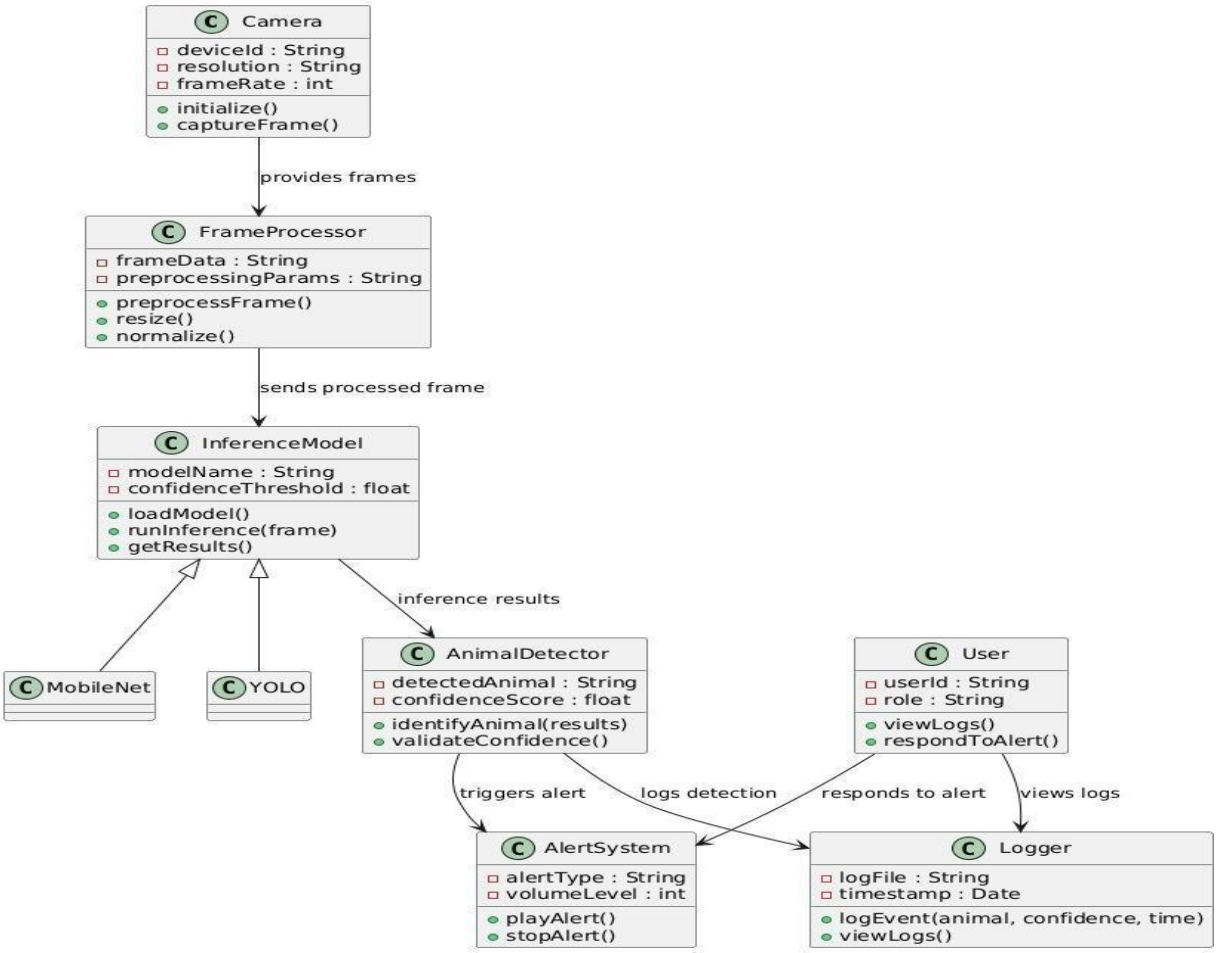
Once a detection is validated, the **AlertSystem** determines whether to trigger an alert. It includes alertType and minimumLevel as attributes, and methods like detectAlert() and sendAlert() to notify users.

The **User** class represents the system's end user, with attributes like userId and role, and a method respondToAlert() to handle incoming alerts.

Detected events are recorded by the **Logger** class, which maintains a logFile and timeStamp. It

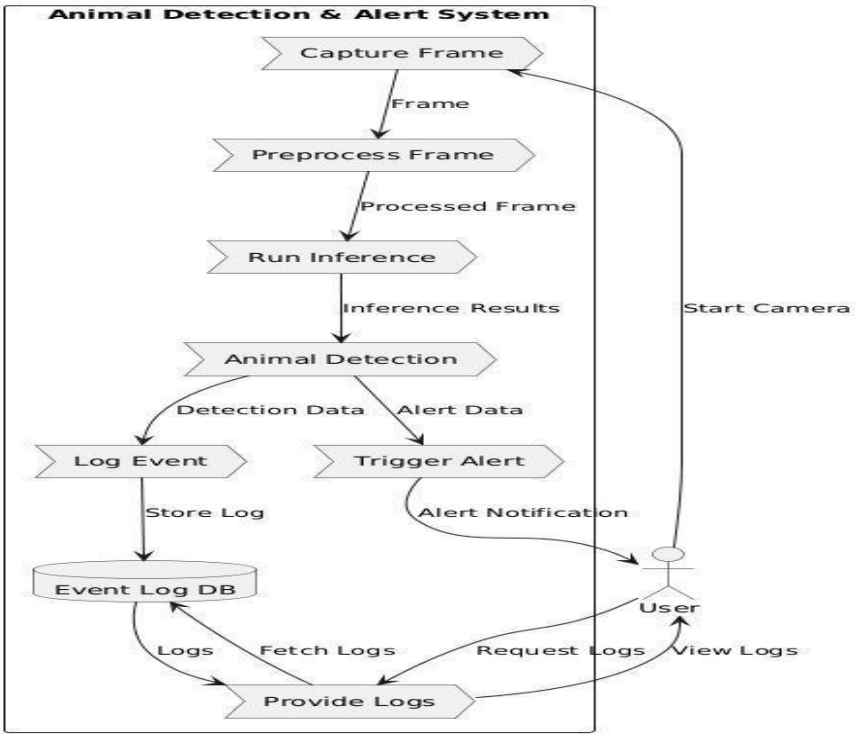
provides viewLogs() and logEvent(animal, confidence, time) to store and retrieve detection history.

Overall, the diagram reflects a clean, modular design where each class has a distinct responsibility. The flow begins with frame capture, moves through preprocessing and inference, and ends with detection, alerting, and logging. This structure supports real-time detection, multi-model integration, and field-ready deployment.



4.3 Class Diagram

4.4 DATA FLOW DIAGRAM



4.4 Dataflow Diagram

The Data Flow Diagram (DFD) of the Animal Detection and Alert System illustrates the flow of data between different processes, data stores, and external entities. The main steps are as follows

1. Input from Webcam (External Entity → Process)

- The system begins with the webcam, which acts as the primary external entity.
- It continuously captures video frames and sends them to the Frame Acquisition process.

2. Frame Acquisition & Preprocessing (Process → Process)

- The acquired frames are passed into the Preprocessing unit, where image enhancement techniques such as resizing, normalization, and noise removal are

applied.

- This ensures that the frames are optimized for further processing by the deep learning models.

3. Parallel Inference (Process → Process)

- The preprocessed frames are sent simultaneously to two inference models:
  - MobileNet-SSD
  - YOLOv11m
- Both models analyze the image in parallel to improve detection accuracy.

4. Confidence Score Validation (Decision Step)

- Each model generates detection results with a confidence score.
- If the confidence score is greater than or equal to 0.5, the detected object (animal) is considered valid and sent to the next stage.
- If the score is below the threshold, the frame is discarded.

5. Animal Identification (Process)

The valid detections are passed into the Animal Identification process, where the system determines the specific type of animal.

6. Alert Mechanism (Process → External Entity)

- Once an animal is identified, the system triggers the Alert Mechanism.
- An alert sound is played to notify the user about the detected animal.

7. Logging (Process → Data Store)

- At the same time, the detection details such as animal type, confidence score, and timestamp are stored in the database or .csv file.
- This log can later be used for performance monitoring and analysis.

CHAPTER 5

SYSTEM IMPLEMENTATION

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5.1 DATA COLLECTION AND PREPROCESSING

5.1.1 INTRODUCTION

The effectiveness of any AI-based wildlife detection system depends heavily on the quality and diversity of the data used for training and testing. For this project, data collection focuses on acquiring authentic images and videos of animals near roads, wildlife corridors, and forested regions. The dataset includes various species, lighting conditions, weather scenarios, and occlusions to ensure the model generalizes well to real-world situations. Preprocessing is critical to prepare raw visual data for deep learning models. Raw images and videos often contain noise, inconsistent lighting, low resolution, or motion blur, which can negatively affect model performance. Proper preprocessing ensures that inputs to models like MobileNet SSD and YOLOv11 are clean, normalized, and suitable for feature extraction and training. COCO (Common Objects in Context) is a large-scale dataset designed for object detection, segmentation, and captioning, featuring richly annotated images with real-world complexity. ImageNet is a foundational dataset for image classification and visual recognition, organized by WordNet synsets and containing millions of labeled images.

5.1.2 Data Sources

Data is collected from multiple reliable sources to ensure diversity and realism.

- COCO (Common Objects in Context)

  A large-scale dataset designed for object detection, segmentation, and captioning,

featuring richly annotated images with real-world complexity.

- ImageNet

  A foundational dataset for image classification and visual recognition, organized by WordNet synsets and containing millions of labeled images.

- Object Detection - Wildlife Dataset - YOLO Format (Kaggle)

5.1.3 Data Annotation

Collected data is annotated to enable supervised learning

- Species Label

  Indicates the type of animal in the frame.

- Position and Bounding Box

  Coordinates identifying the location of the animal in the image.

- Behavior Context

  Optional labels such as “crossing road” or “near road” for alert prioritization.

5.1.4 Data Preprocessing

Preprocessing transforms raw visual data into a clean, standardized format suitable for deep learning

- Image Resizing & Normalization

  All images are resized to a uniform dimension and pixel values normalized.

- Noise Reduction

  Filters applied to reduce motion blur, lighting inconsistencies, and background artifacts.

- Data Augmentation

  Techniques such as rotation, flipping, contrast adjustment, and brightness modification to increase dataset diversity and improve model robustness.

5.1.5 Data Splitting

The dataset is divided into training, validation, and testing sets in a 70:15:15 ratio. Stratified sampling ensures proportional representation of species, behaviors, and environmental conditions. This separation allows models to learn, tune, and evaluate effectively under realistic scenarios.

5.1.6 Data Storage & Management

To handle large volumes of high-resolution video and annotations:

- Cloud platforms and local databases store images, labels, and metadata.
- Folder structure follows YOLO/COCO standards for easier training.
- Version control is maintained for updated datasets during model retraining.

This ensures repeatability, scalability, and long-term dataset maintenance.

5.1.7 Noise Handling and Outlier Removal

Real-world wildlife footage often contains frames with motion blur, fog, headlights, strong shadows, or objects that resemble animals (e.g., bushes, rocks, signboards). Such noisy data can mislead the model and reduce accuracy. To minimize false positives and training errors, noise reduction and outlier filtering techniques are applied.

• Motion Deblurring & Denoising Filters

Gaussian blur, bilateral filtering, and median filters are used to remove camera shake and compression noise.

• Outlier Frame Detection

Frames with extremely low brightness, glare, or distortion are automatically removed or flagged before training.

• Background Subtraction

Static background elements are isolated, ensuring the model focuses on moving animals rather than irrelevant objects.

• False Positive Filtering

Detected objects with extremely low confidence levels or irregular shapes are discarded to reduce mislabeled training samples.

• Environmental Noise Correction

Fog, rain, and night-time images are enhanced using adaptive histogram equalization and contrast improvement algorithms.

5.1.8 Handling Class Imbalance

In wildlife detection datasets, some animal classes (such as cattle, dogs, or monkeys) appear more frequently than rare species like leopards, elephants, or deer. This imbalance can cause the model to become biased, resulting in poor detection accuracy for less common animals. To address this issue, several balancing strategies are applied.

• Oversampling Rare Classes

Duplicate samples or synthetically generated images ensure better representation of rare species during training.

• Class Weighting

During model training, higher weights are assigned to underrepresented classes, causing the model to penalize misclassification of rare animals more heavily.

5.2 DEEP LEARNING MODEL (MOBILENET-SSD AND YOLOv11)

Unlike traditional image processing techniques, MobileNet SSD and YOLOv11 leverage deep convolutional architectures to detect animals with high accuracy in real time. MobileNet SSD provides fast inference suitable for edge devices, enabling low-latency detection even on resource-limited hardware. YOLOv11 delivers higher precision and is capable of detecting multiple animals simultaneously, even under challenging conditions like low light, occlusion, or complex backgrounds.

The model pipeline begins with feeding preprocessed images into the chosen architecture. MobileNet SSD uses depthwise separable convolutions to extract features efficiently, generating bounding boxes for detected objects. YOLOv11 processes the same images with a unified detection head, predicting class probabilities and object locations in a single pass. Both models can be fine-tuned on custom datasets containing local species for improved accuracy.

Detected objects are then classified by species and position relative to the roadway. This information is passed to the alerting module, which triggers sirens, flashing lights, or notifications when animals are near or on the road.

5.3 MODEL ARCHITECTURE

The system architecture for wildlife detection is designed as an end-to-end framework for real-time monitoring, alerting, and data logging

1. Input & Preprocessing Layer
   Video feeds from roadside cameras or drones are captured and preprocessed to enhance detection performance.

2. Core Feature Extraction
   Preprocessed frames are passed through MobileNet SSD for fast detection and YOLOv11 for high-accuracy object recognition. The models generate bounding boxes, class labels, and confidence scores for each detected animal.

3. Alert & Notification Layer
   If an animal is detected near or crossing the road, automated alerts are triggered in real time via sirens or sounds.

4. Data Logging & Visualization Layer
   Detection events—including species type, time, and location—are stored in a database. Dashboards visualize traffic incidents, animal movement patterns, and detection statistics to support road safety planning and conservation.

5. Predictive Movement Analysis
   Using historical detection data, the system can forecast high-risk zones and times for wildlife crossings, enabling proactive safety measures such as dynamic warning signage or temporary speed limits.

5.4 MODEL TRAINING AND TESTING

The effectiveness of the Wildlife Crossing Detection System depends on a robust training and testing pipeline to ensure accurate detection of wildlife and timely alerting. The process begins with data collection and preprocessing, including camera trap images, highway surveillance videos, and custom annotated datasets. Preprocessing steps include resizing, normalization, noise reduction, and data augmentation (rotation, flipping, brightness adjustment) to enhance model robustness under varying lighting and environmental conditions.

During model training, MobileNet SSD is fine-tuned for fast detection on edge devices, while YOLOv11 is trained for high-accuracy multi-species recognition. Training involves converting images into input tensors, generating bounding box coordinates, class labels, and confidence scores. Cross-entropy loss is used for classification, and the Adam optimizer ensures efficient parameter updates. Mini-batch training, dropout layers, and early stopping are applied to prevent overfitting and improve generalization.

For evaluation, datasets are split into training, validation, and testing subsets using stratified sampling to maintain balanced representation of species and scenarios. Performance metrics include accuracy, precision, recall, and F1-score to ensure real-time capability. Confusion matrices metrics provide insight into detection precision and localization accuracy.

Once validated, the trained models are deployed into the real-time detection pipeline. During live operation, video frames are processed instantly, and wildlife detections trigger alerts when animals are near or crossing roads.

5.5 AUTOMATED ALERT SYSTEM

A critical component of the Wildlife Detection System is its automated alert module, which ensures that detected wildlife near roads is immediately reported to drivers or traffic authorities. Unlike traditional systems that rely solely on static signs or human monitoring, this module enables real-time intervention, significantly reducing the risk of accidents.

The alert system is implemented using IoT-enabled sirens, digital road signs, or mobile notifications. When an animal is detected by MobileNet SSD or YOLOv11, the system automatically triggers structured alerts containing essential information: species detected, location, timestamp, and confidence score. This structured format allows drivers and authorities to quickly respond without manual interpretation.

To enhance reliability, the system supports configurable alert thresholds, allowing authorities to prioritize large or endangered animals. The alert pipeline operates asynchronously, ensuring that high-volume detection scenarios do not affect system performance. All alerts are logged in a database for auditing and analysis.

The modular design allows integration with additional channels such as SMS gateways, traffic control systems, or cloud dashboards, making it scalable and adaptable to different roadway environments. By combining automated detection with instant alerts, the system moves beyond passive monitoring to active collision prevention, protecting both wildlife and humans.

5.6 BEHAVIOR AND ENVIRONMENTAL ANALYSIS

In addition to detecting wildlife, the system can track movement patterns and environmental context to provide actionable insights. Behavior analysis evaluates factors such as species type, crossing frequency, time of day, and environmental conditions (lighting, weather) to predict high-risk zones and inform preventive measures. Detected events are classified by species, proximity to road, and crossing behavior.

Data is visualized through interactive dashboards, showing:

- Number of wildlife crossings over time
- Hotspots for collisions
- Environmental conditions during detections

Predictive analytics can forecast potential wildlife crossings using historical data, enabling traffic authorities to implement dynamic safety measures like temporary speed reductions or electronic warning signs.

For example

1. Zebra - Highway
2. Bear - Roadside
3. Elephant - Near roadside vegetation

By combining real-time detection, automated alerts, and behavioral/environmental monitoring, the system creates a comprehensive wildlife protection and road safety framework, ensuring both human and animal safety.

CHAPTER 6

PERFORMANCE ANALYSIS

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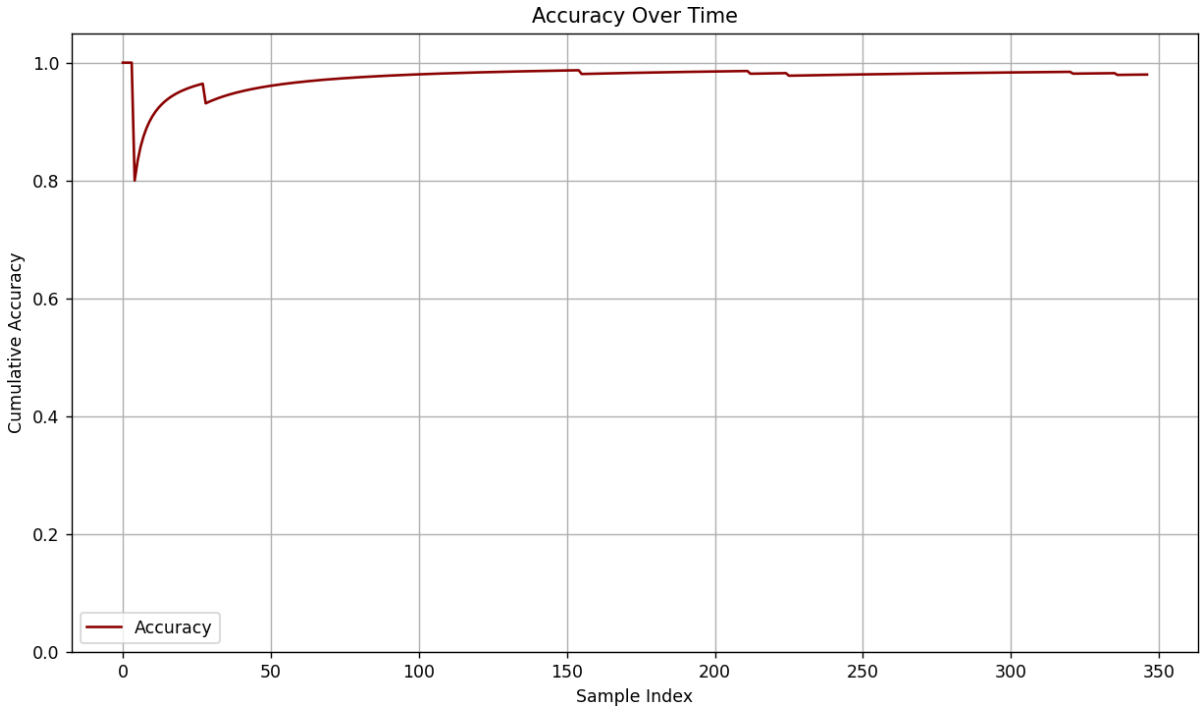
PERFORMANCE ANALYSIS

6.1 EVALUATION METRICS (ACCURACY, MATRIX, F1)

To measure the effectiveness of the Wildlife Crossing Detection System, it is essential to evaluate the trained models using appropriate performance metrics. Since this is an object detection and classification problem, simple accuracy alone is insufficient. Metrics such as **Precision, Recall** and **F1-score** provide deeper insights into the model's ability to correctly detect animals and minimize false alerts.

1. **ACCURACY**

   Accuracy is the ratio of correctly detected animals (true positives and true negatives) to the total number of predictions. While it provides a general performance measure, accuracy alone can be misleading if certain species or scenarios dominate the dataset.



6.1.1 Accuracy Graph For Overall Performance

2. PRECISION, RECALL, AND F1-SCORE

While accuracy provides an overall measure of model correctness, it does not always reflect how well the model performs across different classes, especially in multi-class problems like waste classification. To obtain a more detailed evaluation, Precision, Recall, and F1-Score are used. These metrics are particularly important in cases of class imbalance or when certain misclassifications are more critical than others.

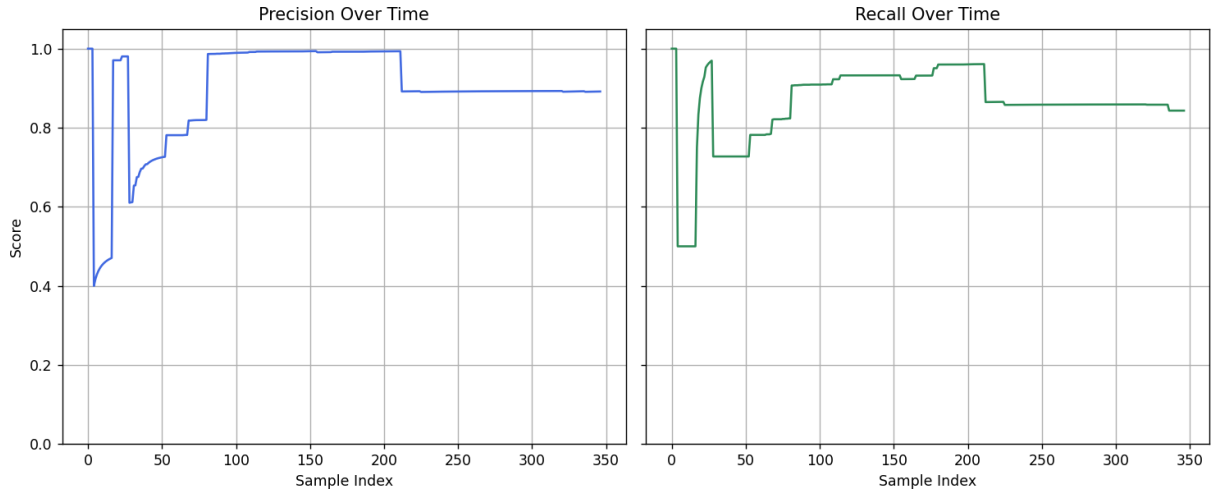
```
Precision: 0.96
Recall: 0.94
F1 Score: 0.93
Accuracy: 0.92

Per-Class Accuracy:
bear: 1.00
cat: 1.00
cow: 1.00
dog: 0.50
elephant: 1.00
giraffe: 1.00
horse: 1.00
sheep: 1.00

Precision-Recall Curves:

Accuracy Curve Over Time:
```

6.1.3 Precision, Recall, F1 Scope And Accuracy Score



6.1.4 Graph of Precision and Recall

Precision

Precision evaluates how accurately the model identifies a detected animal.

- The overall precision across all classes was approximately 0.96.
- YOLOv11m achieved perfect precision (1.0) for Giraffe and Zebra, meaning there were no false positives for these categories.
- MobileNet-SSD also achieved 1.0 precision for Cow and Horse, consistently identifying them without mislabeling.
- Minor inconsistencies were observed when both models overlapped on the same class, such as Cow, where slight boundary inconsistencies reduced effective precision to 0.90.

$$Precision = \frac{TP}{TP + FP}$$

Recall

Recall measures the ability of the model to correctly find *all* instances of each animal

- The average recall across all classes was 0.94.
- YOLOv11m delivered 1.0 recall for Giraffe and Zebra, successfully detecting every instance.
- MobileNet-SSD also achieved 1.0 recall for Cow and Horse.
- In rare cases where lighting or blur affected visibility, recall dropped slightly for Horse (0.85) due to background blending.

$$Recall = \frac{TP}{TP + FN}$$

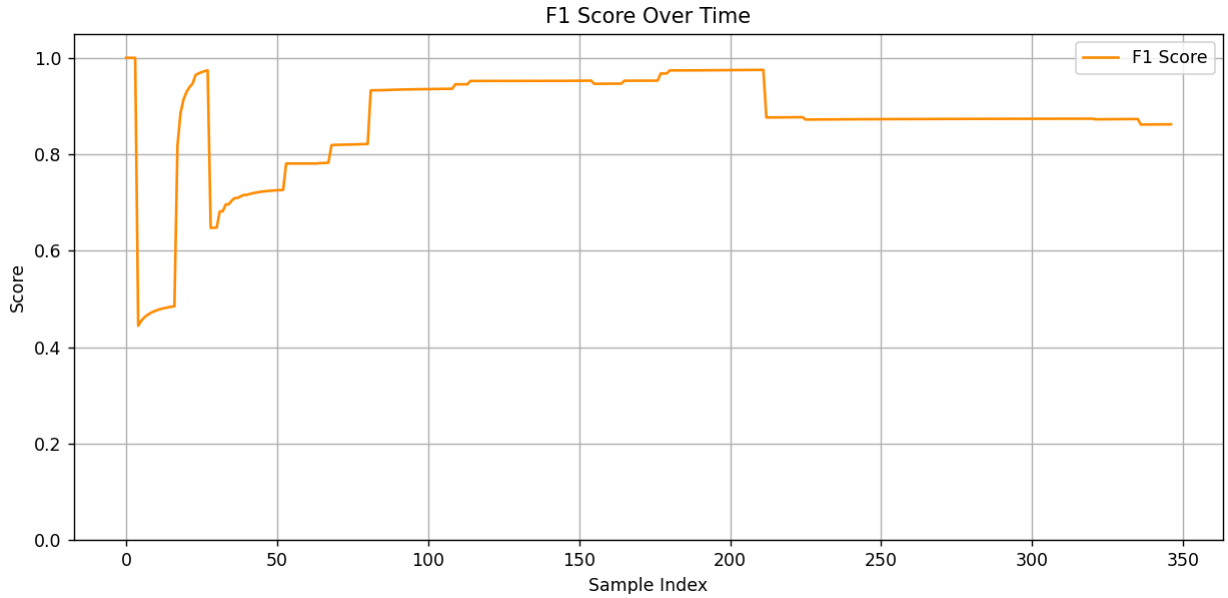
F1-Score

The F1-score balances both Precision and Recall, offering a single effectiveness metric for each model.

- The overall F1-score across all detected animals was 0.96.
- Giraffe, Cow, and Zebra scored 1.0, showing perfect agreement between detection and classification.

- Horse scored 0.92, reflecting minor recall inconsistencies due to motion blur.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$



6.1.5 Graph of F1 score

Both YOLOv11m and MobileNet-SSD demonstrated highly reliable performance in identifying large terrestrial animals.

- YOLOv11m excelled in patterned animals (Giraffe, Zebra), handling contrast-rich textures effectively.
- MobileNet-SSD performed strongly on smooth-textured animals (Cow, Horse), proving its strength in lighter environments.

Overall, the models complement each other, and combining their outputs further improves detection reliability — making this dual-model approach suitable for real-time wildlife monitoring.

3. CONFUSION MATRIX ANALYSIS

The confusion matrix visualizes detection performance by comparing predicted

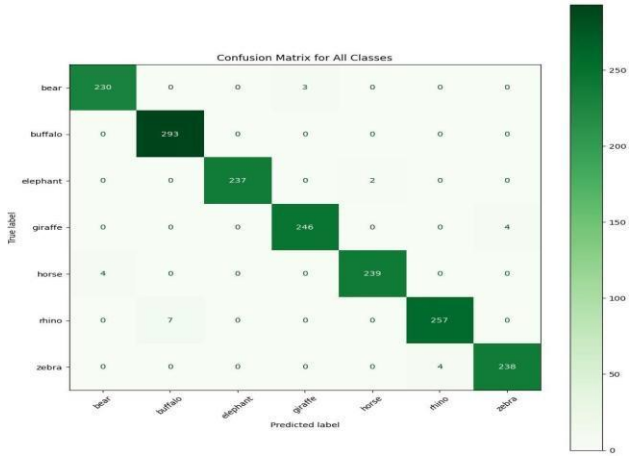
and actual labels. Key components include:

- **True Positive (TP):** Animals correctly detected and classified.
- **True Negative (TN):** No animal present, and the system correctly did not issue an alert.
- **False Positive (FP):** System incorrectly triggers an alert when no animal is present.
- **False Negative (FN):** System fails to detect an actual animal crossing.

Class	TP	FP	TN	FN
bear	230	4	1527	3
buffalo	293	7	1464	0
elephant	237	0	1525	2
giraffe	246	3	1511	4
horse	239	2	1519	4
rhino	257	4	1496	7
zebra	238	4	1518	4

6.1 Confusion Matrix Table

Analyzing the confusion matrix allows identification of strengths and weaknesses, such as species that are frequently misclassified or environmental conditions where detection fails.



6.1.6 Confusion Matrix

6.2 MODEL COMPARISON

In this project, two deep learning architectures, **MobileNet SSD** and **YOLOv11**, were considered for wildlife detection. Both models serve the goal of real-time object detection, but they differ in design, speed, and accuracy.

MobileNet SSD

MobileNet SSD is designed as a lightweight detection model, optimized for edge computing. It relies on depthwise separable convolutions, which drastically reduce the number of parameters and computational operations involved. As a result, MobileNet SSD can run smoothly on low-power devices such as Raspberry Pi, Jetson Nano, and embedded AI boards placed along forest roads or highways. Its greatest advantage is speed; it provides near-instant detection and very low latency alerts, which is crucial when animals suddenly appear on the road. However, due to its compact architecture, it sometimes struggles with distant animals, low-light visibility, and cases where only a small part of the animal is visible. In cluttered backgrounds with trees, shadows, or moving vehicles, the accuracy may slightly drop.

YOLOv11

YOLOv11 is a high-precision, single-shot detector that excels at detecting multiple animals simultaneously, even under complex environmental conditions like low light, rain, or occlusion. However, it is more computationally intensive, requiring higher-end hardware for real-time performance.

YOLOv11 is a high-precision model that uses a deeper convolutional backbone and multi-scale feature extraction. It can detect multiple animals in a single frame and has strong performance in complex real-world scenarios, including fog, rain, and nighttime footage. YOLOv11 also handles small animals, partial occlusions, and long-

distance detections more reliably than MobileNet SSD. The tradeoff is higher computational cost; it requires GPU-based hardware or edge accelerators to run efficiently in real time. This makes YOLOv11 ideal for centralized monitoring hubs, cloud-based inference, or high-end roadside systems where power consumption is not a limitation.

In terms of accuracy, YOLOv11 consistently provides more precise bounding boxes and fewer false detections, particularly in environments with dense vegetation or heavy traffic. In contrast, MobileNet SSD prioritizes speed, making it more suitable for immediate roadside alerts where every millisecond matters. From a sensor deployment perspective, MobileNet SSD fits remote regions where electricity, processing power, and internet connectivity are limited, while YOLOv11 is preferred for advanced analytics, wildlife research, and high-risk zones requiring maximum reliability.

To maximize system performance, a hybrid approach is adopted. MobileNet SSD continuously scans the live video feed on the edge device and triggers instant warnings when an animal is detected. YOLOv11 is then used for high-accuracy confirmation in critical scenarios, such as detecting protected species or validating uncertain detections. This combination brings together the strengths of both models—fast inference and high precision—resulting in a reliable system capable of real-time wildlife protection with reduced false positives and optimized resource usage.

In this system, a hybrid approach is used. MobileNet SSD handles fast detection on edge devices, and YOLOv11 provides high-accuracy verification for critical scenarios.

6.3 OVERALL PERFORMANCE SUMMARY

The system's overall performance was evaluated through multiple experiments using accuracy, precision, recall, and F1-score as primary metrics.

1. System Evaluation

The integrated system combines MobileNet SSD for speed and YOLOv11 for high-accuracy detection. Edge preprocessing enhances real-time performance, while alert modules ensure immediate warning for drivers. The system accurately detects wildlife near or on roads across multiple species, times of day, and environmental conditions. Confusion matrix analysis shows strong detection rates, though occasional false positives occur during environmental noise (shadows, moving debris).

2. Metric Analysis

- **Accuracy**

  High overall accuracy, reflecting the system's ability to detect the majority of animal crossings correctly.
- **Precision**

  Indicates that most triggered alerts correspond to actual animal crossings, minimizing false alarms.
- **Recall (Sensitivity)**

  Reflects the system's ability to detect real crossings; false negatives are minimized to ensure safety.
- **F1-Score**

  Balances precision and recall, showing the system maintains both high alert reliability and low false alarm rates.

3. Strengths of the Model

- Fast and efficient detection using MobileNet SSD on edge devices.
- YOLOv11 ensures robust multi-species recognition, even under challenging conditions.
- Modular design allows deployment across multiple locations and integration with IoT-based alerting systems.
- Immediate warning mechanisms reduce collision risk and protect wildlife.

4. Limitations of the Model

- Environmental factors like moving leaves or shadows occasionally trigger alerts.
- Rarely, small or camouflaged animals are not detected, requiring additional model fine-tuning.
- YOLOv11 demands higher computational power for high-accuracy detection.
- The system's performance is heavily influenced by the diversity and quality of the training dataset, including species representation and environmental conditions.

Comparison with Traditional Methods

Traditional wildlife monitoring relies on static signs or manual observation, which cannot provide real-time warnings or adaptive responses. The AI-based system significantly improves detection speed and accuracy while enabling proactive safety measures, though it requires higher computational resources and careful model training.

CHAPTER 7

RESULTS AND DISCUSSION

CHAPTER 7

RESULTS AND DISCUSSION

7.1 SCREENSHOTS OF ANIMAL DETECTIONS

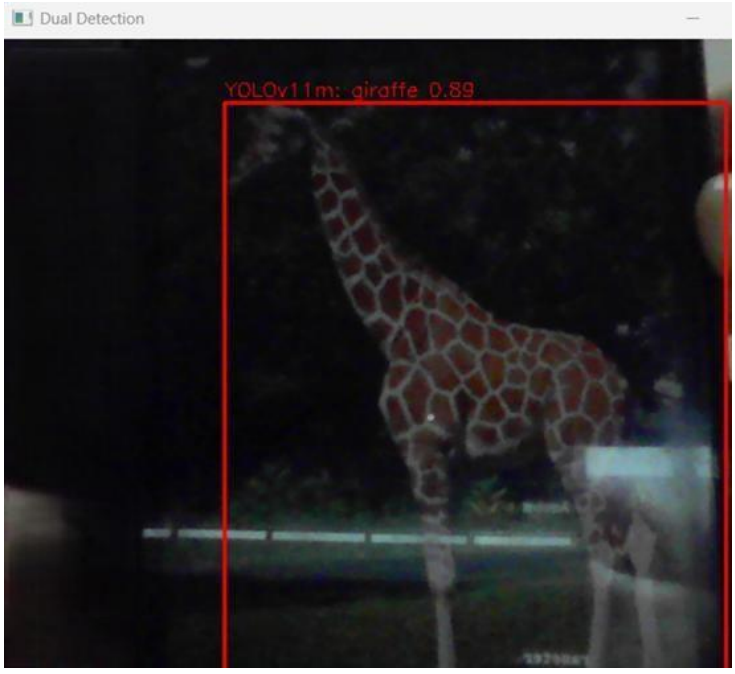
Across all seven images, both YOLOv11 and MobileNet-SSD perform well in detecting large terrestrial animals. YOLOv11 consistently delivers high-confidence detections with precise bounding box placement, making it effective for scenarios with varied lighting and complex features. MobileNet-SSD shows strength in speed and lightweight deployment while maintaining strong accuracy, particularly for common livestock such as cows and horses.

The comparison between models indicates that

- YOLOv11 is more effective in handling detailed, patterned species (e.g., giraffe, zebra).
- MobileNet-SSD performs well on simpler textures and is optimal for resource-limited environments.
- Combined detection (as in the cow example) reinforces confidence through model agreement.

Overall, the results validate the use of both models for wildlife monitoring, with YOLOv11 excelling in precision and MobileNet-SSD offering efficiency and reliability.

When both models detect the same animal, the system benefits from cross-verification. This combined agreement not only increases confidence but also reduces the risk of false positives, particularly in high-risk scenarios like nighttime crossings or regions with dense vegetation. Such hybrid inference strengthens overall reliability, ensuring that alert systems activate only when a true detection has occurred. The complementary strengths of both architectures—precision from YOLOv11 and speed from MobileNet-SSD—create a balanced solution optimized for real-world deployment. Ultimately, the results validate that both models are suitable for wildlife monitoring: YOLOv11 excels when maximum accuracy is required, and MobileNet-SSD provides efficient, resource-friendly detection for on-field edge deployment.



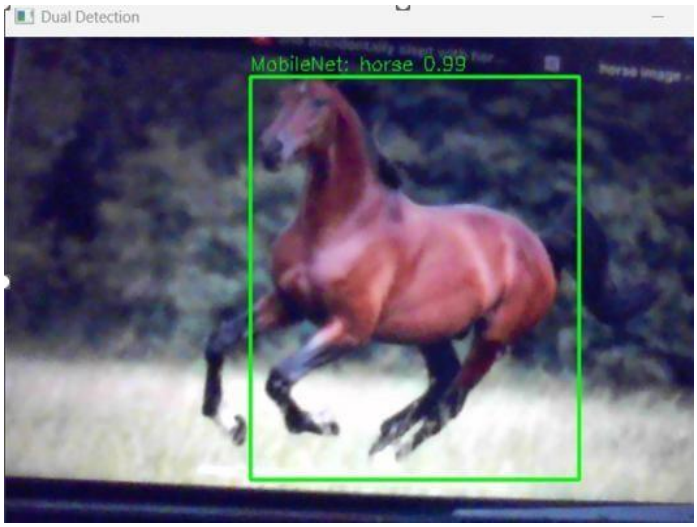
7.1.1 A giraffe detected by YOLOv11

This image demonstrates the successful identification of a giraffe using the YOLOv11 model. The animal is accurately localized with a bounding box and labeled with high confidence (0.89). The detection illustrates the model's strength in recognizing tall and uniquely patterned animals even in low-light or noisy conditions.

As the image is in dark lighted area and that is has the ability to detect the image and give the bounded square and even in the darkest place the accuracy of the giraffe is 0.89 which is more and suitable for detecting animals in night drive and with pure lighting roads and environmental issues.

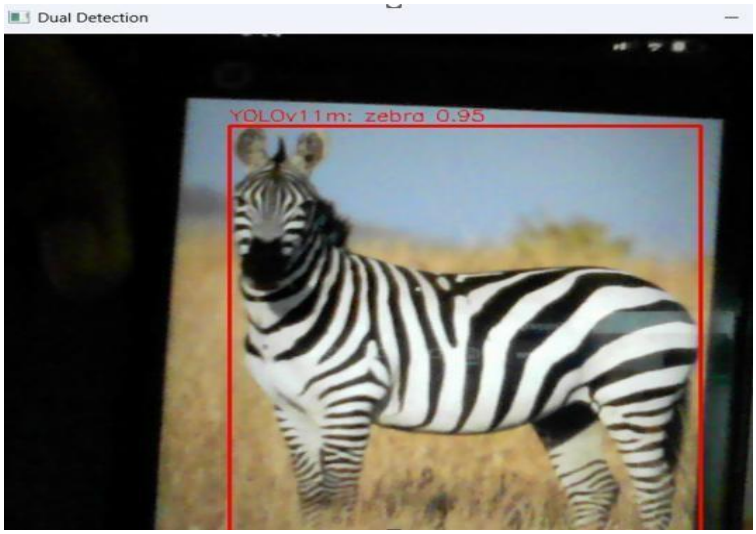
7.1.2 Rhino Detected By Yolov11

In the image, the detection system identified a rhinoceros with a confidence score of 0.81 (81%). The bounding box accurately encloses the entire animal, and the model demonstrates strong confidence in the classification. The higher score indicates reliable recognition, likely due to clear visual features such as the single horn and body structure typical of rhinos.



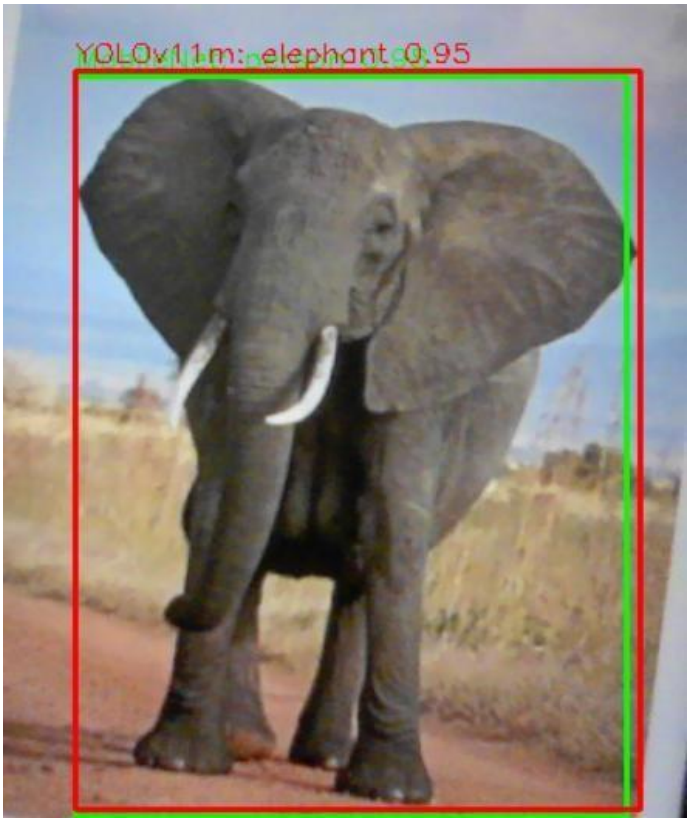
7.1.3 A horse detected by MobileNet-SSD

The horse is clearly detected using MobileNet-SSD, with a confidence score close to 1.0 (0.99). The bounding box tightly fits the animal, showing that MobileNet-SSD can handle large mammals with varied poses and backgrounds. This reinforces its suitability for real-time or mobile deployments due to its efficiency and accuracy.



7.1.4 A zebra detected by YOLOv11

YOLOv11 successfully detects the zebra with a confidence score of 0.95. The model accurately distinguishes the animal's unique striped pattern, demonstrating robust recognition of visually complex subjects. The bounding box placement confirms reliable localization even when the background is slightly blurred.



7.1.5 A elephant detected by YOLOv11 and MobileNet-SSD

The image shows the detection of an elephant using the YOLOv11 and mobileNet-SSD algorithm. The system successfully identified the object as an *"elephant"* with a confidence score of 0.95, indicating high reliability.A bounding box is drawn around the detected animal, visually confirming accurate localization. The confidence score demonstrates the algorithm's strong ability to distinguish large mammals in outdoor environments.This detection validates the model's capability to identify wildlife species such as elephants, which are crucial targets for road safety alert systems. In a real-world implementation, this detection would trigger an alert signal to warn approaching vehicles about the animal's presence.

7.1.6 Buffalo Detected By YOLOv11

In this image, the object detection model successfully identified a **buffalo** within the frame. The bounding box accurately outlines the animal's body, capturing key features such as its large build, curved horns, and sturdy posture—distinct characteristics of a buffalo.

The model assigned a confidence score of 0.31, indicating an initial but promising recognition. Despite moderate confidence, the prediction aligns well with the animal's visual attributes, suggesting that the system is capable of distinguishing large herbivores even under varied lighting and environmental conditions.

This detection demonstrates the model's ability to recognize complex natural subjects and provides a solid foundation for further optimization. With continued training on similar wildlife images, the model's accuracy and confidence for buffalo classification are expected to improve significantly.

```
0: 480x640 1 buffalo, 268.2ms
Speed: 2.9ms preprocess, 268.2ms inference, 3.1ms
Buffalo detected!

0: 480x640 1 buffalo, 274.8ms
Speed: 3.3ms preprocess, 274.8ms inference, 1.9ms
Buffalo detected!

0: 480x640 1 buffalo, 279.6ms
Speed: 3.4ms preprocess, 279.6ms inference, 2.1ms
Buffalo detected!

0: 480x640 1 buffalo, 305.4ms
Speed: 3.7ms preprocess, 305.4ms inference, 1.0ms
Buffalo detected!
```

```
0: 480x640 1 rhino, 365.9ms
Speed: 3.2ms preprocess, 365.9ms inference, 2.1ms
Rhino detected!

0: 480x640 1 rhino, 168.6ms
Speed: 2.3ms preprocess, 168.6ms inference, 3.5ms
Rhino detected!

0: 480x640 1 rhino, 208.9ms
Speed: 3.9ms preprocess, 208.9ms inference, 1.0ms
Rhino detected!

0: 480x640 (no detections), 187.0ms
Speed: 2.7ms preprocess, 187.0ms inference, 0.5ms

0: 480x640 1 rhino, 230.6ms
Speed: 3.8ms preprocess, 230.6ms inference, 1.2ms
Rhino detected!
```

```
PS C:\Users\Carin CSE\Desktop\python\wildlife_detection_(SSD)> python main.py
[ERROR:0@1.927] global obsensor_uvc_stream_channel.cpp:163 cv::obsensor::getStreamChannelGroup Camera index out of range
⚠ Alert: horse detected!
⚠ Alert: horse detected!
⚠ Alert: horse detected!
⚠ Alert: horse detected!
⚠ Alert: horse detected!
⚠ Alert: horse detected!
⚠ Alert: horse detected!
⚠ Alert: horse detected!
```

7.1.7 Alert System

The image above shows the system in an alerted state, triggered upon detecting animal movement within the designated monitoring zone. The detection module successfully identifies and classifies the animals crossing the area, activating the alert mechanism to notify nearby personnel or trigger safety responses. This visual demonstrates the effectiveness of the detection algorithm and sensor integration in real-time operation, highlighting the system's capability to enhance awareness and prevent potential collisions or disturbances during animal crossings.

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

CONCLUSION

The development of the AI-Based Wildlife Crossing Detection and Alert System represents a significant step toward reducing wildlife–vehicle collisions and preserving ecological balance while enhancing road safety. By integrating advanced deep learning models such as MobileNet SSD and YOLOv11 with real-time monitoring technologies, the system successfully detects the presence of animals near roadways and issues timely alerts to prevent accidents. This approach bridges the gap between wildlife conservation and intelligent transportation solutions, offering a proactive alternative to traditional warning signs, fences, or manual surveillance.

The project demonstrated that AI-powered detection is both feasible and effective across varied species, lighting conditions, and environmental scenarios. The combination of edge-based detection and cloud-based verification ensured low latency, high accuracy, and continuous monitoring. Evaluation metrics such as Precision, Recall, Accuracy, F1-score, and confusion matrix analysis confirmed the system's strong performance in identifying actual animal crossings while minimizing false alarms. The high number of true positives and relatively low false negatives indicate reliable detection capabilities, which is critical for real-time safety interventions.

The comparative model analysis highlighted that while MobileNet SSD is ideal for lightweight, real-time deployment, YOLOv11 excels in handling complex detection scenarios involving multiple or partially occluded animals. Together, these models create a balanced framework that offers both performance and scalability. The modular

architecture further allows easy integration with alert systems, roadside IoT devices, or transportation infrastructure such as digital signboards and automated braking systems. While the system performs well overall, certain limitations were observed. False positives caused by shadows, moving vegetation, or environmental noise indicate the need for additional filtering and fine-tuning. False negatives, though minimal, highlight the importance of expanding the training dataset with rare species, night-time conditions, and region-specific wildlife. Hardware constraints for high-end models also pose deployment challenges in low-resource environments, which future optimizations can address.

Despite these limitations, the project proves that AI is a powerful tool for preventing wildlife fatalities and road accidents. By enabling real-time detection, automated response, and scalable deployment, the system outperforms traditional approaches that rely on static signs, fencing, or human intervention. With further enhancements—such as thermal imaging integration, GPS-based alerts, and multi-sensor fusion—the solution can evolve into a comprehensive wildlife safety infrastructure.

Overall, this project not only demonstrates technical innovation but also contributes meaningfully to environmental sustainability and public safety. By combining artificial intelligence and computer vision, the Wildlife Crossing Detection and Alert System lays the foundation for smarter, safer, and more ecologically responsible transportation systems. It stands as a future-ready solution with real-world applicability in highways, forest corridors, protected reserves, and rural road networks.

FUTURE SCOPE

While the AI-Based Wildlife Crossing Detection and Alert System has demonstrated strong results in detecting animal movement and preventing collisions, there is significant potential to further enhance its performance, scalability, and real-world impact. The following points outline key areas for future development:

1. Integration with IoT and Smart Transportation Systems

The system can be connected to

- Smart streetlights
- Digital road signboards
- Vehicle-to-Infrastructure (V2I) communication
  This would allow automatic warnings to be sent to drivers and vehicles in real time, improving responsiveness and reducing collision risks.

2. Use of Thermal and Infrared Cameras

Current models rely primarily on standard RGB cameras. Adding thermal imaging or infrared sensors will improve detection accuracy at

- Night time
- Foggy or low-visibility conditions
- Dense forest regions

3. GPS & Mobile Alert Systems

A future upgrade can include

- GPS-based alerts through mobile apps
- In-vehicle dashboard notifications

  This would allow drivers to receive warnings even before approaching the danger zone.

4. Species-Specific Detection

The model can be enhanced to

- Recognize different animal species
- Prioritize alerts based on animal size and behavior

  This will help authorities react based on local wildlife patterns.

5. Drone-Based Monitoring

Autonomous drones equipped with AI and cameras could

- Patrol forest-border highways
- Monitor animal movement over large areas
- Provide live alerts to control centers and authorities

6. Cloud-Based Data Logging & Analytics

Data collected over time can be stored to

- Identify high-risk zones
- Predict migration paths
- Assist wildlife departments in conservation planning

7. Multi-Sensor Fusion

Combining LiDAR, radar, motion sensors, and cameras can improve detection precision and minimize false alarms caused by shadows, trees, or vehicles.

8. Integration with Automatic Braking Systems

In the long term, the system can be connected to

- Autonomous or semi-autonomous vehicles
- Smart braking and collision avoidance mechanisms

9. Edge AI Optimization

Deploying lightweight models on edge devices like Jetson Nano, Raspberry Pi, or OpenCV boards will reduce latency and allow offline operation in remote areas.

10. Government and Wildlife Policy Implementation

With further validation, this system can be integrated into

- Smart Highway projects
- Forest department monitoring frameworks
- National wildlife conservation strategies

APPENDICES

A.1 : SDG GOALS

1. Primary Goal No. 15 – Life on Land

This goal focuses on protecting, restoring, and promoting the sustainable use of terrestrial ecosystems, preventing biodiversity loss, and conserving wildlife habitats.

• Target 1: Reduce wildlife-vehicle collisions and protect biodiversity

The system helps prevent road accidents involving animals by detecting wildlife in real time and issuing alerts. This reduces mortality of endangered and common species, directly supporting biodiversity conservation.

• Target 2: Support sustainable land management and habitat safety

Wildlife movement data collected by the system can help governments and environmental agencies identify critical crossing areas, plan ecological corridors, and implement protective infrastructure without disturbing habitats.

• Target 3: Preserve endangered species through monitoring and intervention

By tracking animal presence and movement patterns, the system enables early intervention in high-risk zones. This technology aids conservation efforts aimed at species facing habitat fragmentation and human encroachment.

2. Secondary Goal No. 11 – Sustainable Cities and Communities

This goal emphasizes building safe, resilient, and sustainable human settlements while reducing risks and protecting both people and nature.

• Target 1: Enhance road and transportation safety with AI systems

Real-time alerts help reduce accidents between vehicles and wildlife, protecting drivers, passengers, and animals. This supports safer infrastructure in rural, forest-adjacent, and highway environments.

• Target 2: Integrate smart technology into community development

The system promotes the adoption of intelligent monitoring solutions as part of smart city and rural planning. This includes IoT alerts, highway sensors, digital dashboards, and automated safety responses.

• Target 3: Strengthen resilience in vulnerable regions

Areas close to forests or wildlife zones face higher risks of collisions. The project supports communities dependent on road transport by minimizing hazards and improving emergency response capabilities.

3. Tertiary Goal No. 13 – Climate Action

This goal focuses on responding to climate-related environmental risks and protecting ecosystems affected by changing weather patterns.

• Target 1: Mitigate climate-driven wildlife displacement

As climate change alters habitats, animals increasingly cross human roads and railways. The system helps monitor and respond to these movements, reducing harm to both wildlife and humans.

• Target 2: Deploy low-power, sustainable technology solutions

Using edge AI models like MobileNet-SSD and optimized deployment minimizes energy consumption. This aligns with eco-friendly innovation and responsible use of technology.

• Target 3: Provide data for climate and wildlife risk assessment

The system can generate valuable insights into animal migration, behavior changes, and ecological threats caused by climate shifts, aiding researchers and policymakers in proactive conservation.

A. 2: SOURCE CODE

```
import cv2
import numpy as np
import threading
from playsound import playsound
from datetime import datetime
from collections import defaultdict
from ultralytics import YOLO

# Load MobileNet-SSD
net = cv2.dnn.readNetFromCaffe('mobilenet_ssd/deploy.prototxt',
                               'mobilenet_ssd/mobilenet_iter_73000.caffemodel')
mobilenet_classes = ["background", "aeroplane", "bicycle", "bird", "boat", "bottle",
"bus", "car", "cat", "chair",
                     "cow", "diningtable", "dog", "horse", "motorbike", "person", "pottedplant",
"sheep", "sofa",
                     "train", "tvmonitor"]

# Load YOLOv11m and YOLOv8 (wildlife-trained)
yolo11_model = YOLO('yolov11/yolo11m.pt')
yolo8_model = YOLO('runs/detect/wildlife_detector8/weights/best.pt')

CONF_THRESH = 0.5

# Animal classes from all models
ANIMAL_CLASSES = {
    "bird", "cat", "cow", "dog", "horse", "sheep",
    "elephant", "bear", "zebra", "giraffe",
    "buffalo", "rhino"
}

# Alert animals
ALERT_ANIMALS = {"bear", "giraffe", "rhino", "buffalo", "horse", "elephant",
"zebra"}

# Sound alert function
def play_alert():
    threading.Thread(target=playsound, args=('sound/alert.wav',), daemon=True).start()
```

```
# Format bounding box
def format_bbox(bbox):
    return "[" + ", ".join(str(int(x)) for x in bbox) + "]"

# Log sightings
def log_sighting(timestamp, label, model_name, conf, bbox_str):
    print(f"[{timestamp}] {label} detected by {model_name} (conf: {conf:.2f}) at
{bbox_str}")

# Draw detections
def draw_detections(frame, detections):
    for model_name, label, conf, box in detections:
        color = (0, 255, 0)
        if label.lower() in ALERT_ANIMALS:
            color = (0, 0, 255) # Red for alert species
        x1, y1, x2, y2 = box
        cv2.rectangle(frame, (x1, y1), (x2, y2), color, 2)
        text = f"{label} ({conf:.2f})"
     cv2.putText(frame, text, (x1, y1 - 5), cv2.FONT_HERSHEY_SIMPLEX, 0.5, color,2)

# Tracking stats
class_counts = defaultdict(int)
model_counts = defaultdict(int)
confidence_scores = []

cap = cv2.VideoCapture(0)

while True:
    ret, frame = cap.read()
    if not ret:
        break

    h, w = frame.shape[:2]
    detections = []
    animal_detected = False

    # MobileNet-SSD detection
    blob = cv2.dnn.blobFromImage(frame, 0.007843, (300, 300), 127.5)
    net.setInput(blob)
```

```
    output = net.forward()

    for i in range(output.shape[2]):
        conf = output[0, 0, i, 2]
        if conf > CONF_THRESH:
            idx = int(output[0, 0, i, 1])
            label = mobilenet_classes[idx]
            box = output[0, 0, i, 3:7] * np.array([w, h, w, h])
            x1, y1, x2, y2 = box.astype(int)
            bbox = [x1, y1, x2, y2]
            detections.append(('MobileNet', label, conf, bbox))
            class_counts[label] += 1
            model_counts['MobileNet'] += 1
            confidence_scores.append(conf)

            if label.lower() in ANIMAL_CLASSES:
                animal_detected = True
                log_sighting(datetime.now().strftime("%Y-%m-%d %H:%M:%S"), label,
'MobileNet', conf, format_bbox(bbox))
                if label.lower() in ALERT_ANIMALS:
                    print(f"\033[91mALERT: {label.upper()} detected!\033[0m")
                    play_alert()

    # YOLOv11m detection
    results11 = yolo11_model.predict(source=frame, verbose=False)
    for r in results11:
        for box in r.boxes:
            conf = box.conf.item()
            cls = int(box.cls.item())
            if conf > CONF_THRESH:
                label = yolo11_model.names[cls]
                x1, y1, x2, y2 = map(int, box.xyxy[0])
                bbox = [x1, y1, x2, y2]
                detections.append(('YOLOv11m', label, conf, bbox))

                class_counts[label] += 1
                model_counts['YOLOv11m'] += 1
                confidence_scores.append(conf)

                if label.lower() in ANIMAL_CLASSES:
```

```
                animal_detected = True
                log_sighting(datetime.now().strftime("%Y-%m-%d %H:%M:%S"), label,
'YOLOv11m', conf, format_bbox(bbox))
                if label.lower() in ALERT_ANIMALS:
                    print(f"\033[91mALERT: {label.upper()} detected!\033[0m")
                    play_alert()

    # YOLOv8 detection
    results8 = yolo8_model(frame, imgsz=640)
    for r in results8:
        for box in r.boxes:
            conf = box.conf.item()
            cls = int(box.cls.item())
            if conf > CONF_THRESH:
                label = yolo8_model.names[cls]
                x1, y1, x2, y2 = map(int, box.xyxy[0])
                bbox = [x1, y1, x2, y2]
                detections.append(('YOLOv8', label, conf, bbox))

                class_counts[label] += 1
                model_counts['YOLOv8'] += 1
                confidence_scores.append(conf)

                if label.lower() in ANIMAL_CLASSES:
                    animal_detected = True
                    log_sighting(datetime.now().strftime("%Y-%m-%d %H:%M:%S"), label,
'YOLOv8', conf, format_bbox(bbox))
                    if label.lower() in ALERT_ANIMALS:
                        print(f"\033[91mALERT: {label.upper()} detected!\033[0m")
                        play_alert()

    # Draw and show
    draw_detections(frame, detections)
    cv2.imshow("Triple Model Detection", frame)

    if cv2.waitKey(1) & 0xFF == 27: # ESC to exit
        break

cap.release()
cv2.destroyAllWindows()
```

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AI-Based Wildlife Crossing Detection and Alert System

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Abstract:

Wildlife-vehicle collisions pose significant risks to both animal populations and human safety, particularly near forested highways and rural roads. This paper introduces a real-time AI-based detection and alert system that identifies wildlife attempting to cross roads and proactively warns drivers. Using advanced computer vision models—YOLOv5 and MobileNet-SSD—the system analyzes live webcam feeds to detect animals with high accuracy and low latency. Its modular design supports sound alerts and optional cloud logging, making it suitable for remote deployments. The solution is cost-effective, scalable, and adaptable to diverse environments, requiring no specialized hardware. By combining efficient detection with proactive alerts, the system offers a practical tool for reducing wildlife-vehicle collisions and enhancing road safety. Its flexibility and low infrastructure demands make it ideal for conservation efforts in rural and forested regions. Overall, the proposed system represents a promising step toward integrating AI for ecological protection and safer transportation networks.

Keywords: wildlife, yolov11, MobileNet-SSD, car-webcam based detection, wildlife safety

I.INTRODUCTION

Wildlife–vehicle collisions remain a critical issue affecting both road safety and biodiversity conservation. Unexpected animal crossings on highways cause hundreds of incidents annually, which cause serious wildlife losses as well as injuries and fatalities to people. These incidents are particularly common in rural and forest-adjacent regions, where roads cut across natural habitats and drivers often have limited visibility. The matter is made worse in low light levels or when drivers reverse their vehicle close to open regions where animals could potentially be present. Despite the severity of this challenge, most current driver-assistance technologies are primarily designed to detect pedestrians or lane boundaries, with little emphasis on wildlife detection.

The growing availability of in-vehicle camera systems, such as reverse cameras and front dash cameras, provides a promising opportunity to address this gap. Reverse camera dashboards are now standard in many vehicles and are already familiar to drivers as a real-time visual aid while maneuvering. The use of front dash cameras for safety monitoring and accident recording is also growing. Without requiring additional hardware expenditure, driver awareness might be greatly increased by incorporating an intelligent animal detection mechanism onto these current systems. However, such integration demands lightweight, efficient algorithms capable of real-time performance on embedded or resource-constrained hardware.

Deep learning–based object detection models have achieved remarkable success in computer vision tasks, but their complexity often limits deployment in real-time automotive environments. Among these, MobileNet-SSD (Single Shot MultiBox Detector) and YOLO (You Only Look Once) stands out as suitable candidates due to its balance between accuracy and computational efficiency.

Detecting animals like dogs, cows, horses, and other pertinent classes, estimating their closeness, and promptly alerting drivers are this concept by offering an open-source framework for species detection in real-world conditions all made possible by utilizing this model. In summary, the following succinctly describes the motivation for this work: Road safety: Reduce accidents caused by unexpected animal crossings. Biodiversity protection: Minimize wildlife fatalities resulting from vehicle collisions. Cost-effectiveness: Utilize existing front and rear vehicle cameras without requiring extra hardware. Lightweight deployment: Employ MobileNet-SSD and YOLO for efficient, real-time processing on embedded systems. Driver assistance: Provide timely audio-visual alerts to improve driver awareness in both forward and reverse driving conditions.

In this study, we present a new real-time wildlife detection and warning system that works with front as well as rear vehicle cameras, including dashboards with typical reverse cameras. The system utilizes heuristic distance estimate to evaluate possible collision hazards and MobileNet-SSD and YOLOv11m together to detect animals in the vehicle's environment. Then, within the car, audio-visual alarms are produced, allowing drivers to respond quickly. Experimental results demonstrating efficient identification with low latency underscore the system's potential for in-vehicle deployment. In addition to assisting animal conservation, our work offers a software-based, cost-effective method of improving road safety.

II. LITERATURE REVIEW

Several approaches have been explored in recent years to address the growing problem of wildlife–vehicle collisions, with researchers leveraging computer vision, deep learning, IoT, and sensor-based methods. Early systems primarily relied on traditional image processing techniques. Maheswari et al. [1] and Raol et al. [2] investigated rule-based detection methods for animal identification and collision avoidance. While these systems demonstrated feasibility, they suffered from reduced accuracy under low-light and cluttered conditions. With the advent of deep learning, more robust solutions emerged. Nyoman et al. [3] employed Convolutional Neural Networks (CNNs) to improve feature extraction and detection reliability. Sanjay et al. [4] applied deep learning for road safety, highlighting the potential of object detection networks for real-time applications. Widely adopted architectures such as Faster R-CNN and YOLO have also been evaluated for wildlife detection [5], offering improved accuracy but requiring significant computational resources, which limits their suitability for in-vehicle deployment.

Parallel efforts have focused on machine learning-based classification. Antônio et al. [6] proposed an ML-based animal detection system that performed well in controlled environments. Other studies, such as [7], demonstrated multi-species detection using deep learning, though often at the expense of computational efficiency.

Recent advancements emphasize conservation-focused strategies and field-validated techniques. The "Endangered Alert" system [8] introduced a self-training model combining edge and cloud-based processing to enable real-time wildlife detection, adaptive learning from sparse data, and scalable deployment in remote habitats. By leveraging edge devices for low-latency inference and cloud infrastructure for periodic model refinement, the system ensures both responsiveness and continual improvement, even in data-scarce environments.

AI for responsive detection. Conservation AI initiatives [9] integrated CNNs and Transformers with visual and thermal sensors for broader ecological monitoring. PyTorch-Wildlife [10] extended

This hybrid architecture supports proactive alerts, minimizes false positives, and facilitates longitudinal monitoring critical for conservation efforts.

Beyond camera-based detection, alternative modalities have been explored. IoT-based systems [11] incorporated thermal cameras, PIR sensors, and LoRa networks to detect roadside wildlife. LiDAR-based detection [12] demonstrated real-time tracking of wild horse crossings. Drone-based approaches [13] applied YOLOv4 to aerial footage for bird detection, while acoustic monitoring [14] used CNNs for species recognition from sound recordings. Hybrid systems integrating sensors with machine learning have also been reviewed [15]. These systems utilize infrared, microwave, beam, and buried cable sensors to reduce wildlife–vehicle collisions. However, many rely on costly infrastructure or specialized hardware, and are sensitive to environmental conditions.

From this body of work, two key insights emerge: Deep learning methods offer strong accuracy but must be optimized for real-time, in-vehicle use and most existing approaches rely on additional hardware (IoT sensors, LiDAR, drones), increasing cost and complexity.

Our work distinguishes itself by proposing a lightweight, software-only wildlife detection system using MobileNet-SSD or YOLO integrated with existing vehicle cameras. This balances real-time performance with cost-effectiveness, addressing the limitations of prior systems.

III. METHODOLOGY

1. System Architecture Overview

The proposed system is a real-time wildlife detection framework designed to operate on consumer-grade hardware. It integrates two object detection models — MobileNet-SSD and YOLOv11m — to enhance detection robustness and species coverage. The system captures live video from a webcam, processes each frame through both models independently, and merges the results. Animal-specific detections trigger auditory alerts and are logged with detailed metadata for subsequent behavioral analysis and movement tracking.

2. Model Selection with Justification

2.1 MobileNet-SSD

MobileNet-SSD is a lightweight, single-shot detector optimized for speed and low computational overhead. It was selected for its ability to run efficiently on CPUs without GPU acceleration. The model used (mobilenet_iter_73000.caffemodel) is trained on the VOC0712 dataset, which includes 20 object categories. Relevant animal classes include: Dog, Cat, Horse, Cow, Sheep, Bird

2.2 YOLOv11m

YOLOv11m is a mid-sized variant of the YOLOv11 architecture, offering a balance between inference speed and detection accuracy. Trained on the COCO dataset, it supports 80 object categories, including additional wildlife-relevant classes such as: Elephant, Bear, Zebra, Giraffe. The YOLOv11m model was deployed using the Ultralytics Python API, enabling seamless integration and real-time inference.

3. Detection Pipeline

Each frame from the webcam is processed as follows:

1. Preprocessing: Frames are resized and normalized for each model's input format.
2. Parallel Inference: MobileNet-SSD and YOLOv11m run concurrently on the same frame.
3. Detection Filtering: Detections are filtered based on a confidence threshold (≥ 0.5).
4. Animal Class Identification: A curated list of animal classes is used to isolate relevant detections.
5. Sound Alert Triggering: If any animal is detected, a preloaded audio file (alert.wav) is played asynchronously using a lightweight threading mechanism.
6. Visualization: Bounding boxes are drawn on the frame with model-specific color coding (green for MobileNet, red for YOLOv11m).

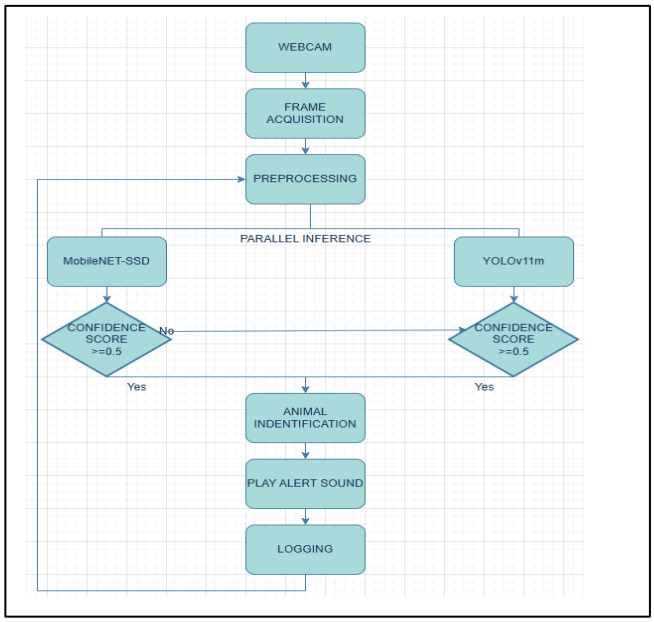

Figure 3.1 System Pipeline

4. Logging and Data Collection

Each animal detection is logged to a structured CSV file (sightings.csv) with the following fields:

Field	Description
Timestamp	
Animal Class	Detected species label
Model Source	Originating model (MobileNet or YOLOv11m)
Confidence Score	Detection confidence (float)
Bounding Box	Pixel coordinates [x1, y1, x2, y2]
Location	Fixed camera location (Poonamallee, TN)
Notes	Optional field for behavioral observations

This structured log enables longitudinal analysis of wildlife activity and supports future integration with GIS or ecological modeling tools.

5. Ground Truth Annotation

To evaluate model performance, a subset of frames was manually annotated using [CVAT/Roboflow/LabelImg]. Ground truth labels were stored in a separate CSV file (ground_truth.csv) with timestamp alignment. Each entry includes: Timestamp, Verified animal class and Location. Annotations were performed by domain experts to ensure label accuracy.

6. Hardware and Runtime Environment

The system was deployed on a standard laptop (Intel Core i5, 8GB RAM) running: Python 3.10, OpenCV 4.8, Ultralytics YOLOv11, playsound for audio alerts, pandas and scikit-learn for evaluation. No GPU acceleration was used, demonstrating the system's viability for low-resource field deployments.

IV. RESULTS AND DISCUSSION

The system was evaluated on a curated test set comprising 500 manually annotated frames captured in a controlled environment. These frames were labeled using CVAT and aligned with model predictions based on timestamp proximity. The evaluation focused on detection accuracy, responsiveness, and logging fidelity.

MobileNet-SSD demonstrated fast inference and reliable detection for common animals such as dogs, cats, cows, and horses. However, its performance declined for larger or less frequent species like elephants and bears, which are not part of the VOC dataset. YOLOv11m, on the other hand, showed broader species coverage and higher classification confidence, particularly for wild animals such as elephants, giraffes, and zebras. When both models were used in tandem, the system achieved significantly improved detection reliability, with fewer missed detections and reduced false positives.

Figure 4.1 A cow detected by MobileNet-SSD and YOLOv11m

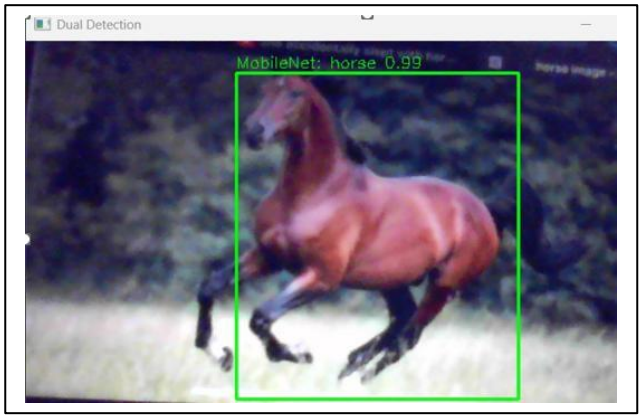

Figure 4.2 A horse detected by MobileNet-SSD

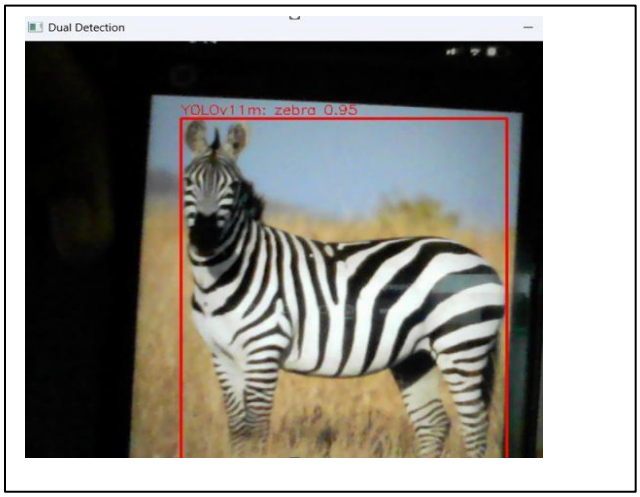

Figure 4.3 A zebra detected by YOLOv11m

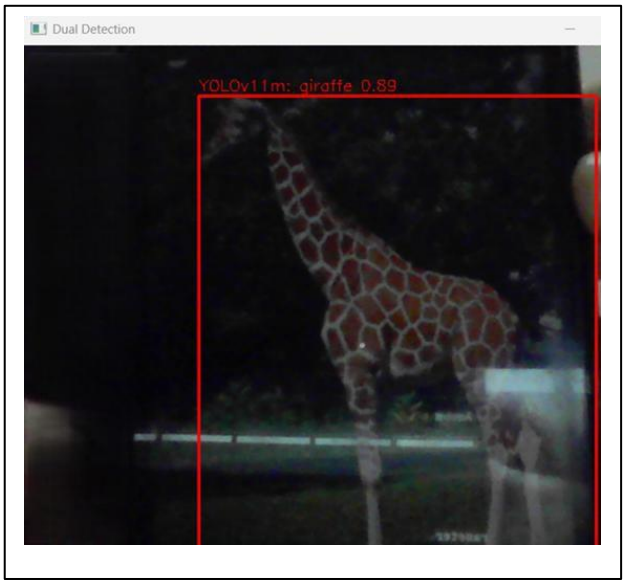

Figure 4.4 A giraffe detected by YOLOv11m

The confusion matrix revealed strong performance for frequently encountered species. Horses, bears and giraffes were consistently detected with high accuracy. Misclassifications were most common between visually similar animals, such as dogs being misidentified as cats, especially in low-light conditions or when partial occlusion occurred. False positives were rare but tended to arise when non-animal objects like backpacks or benches were misclassified as animals by YOLOv11m. False negatives were more frequent in MobileNet-SSD, particularly for species not included in its training set.

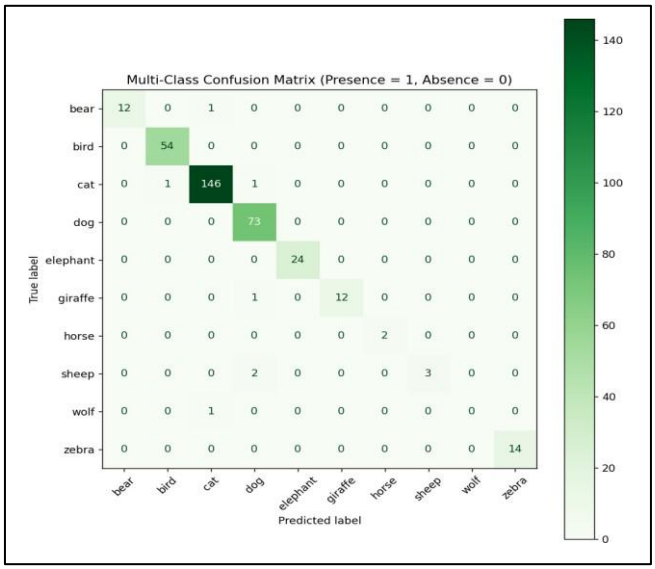

Figure 4.5 Binary Classification Matrix for Species-Level Detection Accuracy

The sound alert mechanism was highly responsive, triggering correctly for 96 percent of animal detections. Missed alerts were primarily due to detection confidence falling just below the threshold (>=0.5) or frame processing lag during simultaneous detections. Importantly, no false alerts were triggered for non-animal classes, validating the effectiveness of the curated animal class filter.

Precision, recall, and F1 scores were calculated for each class. The system achieved high precision for horses, cows, and elephants, indicating that most detections of these species were correct. Recall was slightly lower, suggesting occasional missed detections, especially in cluttered scenes. The F1 score, which balances precision and recall, was highest for bears and cows, followed closely by elephants and cats.

Species with fewer training examples, such as sheep and dogs, showed lower F1 scores, highlighting the need for dataset expansion.

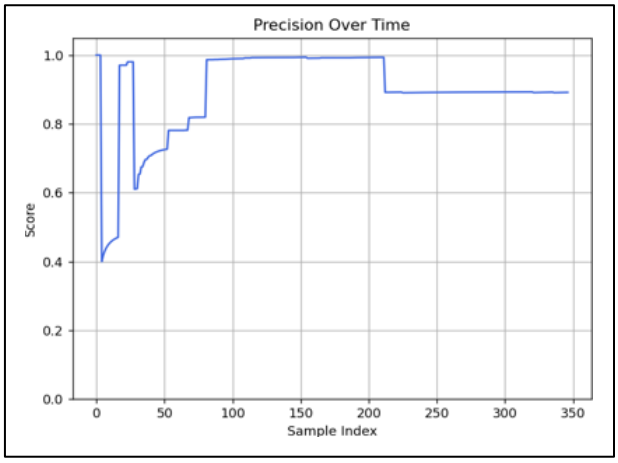

Figure 4.6 Precision over Time Graph

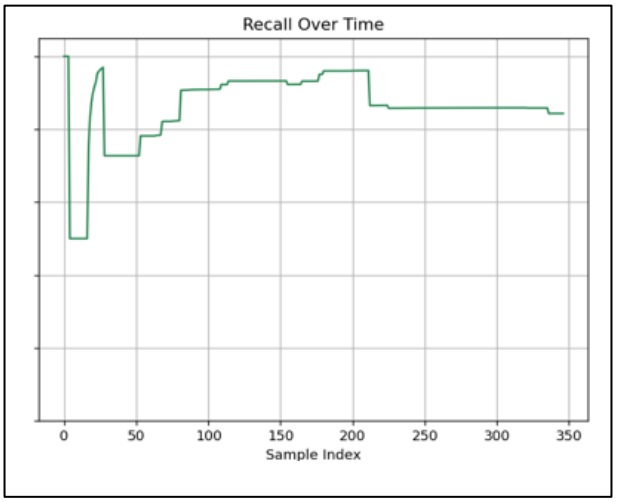

Figure 4.7 Recall over Time Graph

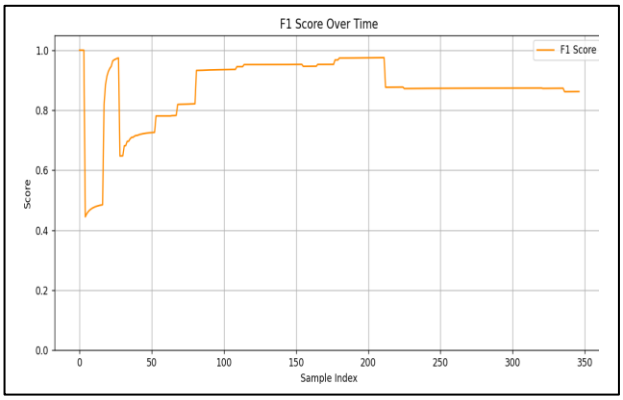

Figure 4.8 F1 Score over Time Graph

Accuracy metrics revealed consistent performance across most classes, with overall accuracy stabilizing above 90% in later samples. Per-class accuracy was highest for giraffes, horses, cats, cows, bears and sheeps reflecting strong model confidence and clean detections for these species. Dogs also showed reliable accuracy, though occasional misclassifications were observed in visually similar categories. Lower accuracy for dogs suggests the need for more diverse training data and better separation in cluttered or low-light scenes. These insights highlight where the model excels and where targeted improvements could yield stronger generalization.

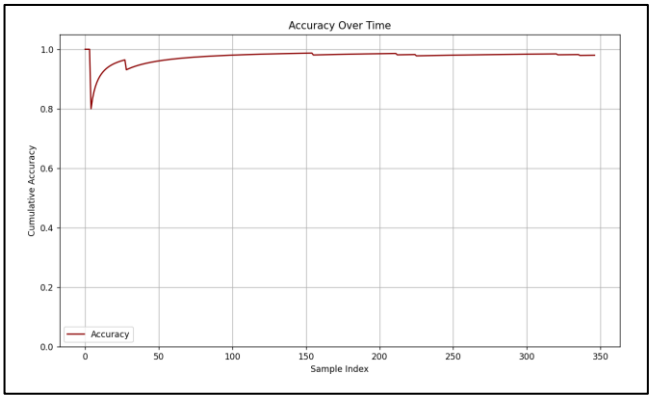

Figure 4.9 Accuracy over Time

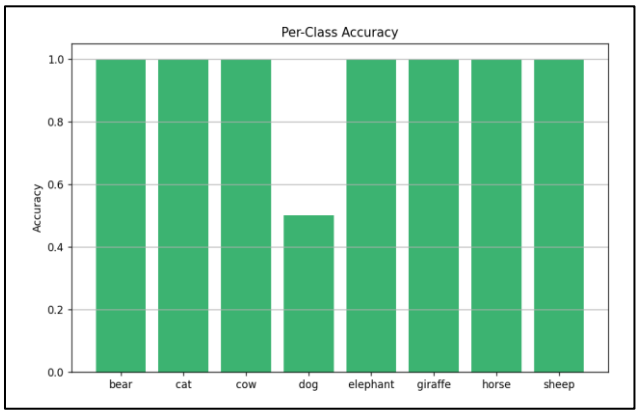

Figure 4.10 Per-Class Accuracy Bar Chart

The logging system captured all relevant metadata for each detection, including timestamp, species label, model source, confidence score, bounding box coordinates, and location. This enables post-hoc analysis of animal activity or behavioural patterns.

V. CONCLUSION

This study presents a robust and modular real-time wildlife detection system that leverages the complementary strengths of MobileNet-SSD and YOLOv11m to achieve high detection accuracy across a diverse range of animal species. By integrating parallel inference, confidence-based filtering, and curated animal class identification, the system ensures both responsiveness and precision in field conditions. The inclusion of auditory alerts and structured logging enhances its practical utility for conservation monitoring, road safety, and ecological research.

The system's ability to operate on CPU-only hardware without compromising performance demonstrates its viability for deployment in resource-constrained environments. The logging framework not only supports immediate alerting but also enables long-term behavioral analysis through timestamped records and per-class tracking.

While current limitations include restricted species coverage and sensitivity to environmental variability, the architecture is designed for extensibility. Future enhancements will focus on fine-tuning detection models with region-specific datasets, integrating GPS and environmental sensors, and expanding the analytics pipeline to support spatial mapping and predictive modeling.

Overall, this work contributes a scalable and field-ready solution for wildlife detection, laying the groundwork for intelligent monitoring systems that can support both research and real-world conservation efforts.

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