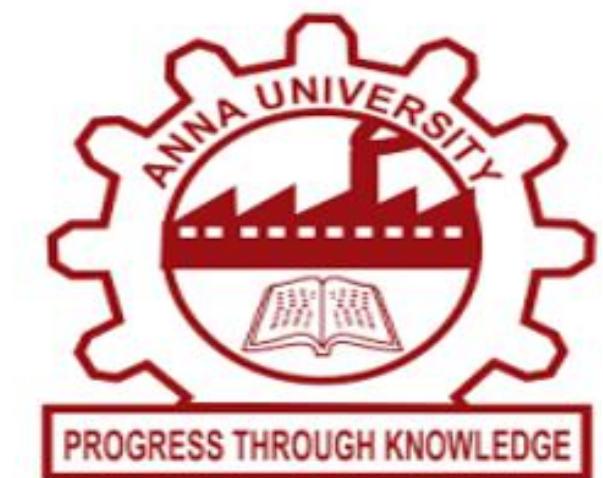




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Department of Computer Science and Engineering

AI-Based Wildlife Crossing Detection and Alert System

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BATCH NUMBER : A6

DATE : 31/10/2025

DOMAIN : ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

COORDINATOR NAME & DESIGNATION

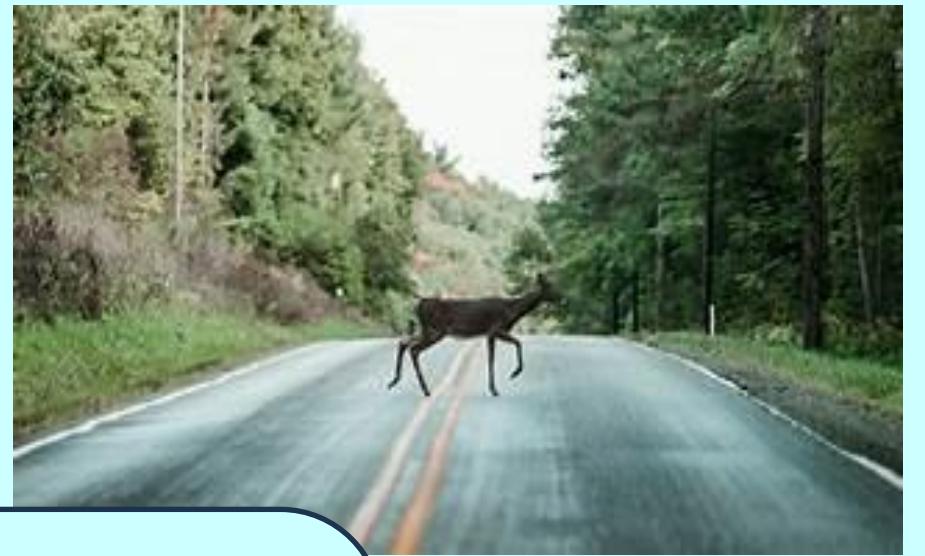
DR.KAVITHA SUBRAMANIAM
PROFESSOR

AGENDA

- 1. Introduction:** Overview of wildlife-vehicle collision risks and the need for intelligent detection. Highlight the project's goals in conservation and road safety.
- 2. Motivation and Impact:** Reducing collisions protects endangered species and improves driver safety. The system offers scalable, low-cost deployment in rural and forested zones.
- 3. Proposed AI Solution:** Real-time animal detection using YOLOv11 and MobileNet-SSD models. Alerts drivers proactively using sound and visual cues.
- 4. Detection Models:** YOLOv11 for fast, accurate detection; MobileNet-SSD for lightweight inference. Each model contributes to ensemble robustness and class coverage.
- 5. Alert Logic and Deployment:** Triggers sound alerts for key species with minimal false positives. Supports edge deployment with optional cloud-based logging.

ABSTRACT

- Wildlife-vehicle collisions cause animal deaths and endanger human lives.
- Our project uses AI and computer vision to detect animals near roads in real-time.
- It runs on a laptop only — no external hardware required.
- Based on MobileNet-SSD and YOLOv11 the system identifies animals like bear, horse, rhino, zebra, etc.
- Triggers alerts and logs detections with timestamp and confidence score.
- Helps prevent accidents and supports wildlife conservation.
- Aligns with SDG 15 – Life on Land, promoting biodiversity protection.
- Demonstrates a cost-effective, software-based solution for safer ecosystems.



INTRODUCTION

- Developed a real-time wildlife detection system using AI and deep learning.
- Successfully identified animals (e.g., bear, rhino, horse, buffalo) from video or webcam input.
- Implemented an alert mechanism (audio/visual) to warn about animal presence.
- Logged detection events with timestamp and confidence score for monitoring.
- Contributed to wildlife protection and road safety with a cost-effective solution.
- Aligned with UN SDG 15 – Life on Land, promoting biodiversity and ecological balance.

OBJECTIVE

Develop a real-time animal detection system

Utilize deep learning models (YOLO, MobileNet-SSD) to identify wildlife near roads with high accuracy and low latency.

Minimize wildlife-vehicle collisions

Proactively alert drivers to animal crossings, reducing accidents and protecting endangered species.

Design a modular and scalable architecture

Ensure the system is adaptable to various environments, supports edge deployment, and integrates easily with existing infrastructure.

Enable low-cost, field-ready deployment

Use standard webcams and lightweight models to make the solution accessible for rural and forested regions.

LITERATURE REVIEW

Author(s) / Year	Key Contribution / Summary
Nyoman Y. P. Darma et al. (2023)	Implements CNNs for real-time animal detection to alert drivers and reduce collisions.
William H. S. Antônio et al. (2023)	Uses ML models like SVM and decision trees to detect and classify animals near roads.
S Sanjay Sudhir Sidhaarthan Balamurugan et al. (2022)	Uses YOLOv3 for real-time animal detection to improve road safety.
E. Maheswari, Dr. V. Balaji, Dr. S. Siva Rajeswari (2022)	Proposes a vision-based system to detect animals on roads and prevent collisions.
Aditiba Raol, Viral Parekh, Shaktisinh Parmar (2023)	Develops an onboard system using cameras and image processing to identify animals.

LITERATURE REVIEW

Author(s) / Year	Key Contribution / Summary
Shengke Wang et al. (2024)	Proposes a self-training AI system using edge/cloud models for endangered species detection near roads.
Tharindu Silva et al. (2024)	Uses CNNs and Transformers with thermal and visual cameras for real-time wildlife detection.
C. Stember et al. (2024)	Provides an open-source deep learning toolkit for wildlife classification and monitoring.
Rahul Sharma et al. (2023)	Combines PIR, thermal sensors, and LoRaWAN to detect wildlife in roadside environments.
Chethan J. et al. (2024)	Uses roadside LiDAR and machine learning to detect horse crossings in open terrain.

LITERATURE REVIEW

Author(s) / Year	Key Contribution / Summary
F. Nakamura, Y. Sato	Thermal imaging and CNN fusion for nocturnal animal detection in low-visibility highway conditions.
D. Hernández, S. Rao, M. Patel	Deep learning–enabled camera trap analytics for wildlife monitoring using ecological modeling and intelligent processing.
J. K. Osei, L. van Dyk, P. Mensah	Hybrid LiDAR–vision system for early detection of roadside animals in intelligent vehicle environments.
T. Al-Mutairi, R. Sharma, M. Bansal	Real-time edge AI system to prevent wildlife–vehicle collisions using IoT-based sensing and fast inference.
K. Lopez, D. Green, S. Rajan	Drone-assisted wildlife tracking using YOLO-based detection for improved monitoring coverage.

LITERATURE REVIEW

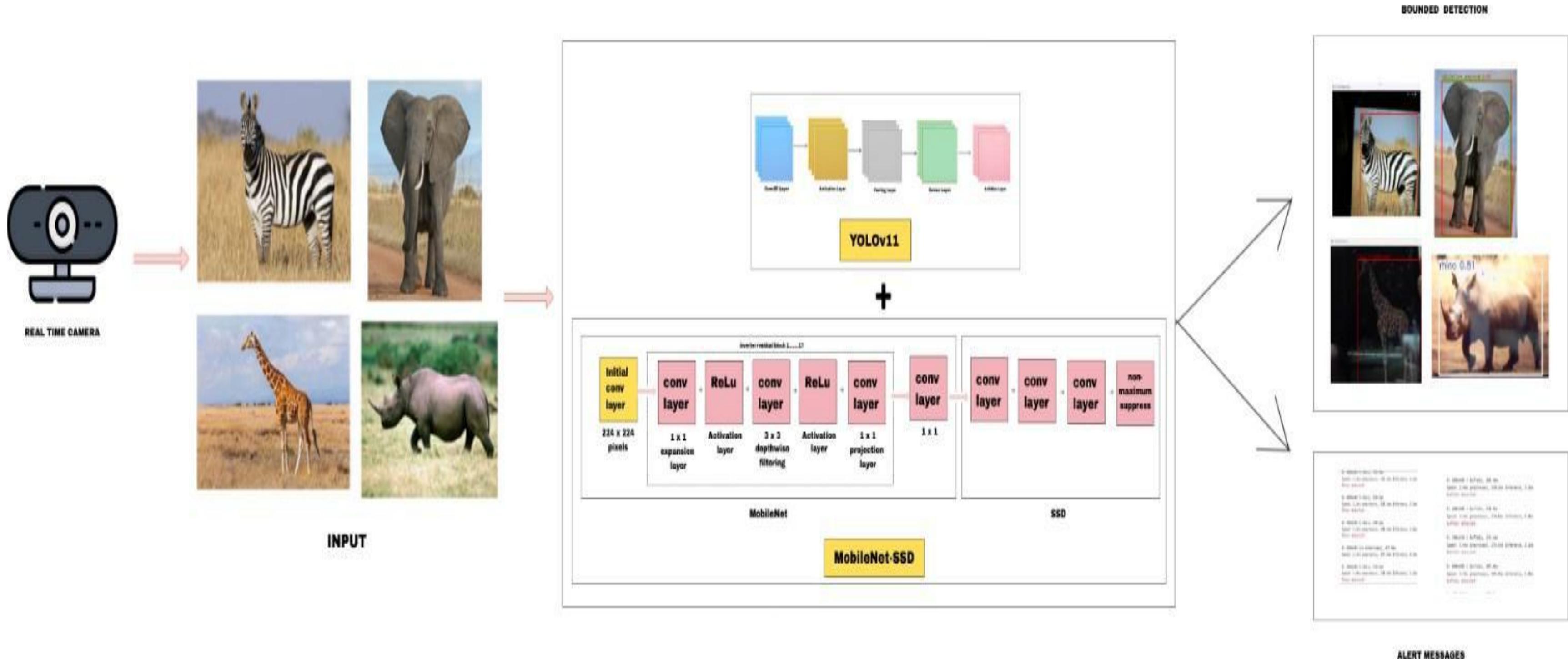
Author(s) / Year	Key Contribution / Summary
H. Qureshi, V. Pradhan, S. Rao	Smart roadside units with multimodal sensing to avoid animal–vehicle collisions.
Vigneshwaran Palanisamy et al.	Explores deep learning ideas relevant to the detection and recognition of wildlife animals.
G. Chaturvedi, S. Kulkarni, P. Dey	Vision Transformers for robust animal detection in low-visibility road scenarios.
Y. Zhang, J. Luo, P. Singh	Multisensor fusion with radar and AI for detecting large mammals near transport corridors.
M. Ortega, C. Wilson	AI-driven predictive modeling to forecast wildlife movement and reduce traffic collision risks.

PROBLEM STATEMENT

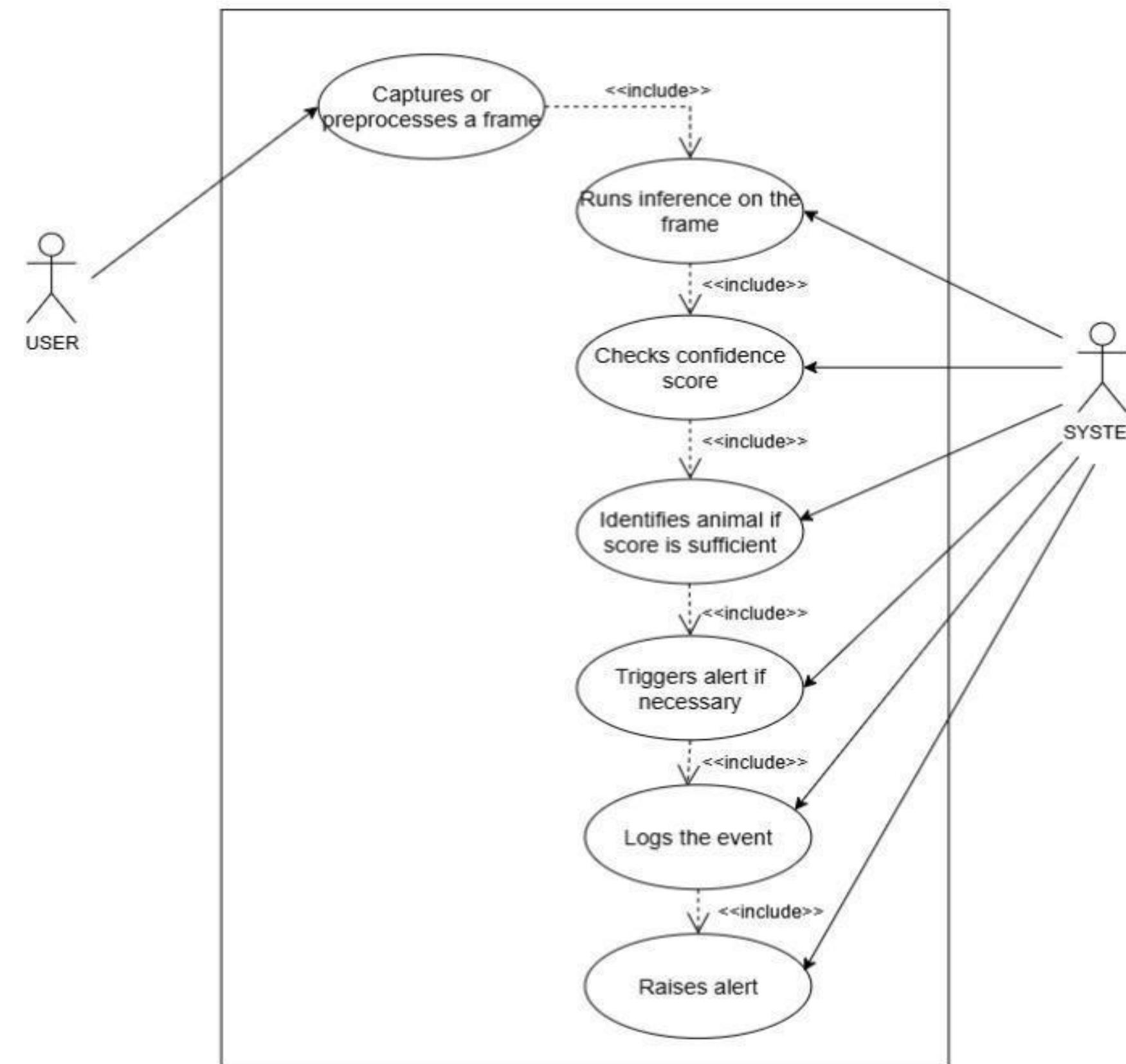
- Wildlife-vehicle collisions are a rising concern in forest and rural zones.
- Lack of intelligent warning systems endangers both animals and drivers.
- Manual fencing or signs are outdated and ineffective at night or in low-visibility areas.
- An AI-driven solution can proactively detect, predict, and alert when animals are near roads.



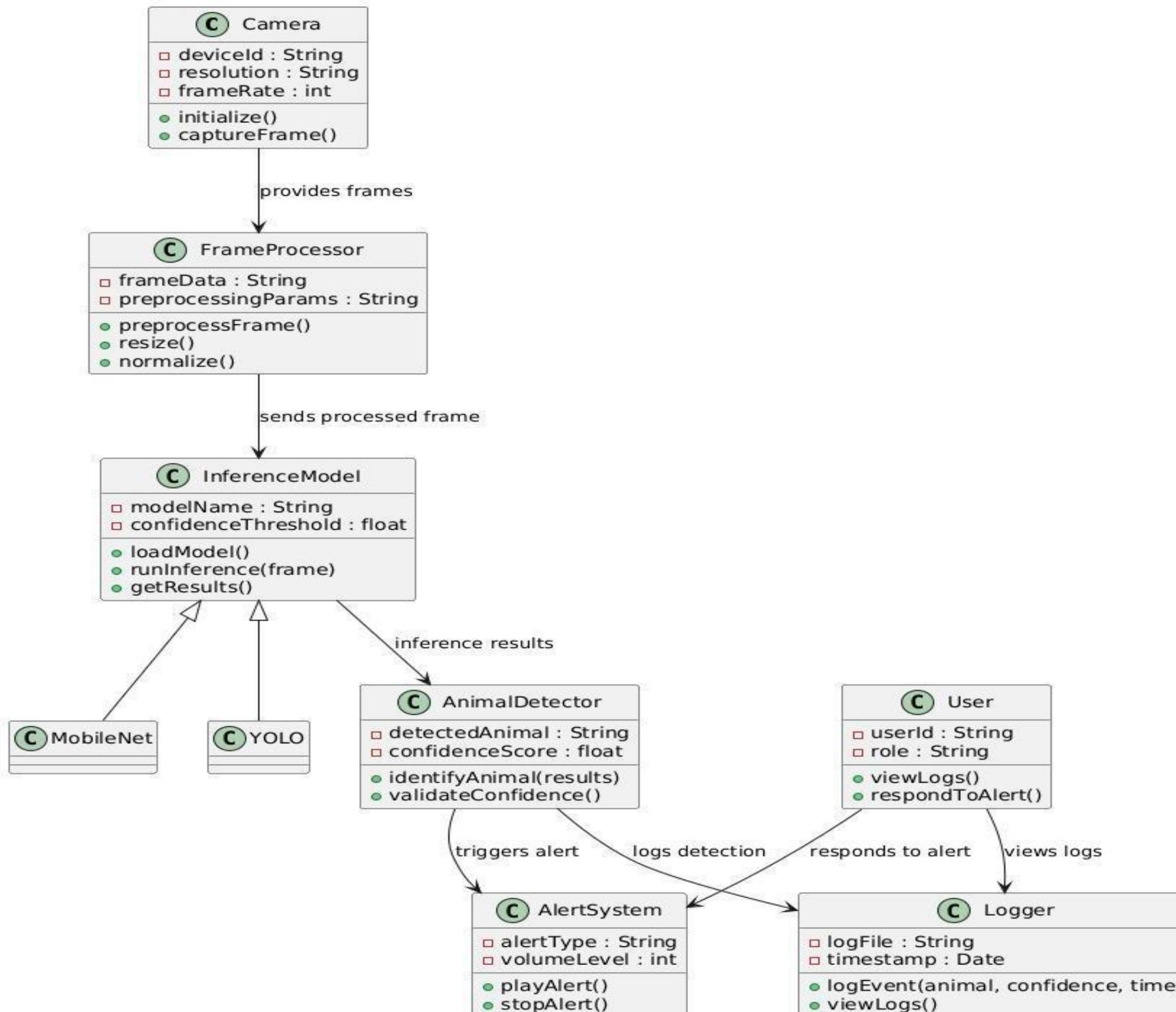
ARCHITECTURE DIAGRAM



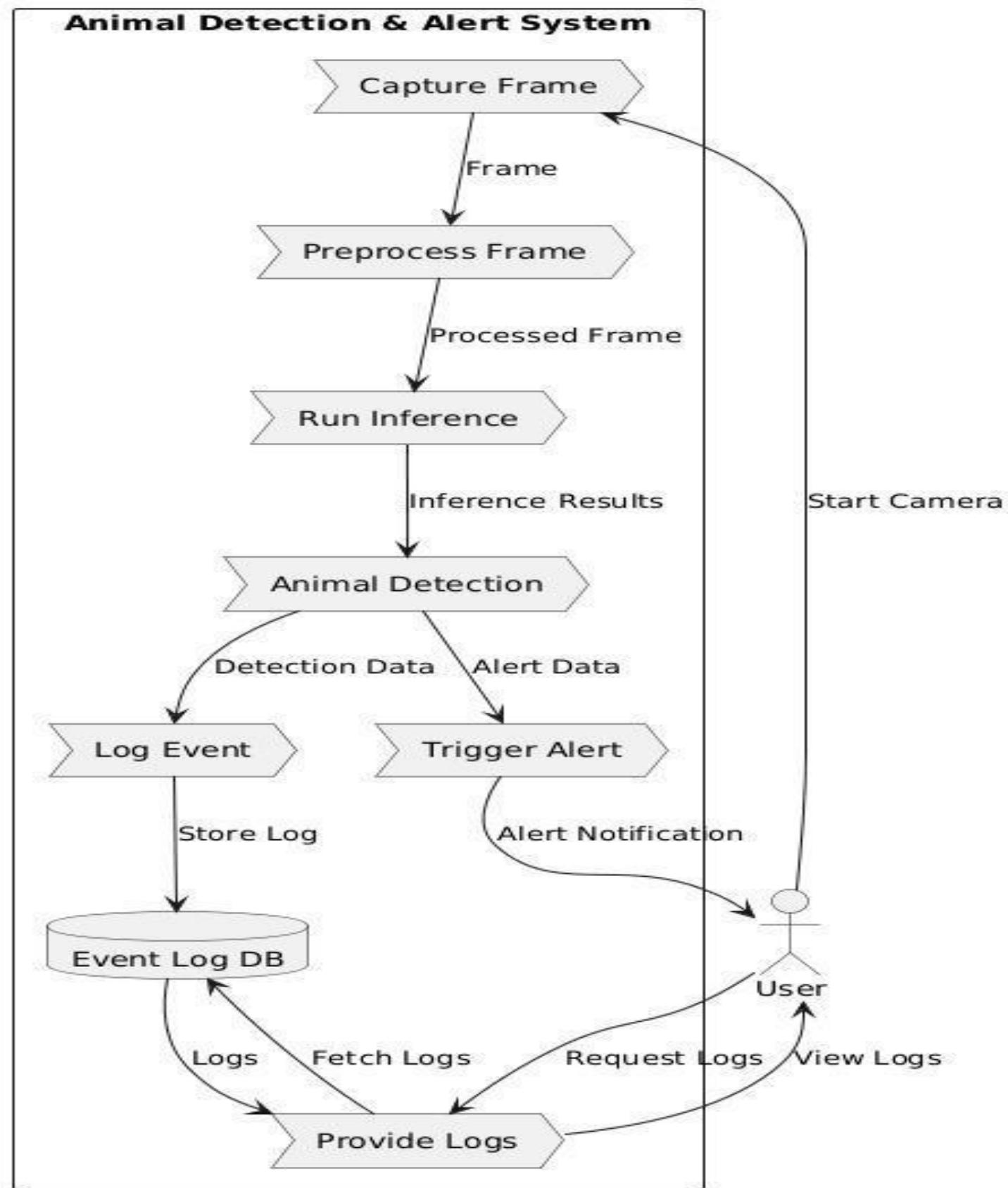
Use Case Diagram



Class Diagram



Data Flow Diagram



MODULES

1. Data Acquisition

Captures real-time video streams from webcams or edge cameras.
Feeds raw frames into the detection pipeline for processing.

2. Preprocessing

Resizes, normalizes, and formats frames for model input. Ensures consistent quality across lighting and resolution conditions.

3. Detection Engine

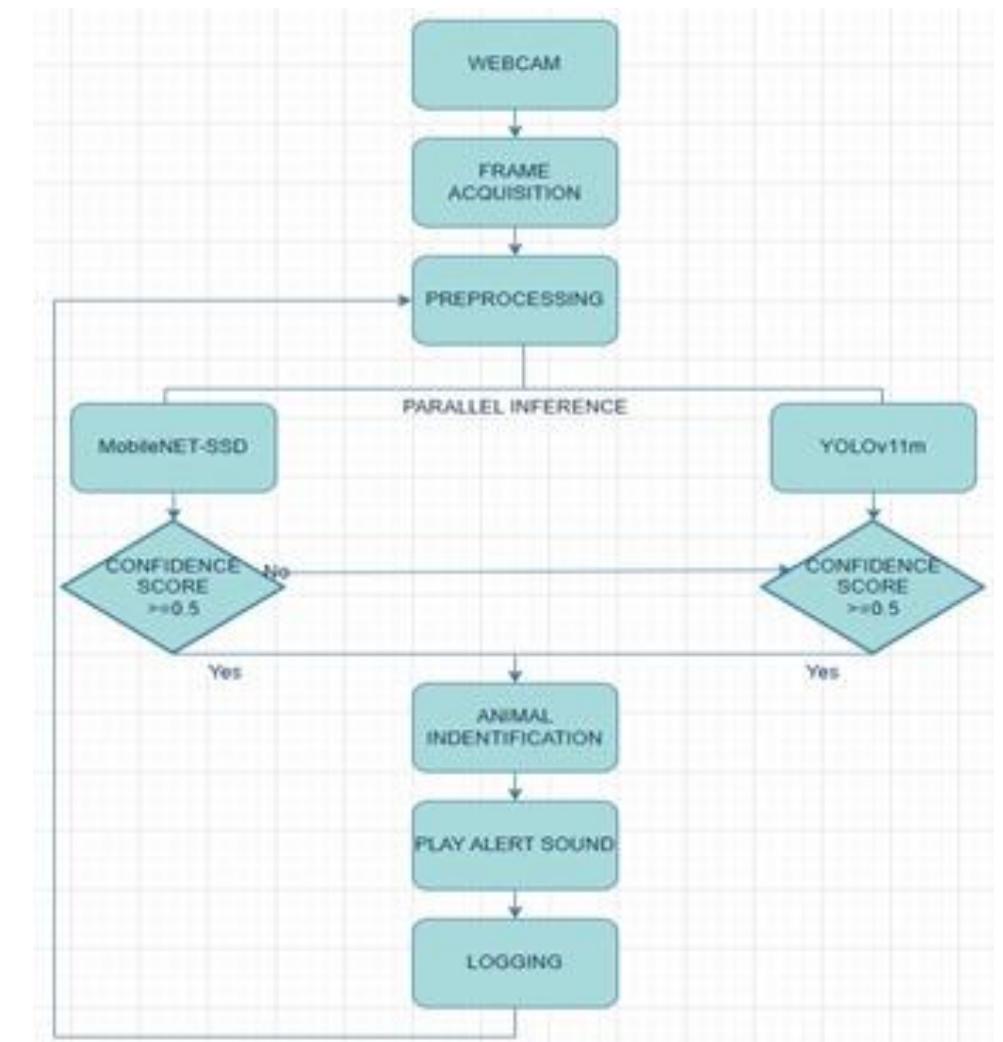
Runs MobileNet-SSD, and YOLOv11 in parallel. Identifies animal classes with bounding boxes and confidence scores.

4. Alert Logic

Triggers sound or visual alerts for key species (e.g., elephant, bear).
Implements threshold-based filtering to reduce false positives.

5. Logging and Export

Stores detection results with timestamps and class labels. Supports CSV export for analysis, benchmarking, or publication.



METHODOLOGY

1. Data Collection

Captured wildlife footage from roadside cameras and public datasets. Ensured diverse lighting, angles, and species for robust training.

2. Preprocessing

Resized frames, normalized pixel values, and filtered noise. Prepared consistent input format for all detection models.

3. Model Selection and Integration

Used MobileNet-SSD, and YOLOv11 for ensemble detection. Balanced speed, accuracy, and resource efficiency across models.

4. Detection Pipeline Design

Built modular scripts to run models in parallel with unified output. Implemented bounding box extraction and class confidence scoring.

5. Alert Logic Implementation

Defined key species for red-alert triggers (e.g., elephant, deer). Added sound notifications and optional logging for each detection.

TESTING

1. Dataset Validation

Used diverse wildlife datasets with varied lighting, angles, and species. Ensured balanced representation across key animal classes.

2. Model Accuracy Checks

Evaluated MobileNet-SSD, and YOLOv11m on test sets. Measured precision, recall, and F1-score for each class.

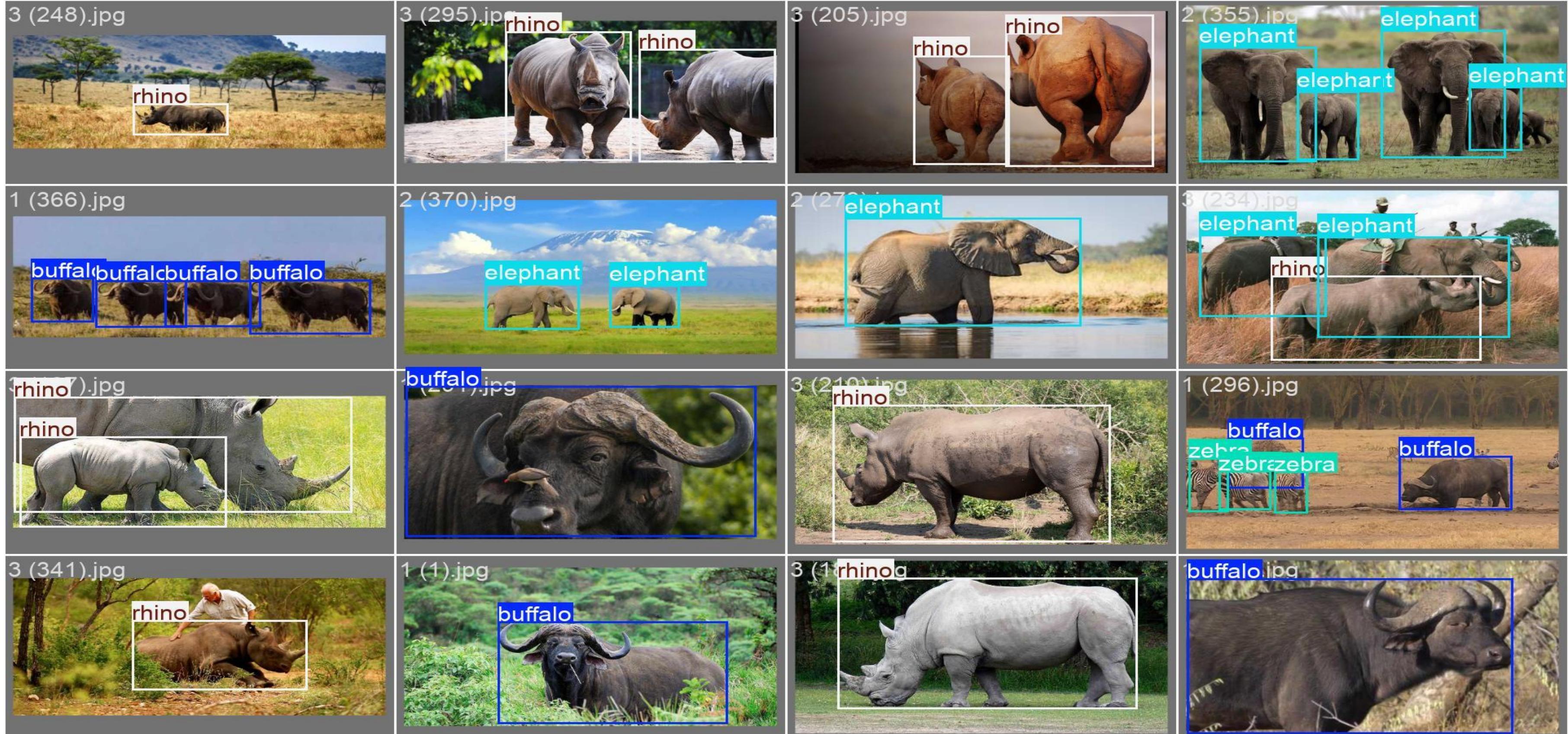
3. Real-Time Performance

Tested system on live webcam feeds in simulated conditions. Verified the detection rate for every frame acquired.

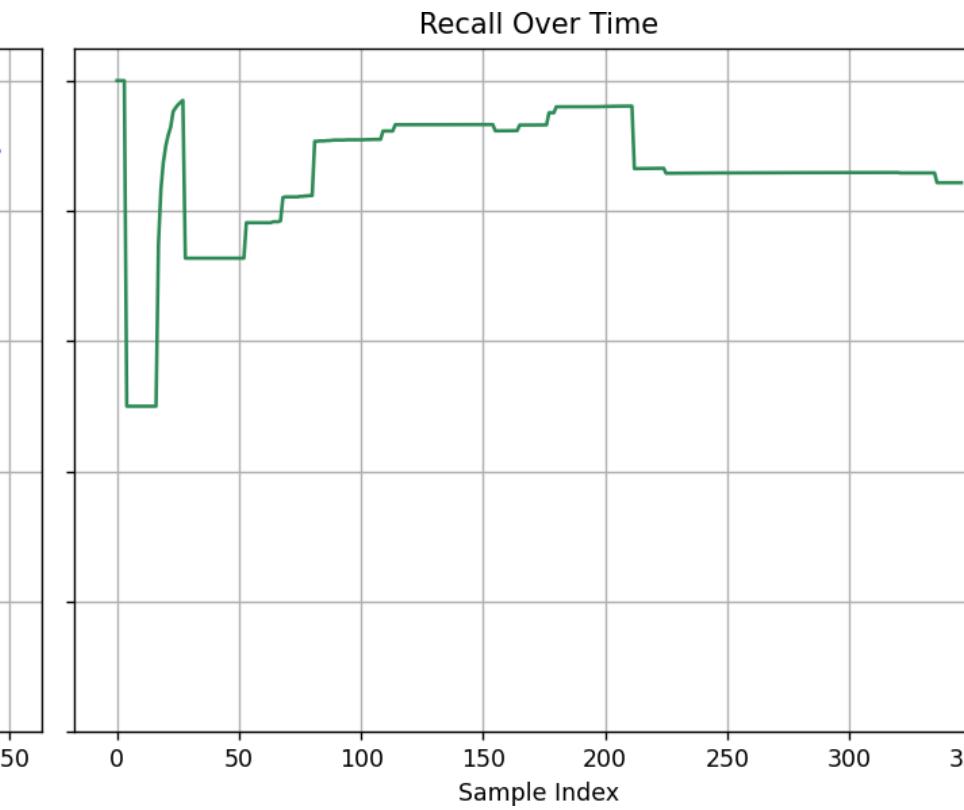
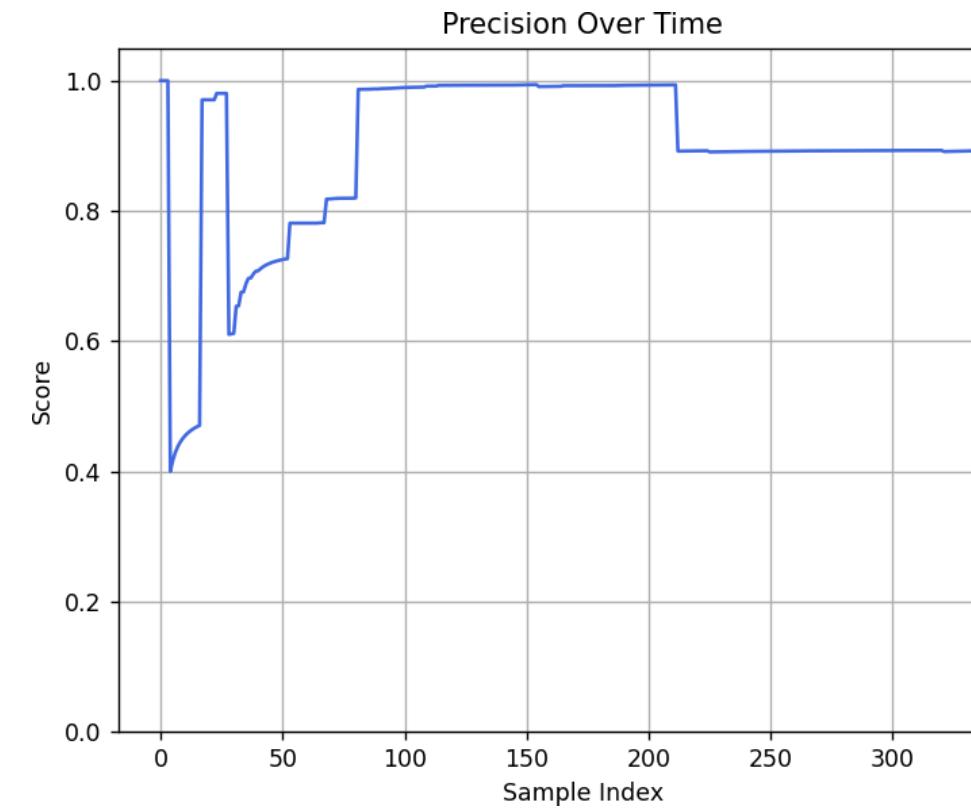
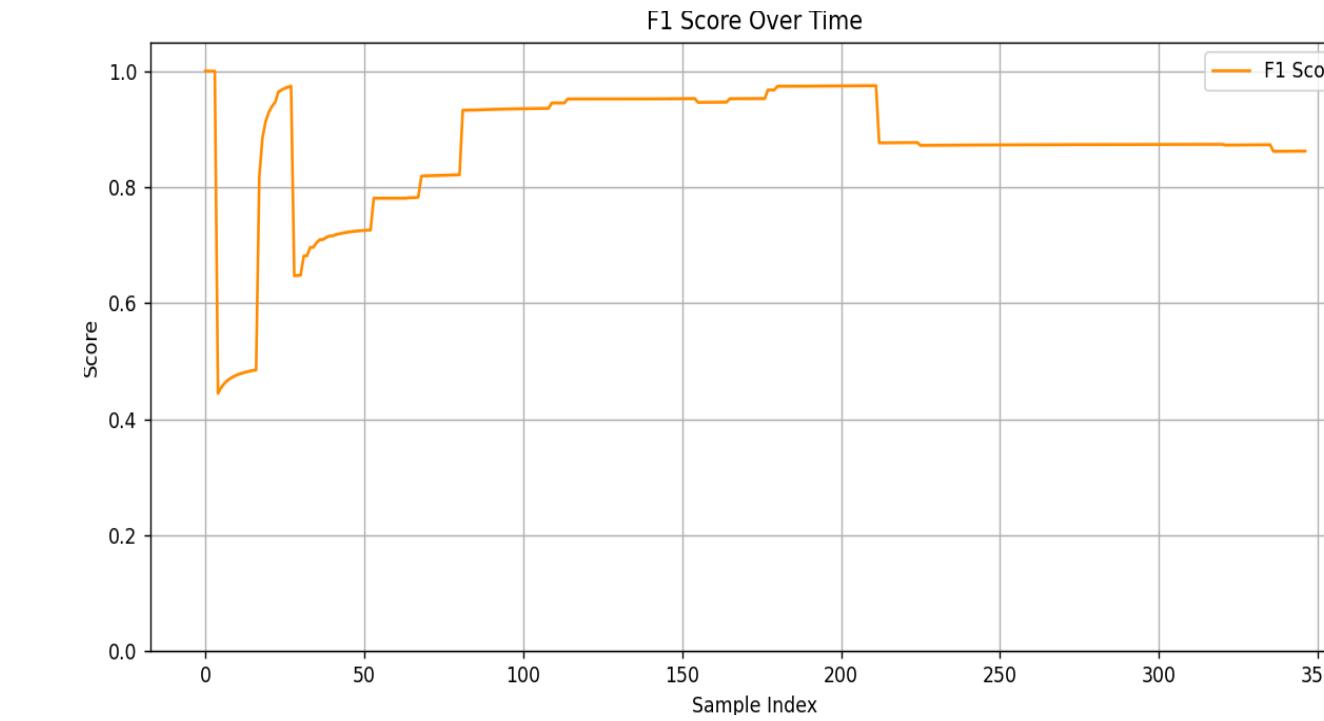
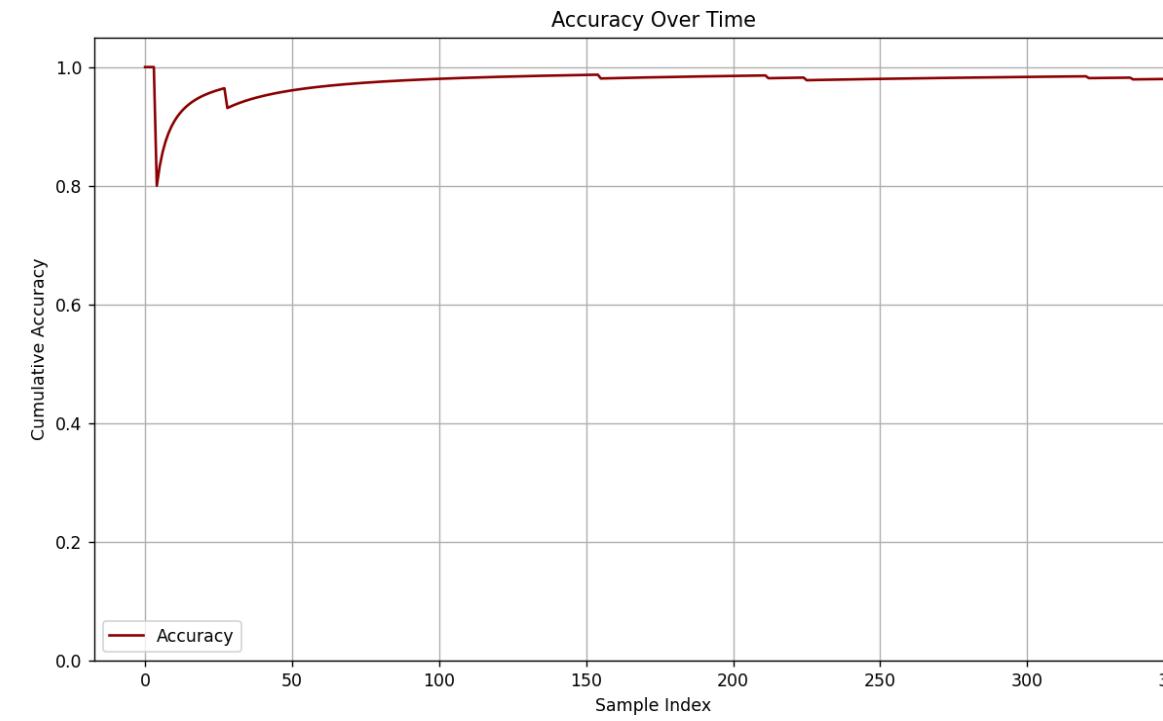
4. Alert Logic Verification

Confirmed sound alerts trigger only for target species. Checked threshold tuning to minimize false positives.

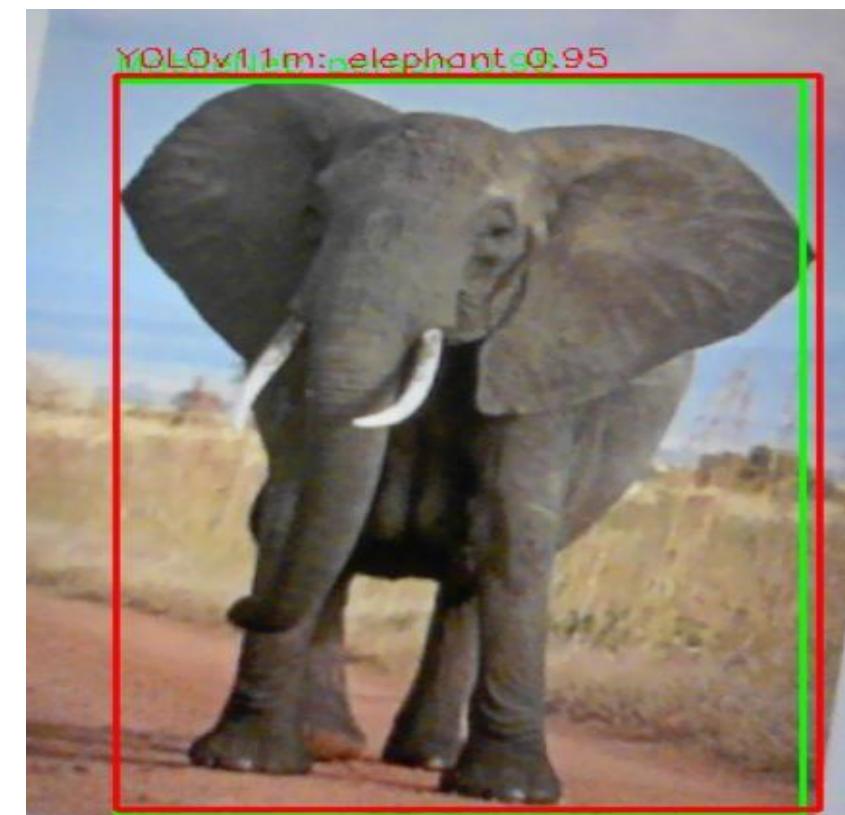
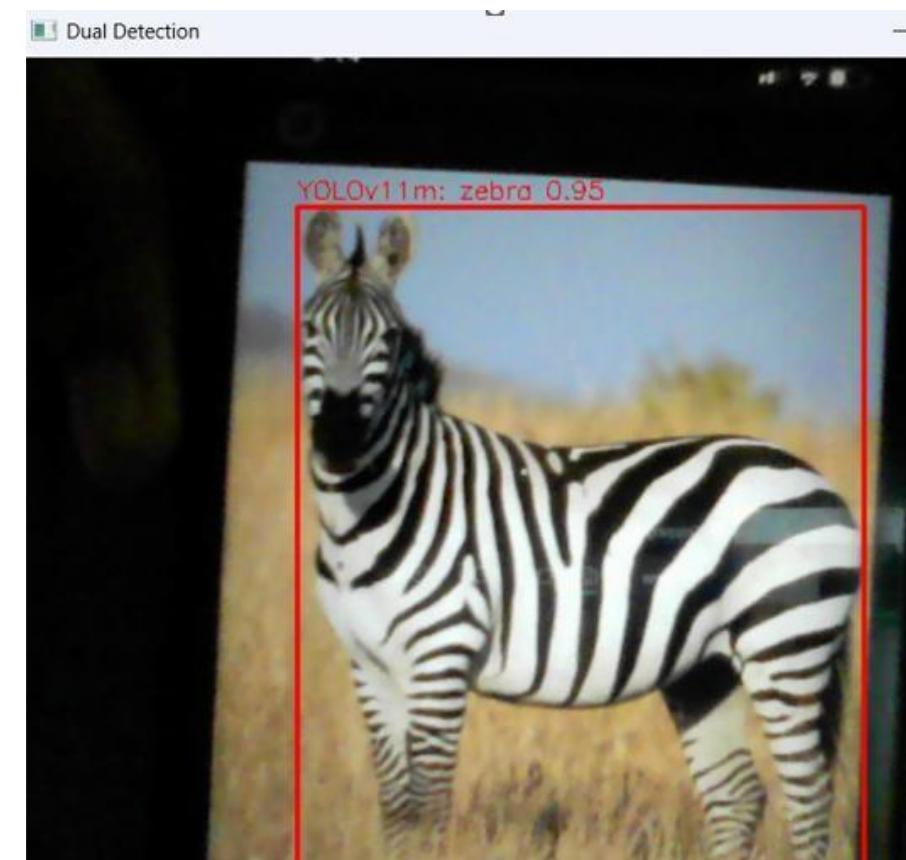
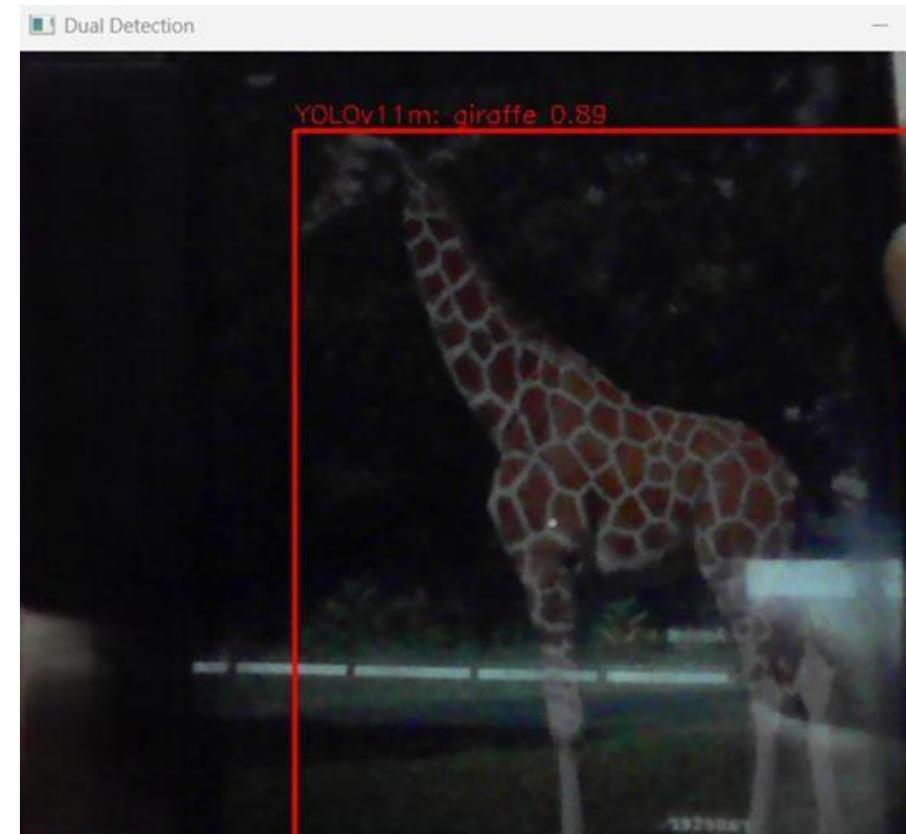
TEST CASES



PERFORMANCE ANALYSIS



SCREENSHOTS



CONCLUSION

- Real-time AI detection can significantly reduce wildlife-vehicle collisions, protecting both animals and drivers. Your system demonstrates how deep learning models can be deployed effectively in field conditions.
- Modular architecture and multi-model integration ensure scalability and robustness. The pipeline supports edge deployment, alert logic, and performance logging for real-world use.
- Experimental results validate the system's accuracy and responsiveness. Confusion matrices and other metrics show strong detection performance across diverse species.
- This project bridges technology and conservation, offering a practical solution for safer roads and protected habitats. Future enhancements like thermal imaging and adaptive learning can further elevate its impact.

FUTURE WORK

1. Night-Time Detection Enhancement

Integrate infrared or thermal imaging to improve visibility in low-light conditions. Enhance model robustness against shadows and glare.

2. Radar and Sensor Fusion

Combine visual detection with radar or motion sensors for multi-modal accuracy. Reduce false positives and improve detection range.

3. Adaptive Learning System

Enable online learning from new sightings and edge cases. Continuously refine model performance in changing environments.

4. Cloud-Based Logging and Analytics

Deploy centralized logging for large-scale data collection and analysis. Support conservation studies and traffic pattern insights.

5. Mobile App Integration

Develop a companion app for real-time alerts and community reporting. Empower users to contribute sightings and feedback.

6. Broader Species Coverage

Expand training datasets to include more regional and endangered species. Improve detection diversity and ecological relevance.

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THANK YOU