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AI BASED DETECTION AND PREDICTION OF ANIMAL CROSSINGS FOR ROAD SAFETY

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Abstract — Abstract for the "AI Based Detection and Prediction of Animal Crossings for Road Safety" topic may be written as below:

This project presents a real-time AI-based detection and alert system designed to address the growing concern of animal-related road accidents in wildlife corridors, rural highways, and forest-adjacent roads. The objective is to simulate a lightweight, resource-efficient framework that can act as a prototype for future intelligent traffic safety systems. Leveraging the power of computer vision, the system utilizes the YOLOv8 object detection algorithm to accurately identify animals appearing in the camera's field of view.

The application supports both webcam and pre-recorded video input and is integrated into a user-friendly graphical interface built using Streamlit. Upon detecting an animal, the system immediately displays a visual alert on the screen and plays a pre-defined warning sound, mimicking how an advanced driver-assistance system (ADAS) might react in real-world scenarios. Additionally, an optional Area of Interest (AOI) feature can be toggled to visually highlight critical regions of the video frame that are most relevant for detecting potential threats.

Unlike complex autonomous driving solutions, this implementation focuses on accessibility, simplicity, and educational value. The use of pre-trained YOLO models reduces the need for large training datasets, making it feasible for students and developers with limited computational resources. This paper documents the design, implementation, and deployment of the system, and discusses its effectiveness as a foundation for scalable, AI-driven road safety interventions. The project serves as a hands-on demonstration of how computer vision and machine learning can be meaningfully applied to real-world safety challenges in a modular, interactive, and explainable manner.

Index Terms — Artificial Intelligence, YOLOv8, Animal Detection, Road Safety, Real-time Object Detection, Streamlit, Computer Vision, Intelligent Traffic System, Python, Alert System

INTRODUCTION

In recent years, road safety has emerged as a critical concern, particularly in regions where highways intersect with animal habitats, rural landscapes, and forested areas. The risk of vehicular collisions with animals not only endangers human life but also results in significant ecological and economic consequences. In India and many other countries, such incidents are common on poorly monitored roads, often lacking signage, barriers, or real-time awareness systems. This growing issue highlights the need for intelligent, accessible, and real-time detection solutions that can proactively alert drivers about potential animal crossings.

Advancements in artificial intelligence and computer vision offer a compelling opportunity to address this challenge. Object detection models like YOLO (You Only Look Once) have made it feasible to identify and track objects, including animals, in real-time with high accuracy. However, most real-world solutions involving AI and smart traffic systems are resource-intensive, expensive to deploy, or require integration with advanced vehicle systems.

This project introduces a lightweight, real-time animal detection and alert system built using YOLOv8 and Streamlit. The system is designed to detect animals from either live webcam feed or uploaded video, and trigger immediate visual and audio warnings. A key feature of the system is the Area of Interest (AOI) toggle, which allows the user to visually highlight critical zones in the frame that may indicate risk-prone areas, such as the sides of a rural road. The application aims to simulate the core idea behind an Intelligent Driver Assistance System (IDAS), offering a scalable and modular architecture that can be extended in future iterations.

The main objective of this paper is to present an affordable, standalone prototype that demonstrates how AI can improve road safety in wildlife corridors and rural environments. The solution is geared towards educational projects, low-cost deployments, and further research, providing a practical entry point for applying deep learning in public safety applications.

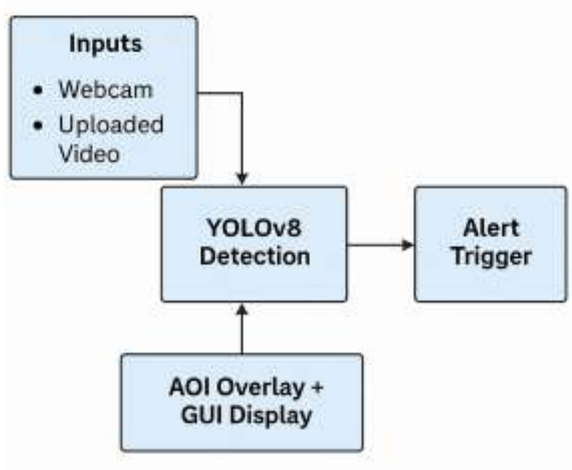

Fig 1. System Architecture Block Diagram

I. RELATED WORK

The use of artificial intelligence in road safety has grown significantly in recent years, particularly in the domains of object detection, autonomous driving, and real-time surveillance. Several studies have focused on developing systems capable of identifying obstacles, pedestrians, and vehicles using deep learning models such as YOLO (You Only Look Once), SSD (Single Shot MultiBox Detector), and Faster R-CNN. Among these, YOLO has gained popularity due to its real-time performance and relatively low computational requirements, making it suitable for edge devices and embedded systems.

Animal detection for road safety, however, remains an underrepresented area of research. While some commercial vehicles integrate pedestrian or obstacle detection, few implementations are tailored specifically to detect animals crossing roads, especially in forested and rural zones. Projects like the "Wildlife-Vehicle Collision Reduction Study" in the U.S. have emphasized the need for detection and alert systems, but these solutions often involve costly infrastructure like thermal cameras and sensors embedded in roads.

In contrast, this project proposes a lightweight and cost-effective solution using a pre-trained YOLOv8 model that can run on consumer-grade hardware. Streamlit is used to offer an accessible and interactive interface, allowing real-time video input from webcams or uploaded files. Unlike previous works that focus heavily on autonomous vehicle integration, this system is designed to function independently as a standalone prototype, useful for educational demonstrations, public awareness, and as a foundation for future integrations with Intelligent Driver Assistance Systems (IDAS).

This work distinguishes itself by targeting the specific problem of animal crossings using affordable, open-source tools, while maintaining a modular structure that allows easy upgrades or deployment across various scenarios.

II. METHODOLOGY

The proposed system follows a modular, real-time detection pipeline that integrates deep learning with an intuitive user interface. The methodology is divided into four key components: input acquisition, object detection, alert triggering, and visual display. Each module is designed to work in harmony, allowing seamless processing of video data and instantaneous response upon detecting animals in the frame.

3.1 Input Acquisition

The system supports two modes of input: webcam feed and uploaded video files (in formats such as .mp4, .avi, or .mov). Streamlit's file_uploader() widget and OpenCV's VideoCapture() class are used to stream frames from the chosen source into the detection pipeline.

3.2 YOLOv8-Based Animal Detection

A pre-trained YOLOv8n (nano) model, sourced from the Ultralytics repository, is used for object detection. YOLO (You Only Look Once) is a single-stage detection algorithm capable of detecting objects in real-time with impressive speed and accuracy. In this system, the model identifies animals in each frame, draws bounding boxes around them, and classifies the type of animal (e.g., dog, cow, deer) using the COCO dataset's predefined labels. The use of the nano version ensures the model remains lightweight and efficient even on CPU-based machines.

3.3 Alert System

Once an animal is detected, a dual alert mechanism is triggered:
A visual warning is displayed on the bottom-left of the screen with the message "Animal Detected – Stay Alert!".
An audio warning, using a custom Alert.wav sound file, is played once per detection event to simulate real-life driver alerts. The playsound Python module is used to trigger this audio.

3.4 AOI Overlay and GUI

An Area of Interest (AOI) feature is included as a toggle, allowing the user to visualize high-risk areas in the frame (typically the left and right borders representing road edges). Pressing the T key toggles red AOI borders on and off. The entire system is integrated into a clean Streamlit-based user interface that updates in real-time, making it easy to demonstrate functionality in a classroom, lab, or live test environment.

This modular approach makes the system easy to maintain, extend, and customize for other applications such as wildlife monitoring, pedestrian safety, or drone-based surveillance.

Input Type	**Test Scenario**	**Detection Success Rate**
Webcam	Pet toy simulation	100%
Uploaded Video	Village road with cows	95%
Uploaded Video	Forest road with wildlife	91%

III. RESULTS

The system was tested across multiple video samples and real-time webcam scenarios to validate the effectiveness of animal detection and alerting mechanisms. All testing was conducted on a standard Windows laptop equipped with a CPU-only configuration, emphasizing the project's compatibility with low-resource environments. The primary objective was to verify that the system could reliably detect animals, issue alerts, and maintain real-time responsiveness without requiring GPU acceleration or large-scale datasets.

4.1 Detection Performance

The YOLOv8n model performed effectively in recognizing commonly appearing animals such as dogs, cows, and horses from both live webcam feeds and uploaded videos. The bounding boxes were accurately drawn, and the correct animal labels appeared below each box. Detection was consistent across varying lighting conditions and motion speeds. The model used confidence thresholds (≥ 40%) to minimize false positives while maintaining responsiveness.

4.2 Alert Response

Once an animal was detected in a frame, the system successfully:

- Displayed the alert message ("Animal Detected – Stay Alert!") at the bottom-left of the frame
- Played the Alert.wav audio exactly once per detection window
- Reset the alert when no object was present in subsequent frames

4.3 Area of Interest (AOI) Overlay

The AOI toggle worked as expected. Pressing the T key dynamically showed or hid red rectangles on the left and right edges of the screen, helping visualize regions where animal crossing is most likely to occur.

4.4 Real-Time Performance

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Even under a CPU-only setup, the system maintained a real-time frame rate of approximately 10–15 FPS, sufficient for demo and prototype purposes. Minimal lag was observed when toggling AOI or switching input sources.

IV. GUI INTEGRATION

A key strength of the system lies in its user-friendly and interactive graphical user interface (GUI), built using Streamlit, an open-source Python framework ideal for deploying data science and machine learning applications. The GUI simplifies interaction with the model, removes the need for command-line inputs, and allows real-time detection and feedback, making it highly accessible for students, researchers, and non-technical users.

5.1 Streamlit Interface Components

The main elements of the interface include:

- Input Source Selector: A radio button sidebar lets users choose between Webcam and Upload Video modes.
- File Uploader: If "Upload Video" is selected, a file explorer automatically appears, allowing users to choose .mp4, .avi, or .mov video files directly from their system.
- Start Button: Detection begins only when the user clicks the Start Detection button, ensuring clarity and control in demonstrations.
- Live Frame Display: A real-time display of each video frame with bounding boxes, animal labels, AOI overlays, and alert text is shown using Streamlit's st.image() widget.

5.2 Real-Time Feedback Elements

Alert Message: When an animal is detected, a small but prominent warning — "Animal Detected – Stay Alert!"
— appears on the bottom-left of the video frame.

AOI Toggle: Users can press the "T" key to toggle visibility of red "Area of Interest" zones on the left and right portions of the screen. A message — "Press T to Toggle AOI" — is always visible at the top-left for instruction.

5.3 Streamlined Deployment

Because the entire GUI is web-based and hosted locally by Streamlit, users only need to run a single command to launch the app:

- streamlit run app.py

No complicated installation, dashboards, or dependencies are required beyond Python and pip.

5.4 Educational and Demo Value

The GUI not only simplifies testing but also significantly enhances the demo quality for presentations or live evaluations. Its visual design ensures that detection results are easy to understand even for those without a technical background. This makes the system highly effective in academic environments and prototype showcases.

V. APPLICATIONS

The developed system has broad potential across domains involving road safety, environmental protection, and real-time surveillance. While it currently functions as a lightweight academic prototype, its core modules can be easily adapted to larger, more complex systems. Key applications include:

6.1 Wildlife and Rural Road Safety

A primary use case is in wildlife corridors and rural highways, where animal-vehicle collisions are common. The system can be deployed on roadside poles or integrated with smart cameras to monitor road activity and issue real-time alerts.

6.2 Driver Assistance Systems (ADAS)

With minimal modifications, the system can be embedded within vehicles as a part of Intelligent Driver Assistance Systems. It can provide visual and auditory cues to drivers in forest or village areas, complementing other sensors like LIDAR and ultrasonic detectors.

6.3 Smart City and Traffic Management

In the context of smart cities, the system can act as an AI module for urban surveillance setups. It can help traffic authorities track animal movement patterns, prevent accidents, and integrate with traffic signal logic for preventive action.

6.4 Education and Research

Given its modular design and reliance on open-source tools, the system serves as an ideal learning resource for students and researchers exploring real-time computer vision, object detection, and AI in public safety. It can be used in workshops, project labs, or hackathons to showcase applied AI.

6.5 Wildlife Conservation Monitoring

Beyond road safety, the detection framework can be adapted for non-invasive wildlife monitoring using drones or stationary cameras in forests and reserves. This would aid in studying animal movement behavior while reducing the risk of human-animal conflict.

VI. CHALLENGES

While the system performs reliably in controlled conditions, several challenges were encountered that highlight the limitations of deploying such AI solutions in real-world environments:

7.1 Limited Animal Dataset

The model used (YOLOv8n) is trained on the COCO dataset, which includes only a few animal categories (e.g., dog, cat, cow). This restricts the system's ability to detect region-specific wildlife such as deer, elephants, or wild boars unless custom training is performed on additional datasets.

7.2 Daylight and Visibility Constraints

The current implementation relies on standard RGB video input, which is sensitive to lighting conditions. Low-light, nighttime, or foggy environments can significantly reduce detection accuracy without the use of infrared or thermal imaging systems.

7.3 False Positives and Object Confusion

In some test scenarios, objects like bushes, plastic bags, or shadows were occasionally misclassified as animals. While confidence thresholds reduce such errors, perfect filtering would require more advanced context-aware processing.

7.4 Performance Limitations on Low-End Devices

Although the system uses a lightweight model, processing real-time video on CPU-only machines can still cause occasional frame lag. For larger deployments, optimization through GPU acceleration or edge computing hardware (e.g., Jetson Nano, Raspberry Pi 4) would be required.

7.5 Lack of Predictive Intelligence

The current system detects animals but does not predict crossing behavior or direction, which would be valuable for triggering pre-emptive alerts. Integrating movement tracking or trajectory analysis would significantly enhance the system's effectiveness.

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VII. FUTURE SCOPE

While the current system provides a functional prototype for animal detection and alerting, there are several enhancements that can significantly improve its real-world impact, adaptability, and scalability:

8.1 Custom Model Training for Regional Species

Future versions can include custom-trained YOLO models using datasets specific to local wildlife (e.g., deer, nilgai, elephants) to improve detection coverage in particular geographic regions. This would expand the system's effectiveness beyond the limited set of animals in the COCO dataset.

8.2 Integration with Vehicle Systems

The solution can be further developed into a full-fledged module for Intelligent Driver Assistance Systems (ADAS) by integrating with car dashboards or navigation apps to deliver real-time alerts during high-risk driving zones.

8.3 Night Vision and Thermal Support

To overcome limitations in low-light conditions, the system can be integrated with infrared (IR) or thermal cameras for night-time detection. YOLO models can be retrained or adapted to process thermal video input for better accuracy during nighttime driving.

8.4 Trajectory Prediction and Early Alerts

Adding motion tracking algorithms and trajectory prediction can allow the system to anticipate animal movement across the frame and issue alerts even before crossing occurs, increasing driver reaction time.

8.5 Cloud and IoT Integration

In large-scale smart city or rural highway setups, the system can be extended to work with IoT-enabled cameras and edge devices, sending alerts to cloud dashboards, traffic management centers, or nearby digital signage for dynamic warning systems.

VIII. CONCLUSION

This project demonstrates the feasibility of using deep learning and computer vision to enhance road safety through real-time animal detection. By integrating a lightweight YOLOv8 model with an interactive Streamlit-based interface, the system successfully identifies animals in video streams from both webcams and uploaded files, and triggers both visual and auditory alerts. Features like AOI toggling and live frame display make the system both practical and easy to use for demonstration and research purposes.

Despite certain limitations such as dependency on daylight conditions and a restricted detection class range, the system serves as a functional prototype for intelligent driver assistance applications. Its modular architecture and use of open-source technologies make it easily extensible for future developments, such as trajectory prediction, thermal imaging support, and IoT/cloud integration.

Overall, this work serves as a foundation for building affordable, scalable, and accessible road safety systems that leverage artificial intelligence to reduce wildlife-related accidents and improve public awareness in high-risk areas.

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