



# Deep Learning Powered Real Time Detection Animal by Capturing Image and Alert System for Roadways

**Jerusha Persis P<sup>1</sup>, Rakshaya V<sup>2</sup>, Kavibala I<sup>3</sup>, Santhavarthini G<sup>4</sup>, Nagulan M<sup>5</sup>, Mohamed Faisal M<sup>6</sup>**

U.G. Student, Department of Computer Science Engineering, Sir Issac Newton Engineering College, Nagapattinam,  
Tamilnadu, India<sup>1234</sup>

Assistant Professor, Department of Computer Science Engineering, Sir Issac Newton Engineering College,  
Nagapattinam, Tamilnadu, India<sup>5</sup>

Assistant Professor and Head, Department of Computer Science Engineering, Sir Issac Newton Engineering College,  
Nagapattinam, Tamilnadu, India<sup>6</sup>

**ABSTRACT:** Road accidents caused by sudden animal crossings on highways and rural roads are a major safety concern, leading to loss of life and property. This project proposes a Deep Learning Powered Real-Time Animal Detection and Alert System for Roadways to minimize such incidents. The system utilizes advanced deep learning techniques, particularly Convolutional Neural Networks (CNN), to detect animals in real-time by capturing images through cameras installed along roadways. The captured images are processed using a trained model that can accurately identify different types of animals under varying environmental conditions such as low light, rain, and motion. Once an animal is detected, the system immediately triggers an alert mechanism, which may include visual signals, alarms, or notifications to drivers and nearby control centers. This ensures timely warnings and helps drivers take preventive actions. Additionally, the system can be integrated with IoT modules for faster communication and data transmission. The collected data can also be stored for further analysis to identify high-risk zones and improve road safety planning. The proposed solution aims to enhance transportation safety, reduce accidents, and provide a cost-effective and scalable approach for smart roadway monitoring systems.

**KEYWORDS:** Deep Learning, Real-Time Detection, Animal Detection, Road Safety, Convolutional Neural Network (CNN), Image Processing, Highway Monitoring, Animal Crossing, Alert System, IoT Integration, Smart Roadways, Accident Prevention, Computer Vision, Environmental Conditions, Data Analysis, High-Risk Zones, Automated Warning System, Transportation Safety, Surveillance System, Intelligent Monitoring

## I. INTRODUCTION

Monitoring animal movement and intrusion has become increasingly important due to rising human–animal conflicts, agricultural losses, and threats to wildlife conservation. In rural and forest-adjacent regions, animals often enter farmlands and residential areas in search of food, causing crop destruction, property damage, and safety risks. Traditional monitoring methods such as fencing, manual patrolling, and repellents are not only labor intensive but also lack the ability to provide real-time alerts. These limitations highlight the urgent need for an automated, intelligent, and responsive surveillance system capable of operating continuously with minimal human intervention. Recent advancements in Artificial Intelligence (AI) and computer vision have transformed surveillance systems by enabling automatic object detection and classification. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in image recognition tasks. Modern object detection algorithms like YOLOv11 offer high-speed and accurate real-time detection, making them suitable for monitoring dynamic environments. By integrating such technologies, it is possible to build a smart animal detection system that can identify multiple species under varying light in and background conditions while maintaining efficiency and scalability. The proposed AI-powered animal surveillance system leverages YOLOv11 combined with CNN-based feature extraction to detect and recognize animals from live camera feeds. The system incorporates transfer learning to improve adaptability and accuracy when trained with diverse datasets. Additionally, it integrates an automated alert mechanism that sends

notifications through alarms, SMS, or email upon detecting animal intrusion. With the support of edge computing, the system ensures reduced latency and faster response times, making it highly reliable for deployment in remote agricultural fields and wildlife sensitive zones.

## II. LITERATURE SURVEY

The literature on animal detection and surveillance systems highlights significant advancements driven by machine learning and deep learning techniques. A comprehensive survey by Araujo et al. [1] outlines the evolution of object detection methods from traditional handcrafted feature-based approaches to advanced convolutional neural network (CNN) architectures, emphasizing the superior performance of deep learning models such as region-based and one-stage detectors in terms of accuracy and real-time capability. Building on this, Ansari et al. [2] demonstrate that deep learning-based object detection significantly enhances animal recognition accuracy compared to conventional image processing methods, particularly when supported by robust feature extraction and diverse datasets.

Similarly, Kishi et al. [3] present an intelligent surveillance system that automates animal behavior analysis using image processing and machine learning, thereby reducing human error and improving reliability. Further studies address challenges in dynamic and complex environments. Malmström et al. [4] propose an extended target tracking framework that integrates machine learning with tracking algorithms to improve localization and prediction of multiple moving animals. Nguyen et al. [5] tackle the issue of detecting camouflaged animals using few-shot learning, enabling effective detection even with limited labeled data.

In addition, Aguilar-Lazcano et al. [6] highlight the benefits of sensor data fusion, demonstrating that combining inputs from multiple sensors enhances detection accuracy and reduces false alarms, although challenges such as data synchronization and system scalability remain. Real-time object detection frameworks have played a crucial role in advancing these systems. Redmon et al. [7] introduce the YOLO (You Only Look Once) model, which enables fast and efficient detection through a single-pass architecture, making it highly suitable for real-time applications. Subsequent improvements, such as YOLOv4 and YOLOv5 proposed by Bochkovskiy et al. [8], further enhance detection performance while maintaining computational efficiency, making them ideal for deployment on embedded and edge devices. In contrast, region-based methods like Faster R-CNN, proposed by Ren et al. [9], offer higher accuracy but at the cost of increased computational complexity, limiting their applicability in real-time scenarios. Additionally, Norouzzadeh et al. [10] demonstrate the effectiveness of deep learning in wildlife monitoring using camera trap images, where automated detection and counting significantly reduce manual effort and improve efficiency, although such systems rely heavily on large annotated datasets. Overall, these studies collectively demonstrate that deep learning, particularly YOLO-based architectures and integrated intelligent systems, provides a strong foundation for developing accurate, efficient, and scalable real-time animal detection and monitoring solutions.

## III. METHODOLOGY

The proposed system introduces an intelligent animal detection and monitoring platform designed to reduce human-animal conflicts and improve farm security. It utilizes the advanced YOLOv11 object detection algorithm combined with Convolutional Neural Networks (CNNs) to detect and recognize animals in real time using live streaming camera feeds. The system is trained using well-organized datasets and enhanced through transfer learning to improve detection accuracy across diverse species and environmental conditions.

In addition to detection and recognition, the system integrates an automated alert mechanism that sends instant notifications via alarms, SMS, or email when animal intrusion is detected. It can also activate deterrent sounds to drive animals away, reducing the chances of damage or conflict. The implementation of edge computing reduces latency by processing data closer to the source, making the system highly responsive and suitable for deployment in remote agricultural fields and wildlife-prone areas.

The system provides an automated alert mechanism for immediate notification of animal intrusion, ensuring quick response. It utilizes advanced computer vision techniques to achieve accurate real-time animal detection. By incorporating YOLOv11 and CNN-based deep learning models, the system improves classification accuracy

significantly. It also reduces monitoring time and enables faster responses to potential threats. Additionally, the design lowers computational complexity while maintaining an efficient and scalable processor .

#### IV. EXPERIMENTAL RESULTS

Figure 1 shows the home page of the system, which provides the main interface for navigation to different modules such as login, detection, and user management. Figure 2 represents the code execution page where the deep learning model runs and processes real-time animal detection. Figure 3 illustrates the admin login page that allows authorized administrators to access system controls. Figure 4 displays the user details page, which contains information about registered users and helps in managing their data. Figure 5 shows the user login page for existing users to access the system, while Figure 6 represents the new user registration page where new users can create an account. Figure 7 demonstrates the email notification page, indicating how alerts are sent to users upon animal detection. Figure 8 shows the animal detection page where real-time detection results are displayed using the trained model. Figure 9 presents the admin detection page, enabling administrators to monitor detection results and system performance. Finally, Figure 10 illustrates the output via email page, showing how detection alerts and details are communicated to users through email notifications.



Figure 1

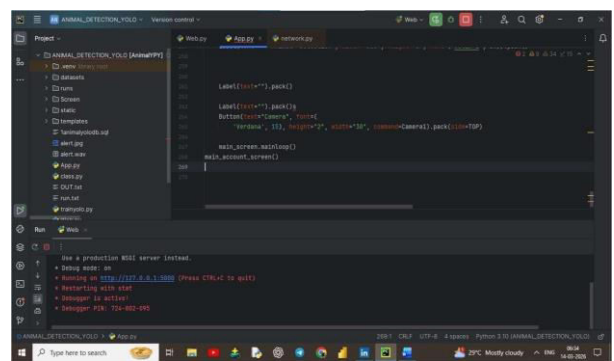


Figure 2

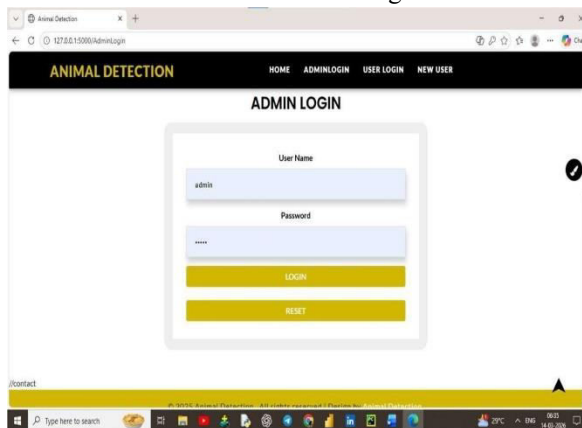


Figure 3

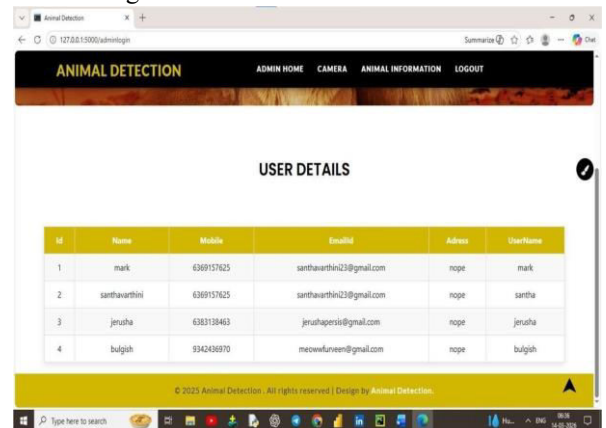


Figure 4

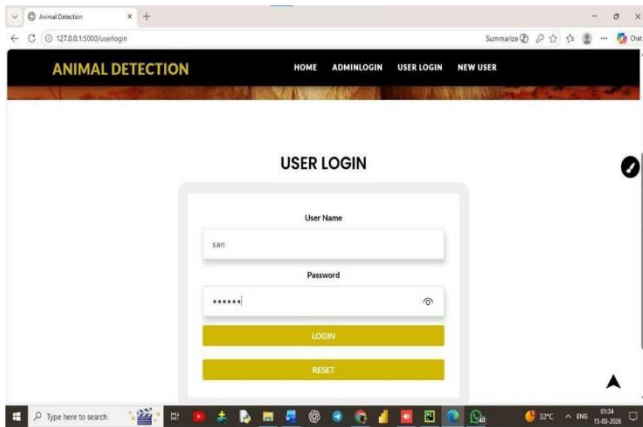


Figure 5

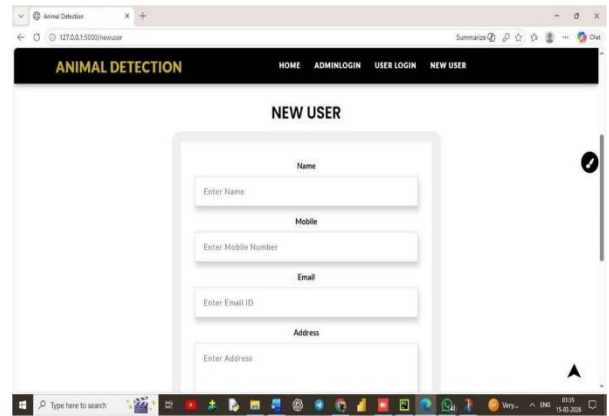


Figure 6

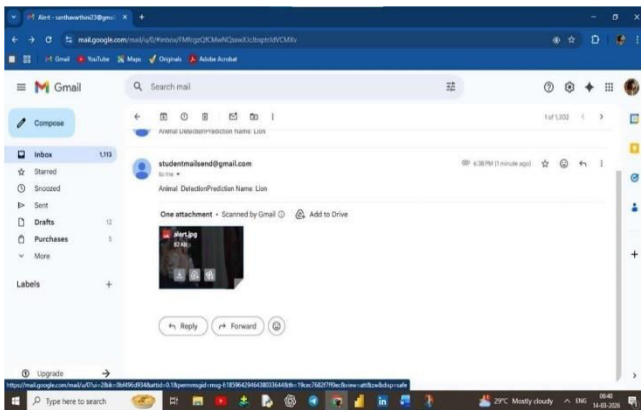


Figure 7

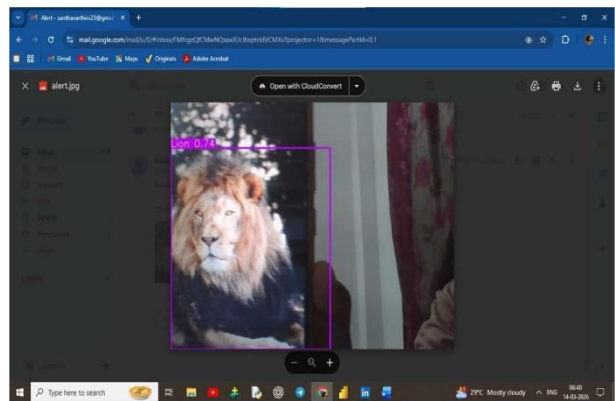


Figure 8

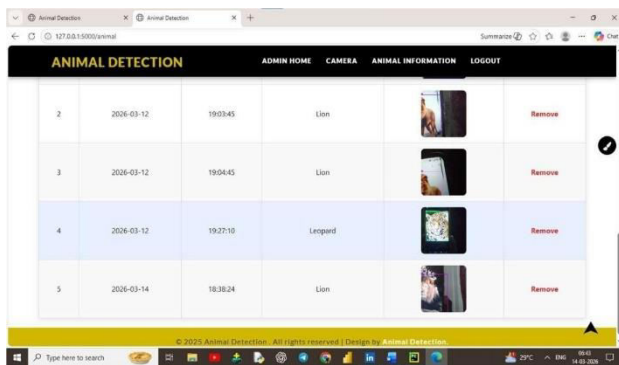


Figure 9

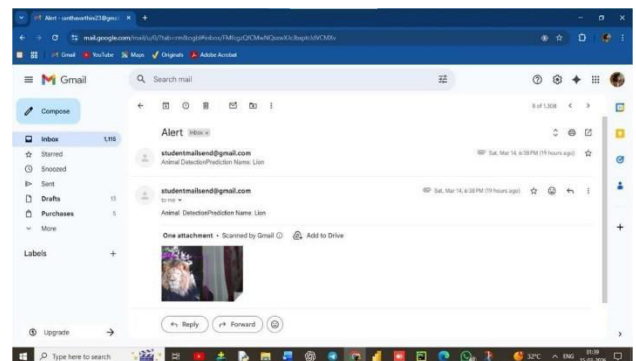


Figure 10

### V. CONCLUSION

The proposed AI-powered animal surveillance system provides an effective solution for human–animal conflict, farm security, and wildlife monitoring by using YOLOv11 and CNNs for accurate real-time detection. It reduces manual effort, improves response time, and enhances safety through automated alerts and edge computing. The system is scalable, cost-effective, and reliable for deployment in remote areas. Future enhancements include improving accuracy with larger datasets, supporting extreme conditions, adding behavior analysis, and integrating IoT devices, cloud storage, and mobile applications, making it suitable for advanced and large-scale monitoring systems.

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