Wild-Guard: A Smart Wild Animal Alert System for Roads in Network Covered Areas

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Abstract— **This paper presents an AI-enabled real-time alert system designed to prevent human–wildlife conflicts in forest and highway regions. The system utilizes computer vision and deep learning techniques, specifically the YOLOv8 model, to detect wild animals through roadside surveillance cameras. Upon detection, the animal snap- shot, GPS location, and timestamp are uploaded to Firebase, and alerts are delivered to nearby users through an Android mobile ap- plication via Firebase Cloud Messaging (FCM). The application provides voice alerts, emergency support, and live location sharing to enhance public safety. The approach offers a scalable, auto- mated, and real-time solution to reduce accidents and protect both humans and animals.**

***Index Terms*— Wild Animal Detection, YOLOv8, Real-Time**
Alert System, Firebase Cloud Messaging, Android Application, Computer Vision, Safety Monitoring.

I. INTRODUCTION

Human–wildlife conflict is a growing concern in areas where highways pass through forest zones. Sudden appearance of animals on the road often leads to serious accidents, endan- gering travelers and wildlife. Traditional warning systems such as signboards and manual monitoring are ineffective because they lack real-time responsiveness. With advance- ments in artificial intelligence, real-time animal detection can be achieved using deep learning and edge computing.
The project titled "WildGuard – A Real-Time Wild Ani- mal Detection and Alert System" aims to automatically de- tect animals using CCTV or surveillance cameras and pro- vide instant alerts to nearby users to prevent accidents and enhance traveler safety.

II. BACKGROUND

Deep learning models such as YOLO are widely used for high-speed object detection due to their ability to pro- cess real-time video streams with high accuracy. Firebase cloud services provide efficient real-time data synchroniza- tion and notification delivery, enabling scalable field deploy- ment. Mobile applications using GPS tracking allow precise identification of users present within a risk zone, enabling location-based targeted alerts.

III. LITERATURE SURVEY

Research indicates that automated wildlife detection sig- nificantly reduces collision risks and improves safety [1]. Real-time image processing frameworks using CNN and YOLO architectures have proven effective in animal detec- tion applications [2]. Cloud-integrated detection systems have demonstrated advantages in event processing and no- tification handling [3]. Studies emphasize the need for auto- mated monitoring infrastructure in wildlife highway cross- ings to prevent human and animal fatalities [4]. Mobile- assisted emergency alert systems have shown strong poten- tial in reducing response delays and improving public safety [5].

IV. METHODOLOGY

The system includes detection processing, database han- dling, and location-based alert delivery.
4.1. Data Collection and Preprocessing
Multiple datasets containing images of wild animals were used to train and fine-tune the YOLOv8 model.

Image pre- processing steps included resizing, augmentation, normal- ization, and annotation using Roboflow. The preprocessing ensured training consistency and improved model general- ization under varying lighting and angle conditions.

4.2. Animal Detection using YOLOv8

YOLOv8 was selected due to its high detection speed and accuracy. The trained model identifies animals in video frames and outputs bounding boxes, class labels. The detec- tion engine runs on laptops connected to cameras and gener- ates real-time recognition results.

4.3. Location-Based User Filtering

Each camera is associated with fixed GPS coordinates stored in Firebase. User GPS location is updated continuously through the Android application. When detection occurs, the system checks whether any registered user is within a 1-km radius by computing geospatial distance and filtering relevant users.

4.4. Alert Generation and Notification

If users are inside the alert zone, the backend generates noti- fication packets that include the timestamp, camera ID, and snapshot and sends them through Firebase Cloud Messaging (FCM). The app displays voice and vibration alerts to notify travelers of nearby animal activity.It provides safety to the travellers.

4.5. System Architecture Design

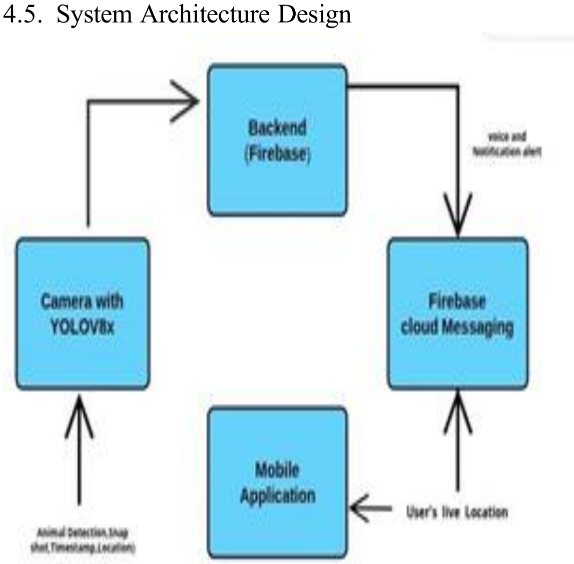

Figure 1: Diagram of System Architecture

4.6. System Design

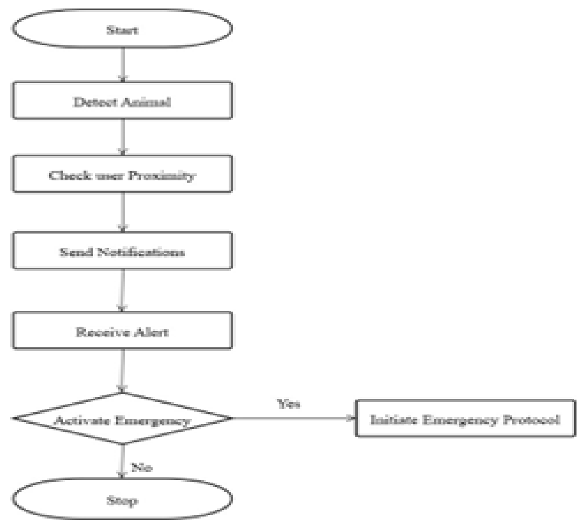

Figure 2: Flowchart of System

V. RESULTS

The YOLOv8 model demonstrated high accuracy in detect- ing animals under real-time video conditions. The alert sys- tem successfully sent notifications to users located within a 1-km radius, providing immediate voice and visual warn- ings. The results confirm the effectiveness of WildGuard in delivering real-time alerts and improving safety along wildlife- prone routes.

VI. SNAPSHOTS

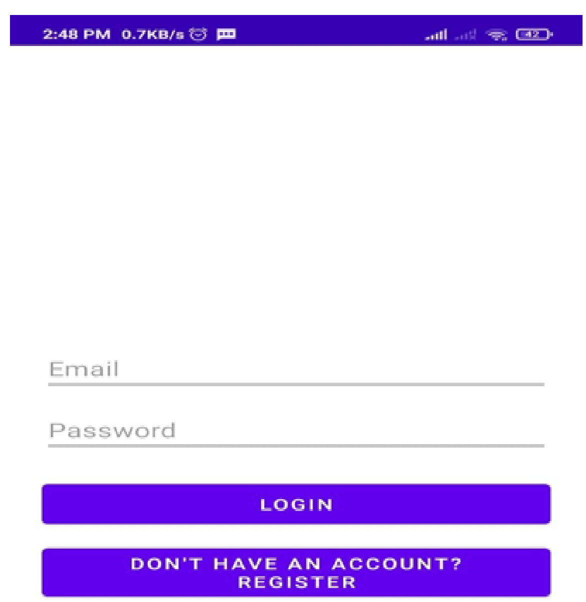

Figure 3: Login Page

Figure 4: Home Page

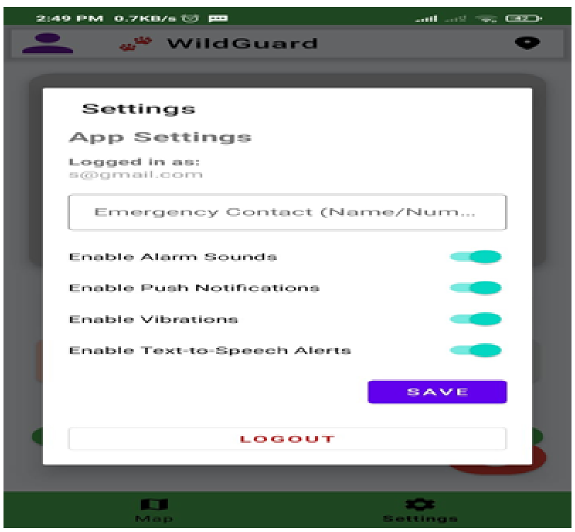

Figure 5: App Settings

Figure 6: Animal Detection

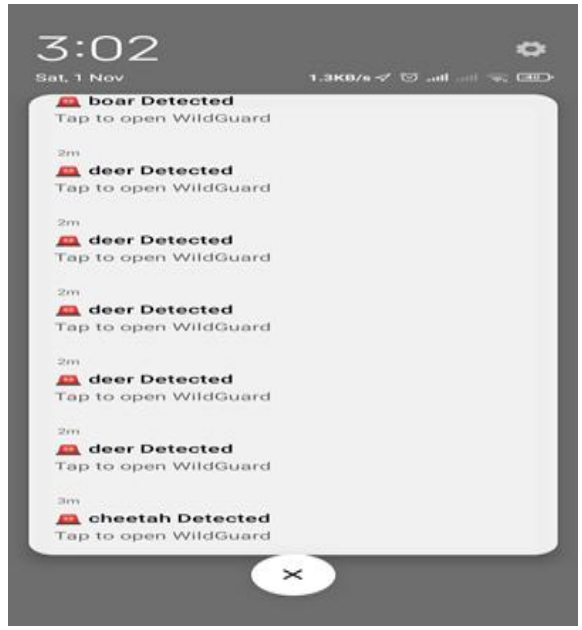

Figure 7: Real Time Notifications

VII. CONCLUSION

The proposed WildGuard system effectively identifies wild animals using real-time video processing and deep learning and delivers instant alerts through a cloud-connected An- droid application. The integration of AI-based detection with GPS-based notification significantly improves traveler safety and reduces human-wildlife conflict risk. The results demonstrate the potential for large-scale deployment across forest and highway regions.

VIII. FUTURE WORK

Future work includes expanding support for drones and ther- mal imaging for nighttime monitoring, implementing pre- dictive analytics to forecast animal movement, adding mul- tilingual interfaces, and enabling offline SMS alerts in poor- connectivity regions. The system can also be integrated with forest department databases for centralized wildlife monitor- ing and decision support.

IX. ACKNOWLEDGMENT

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