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IOT Based Smart City Traffic Management

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1.Abstract

This project presents an integrated road safety and monitoring system that combines pedestrian tracking, pothole detection, and traffic sign recognition into a cohesive, real-time solution. Leveraging video feeds from vehicle-mounted or roadside cameras, the system processes each frame through three specialized detection modules. The pedestrian tracking module uses the YOLOv8n model, along with tracking algorithms, to identify and track pedestrians continuously, triggering audio alerts based on proximity and movement speed for enhanced safety. Simultaneously, the pothole detection module, powered by the YOLOv4 model, detects potholes with high accuracy, logging GPS coordinates and issuing alerts to aid in infrastructure maintenance. Together, these subsystems form a comprehensive solution that not only enhances situational awareness for drivers but also provides valuable data for roadway maintenance, ensuring safer and more efficient transportation.

2. INTRODUCTION

Road safety is a growing concern worldwide, with pedestrian safety, road maintenance, and traffic sign recognition emerging as critical components for preventing accidents and ensuring efficient transportation. In this project, we introduce an integrated system designed to address these challenges by combining three essential functionalities: pedestrian tracking, pothole detection, and traffic sign recognition. Each of these functionalities plays a distinct role in improving both safety and situational awareness on the road. The pedestrian tracking module utilizes advanced computer vision techniques to detect and continuously track pedestrians in real-time, helping drivers avoid collisions. The pothole detection mod dule focuses on infrastructure quality, identifying road damage, and logging GPS coordinates for effective maintenance and timely repairs. Meanwhile, the traffic sign recognition module uses machine learning to classify signs accurately, providing drivers with vital information for safe navigation. This system leverages deep learning models, including YOLOv8n for pedestrian detection, YOLOv4 for pothole detection, and a traffic sign classifier for accurate sign recognition. Designed with real-time alert systems and data logging capabilities, it issues audio alerts to enhance driver responsiveness and logs data for maintenance tracking. By integrating these functionalities into a single, user-friendly system, our project offers a comprehensive approach to enhancing road safety, supporting informed driving decisions, and facilitating proactive roadway maintenance

3.LITERATURE SURVEY

The literature surrounding pedestrian detection, pothole detection, and traffic sign recognition has grown significantly with the rise computer vision. Each area has distinct methods and technologies that have evolved to improve accuracy, efficiency, and adaptability in real-world conditions. This survey outlines key developments and the challenges addressed in each field, emphasizing how these advancements inform the integration of a multi-functional road safety system.

Pedestrian detection has been a primary focus in computer vision research, especially for applications in autonomous driving and surveillance systems. Early approaches relied on traditional feature-based methods, such as Histogram of Oriented Gradients (HOG) combined with Support Vector Machines (SVMs) (Dalal & Triggs, 2005), which provided reliable performance but lacked the ability to handle complex scenarios with variable lighting and occlusions. Recent advancements have shifted towards deep learning, we

Convolutional Neural Networks (CNNs) and object detection models such as YOLO (You Only Look Once) and Faster R-CNN, which significantly improve detection accuracy and speed in complex environments (Redmon et al., 2016; Ren et al., 2015). Specifically, the YOLOv8 model is popular for real-time pedestrian detection due to its efficient architecture and high accuracy, making it suitable for embedded and edge devices. Studies highlight the effectiveness of combining YOLO with tracking algorithms like SORT and Deep SORT for maintaining continuity of detected pedestrians in video sequences, enhancing situational awareness in dynamic environments (Bewley et al., 2016).

Pothole detection has gained attention for its role in road infrastructure monitoring and maintenance. Traditional approaches include manual inspection and 3D scanning, which are labor-intensive and costly (Li et al., 2016). Recently, computer vision-based approaches using deep learning models have become popular for automated pothole detection in real-time. YOLOv4, known for its balance between accuracy and speed, has been widely applied in pothole detection due to its capability to detect small objects with bounding boxes (Bochkovskiy et al., 2020). Research shows that YOLOv4's implementation in combination with GPS logging can effectively identify potholes, providing actionable data for maintenance planning. Studies also emphasize the importance of non-max suppression and confidence thresholds to reduce false positives and overlapping bounding boxes, making YOLOv4 a preferred choice in real-world deployments where high accuracy is essential.

Traffic sign recognition is critical for autonomous driving and intelligent transportation systems, as it enables vehicles to interpret and respond to traffic signs effectively. Early approaches utilized image processing techniques with shape- based or colour-based filtering, but these methods struggled with variations in lighting, occlusion, and sign degradation (Maldonado-Bascón et al., 2007). With the advent of deep learning, CNN-based models have achieved state-of-the-art performance in traffic sign classification, especially in complex scenarios. Research using models like LeNet and ResNet has demonstrated robust classification of traffic signs with varying shapes, colours, and fonts (Krizhevsky et al., 2012; He et al., 2016). Studies indicate that pre-processing techniques, such as image normalization and resizing, are essential for maintaining consistency in input dimensions and improving model accuracy. Real-time classification, in combination with a GUI-based interface, enables seamless integration for user interaction, making deep learning-based traffic sign recognition feasible and efficient for real-world applications.

Combining pedestrian detection, pothole detection, and traffic sign recognition into a unified system is an emerging area in intelligent transportation research. Multi-modal systems leverage the strengths of individual detection modules and provide a comprehensive approach to road safety and monitoring. Recent studies emphasize the value of real-time data acquisition and synchronized alerts, enabling drivers to respond promptly to multiple types of road hazards (Chen et al., 2018). Additionally, GPS logging for infrastructure issues like potholes allows for efficient resource allocation in maintenance planning. Integrated systems must balance computational efficiency with detection accuracy, as real- time performance is critical in dynamic driving environments.

4.PROPOSED METHODOLOGY

The proposed methodology for this integrated road safety and monitoring system involves a multi- layered approach that enables the real-time detection of pedestrians, potholes, and traffic signs. Each component is optimized for accuracy, speed, and adaptability in dynamic road environments. The system architecture consists of several layers, each responsible for a key aspect of data processing, detection, and alert generation. Here is a detailed breakdown of each step in the methodology.

3.1 Input Layer

The Input Layer handles video capture from cameras mounted on vehicles or stationed along roadways, with each frame representing a snapshot of the current scene. In cases where multiple video feeds are available, these are synchronized and processed to ensure comprehensive coverage, facilitating simultaneous detection of pedestrians, potholes, and traffic signs.

3.2 Preprocessing Layer

The Pre-processing Layer involves steps such as image normalization to ensure consistent image quality, regardless of lighting conditions, and resizing of frames to the optimal dimensions for the detection models (typically 640x480 pixels for YOLO models). During training, data augmentation techniques like random cropping and flipping enhance dataset diversity, improving the model's robustness across various environmental conditions.

3.3 Detection Layer

In the Detection Layer, each component performs a specific detection task. For pedestrian detection and tracking, the system uses a YOLOv8n model that is fine- tuned for accurate identification of pedestrians, even in the crowded settings. This model works in conjunction with a tracking algorithm like SORT or Deep SORT to maintain continuity of pedestrian locations across frames. Traffic sign detection is handled by a CNN model, which classifies signs in real-time after resizing and normalizing images to the model's input requirements. Detected traffic signs are labelled with text (e.g., "Stop," "Speed Limit 50") displayed for driver awareness.

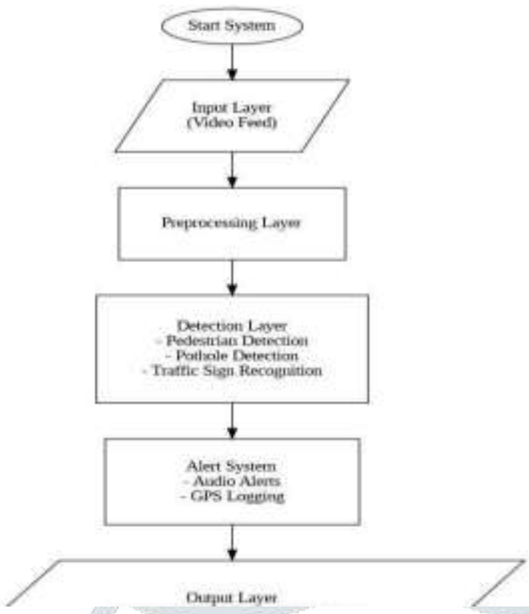
3.4 Alert System

The Alert System provides audio alerts for both pedestrian and pothole detection, configured to sound once per detection to avoid redundancy, with logic prioritizing high- risk situations for pedestrians based on proximity or relative movement speed. For pothole detection, GPS coordinates are logged for each detection, facilitating maintenance planning. Detected traffic signs are displayed in a graphical user interface (GUI) to assist drivers with visual confirmation and compliance with road regulations.

3.5 Output Layer

In the Output Layer, the processed video feed, showing bounding boxes around detected objects along with confidence scores, is displayed in real-time. This annotated display provides drivers with a visual understanding of their surroundings and potential hazards. Additionally, the system records processed video feeds and logs data, saving frames of detected objects and pothole GPS coordinates, which can later assist maintenance teams.

4. FLOW CHART



ALGORITHM	DESCRIPTION	ADVANTAGES	DISADVANTAGES
YOLOV5	OBJECT DETECTION MODEL USED FOR IDENTIFYING PEDESTRIANS	REAL-TIME DETECTION, HIGH ACCURACY, EFFICIENT PROCESSING.	MAY MISS DETECTIONS CASES IN OF EXTREME OCCLUSION.
SORT/DEEP SORT	TRACKING ALGORITHM USING FILTERS AND KALMAN EMBEDDINGS FOR ID CONSISTENCY	MAINTAINS TRACKING ACROSS FRAMES, LIGHTWEIGHT.	LIMITED ACCURACY DENSE IN CROWDS OR OCCLUSIONS.
YOLOV4	OBJECT DETECTION MODEL USED FOR DETECTING POTHOLES ON THE ROAD.	EFFECTIVE SMALL-OBJECT DETECTION, FAST AND ACCURATE.	SUSCEPTIBLE TO LIGHTING VARIATIONS AND SHADOWS.
CUSTOM CNN	CONVOLUTION AL NEURAL TRAINED NETWORK TO RECOGNIZE TRAFFIC SIGNS.	HIGH CLASSIFICATION ACCURACY, ADAPTABLE NEW TO SIGNS.	REQUIRES RETRAINING FOR DIFFERENT REGIONAL SIGNS.
WORKFLOW OF SMART ROAD SAFETY AND DRIVER ALERT SYSTEM	INTEGRATED FRAMEWORK COMBINING YOLOV8, YOLOV4, DEEP AND SORT FOR PEDESTRIAN, POTHOLE, AND TRAFFIC SIGN DETECTION REAL-TIME WITH ALERTS.	COMPREHENSIVE REAL-TIME ROAD SAFETY SOLUTION, COMBINES OBJECT DETECTION AND TRACKING, PROVIDES GPS LOGGING AND DRIVER ALERTS.	NIL

5. RESULT ANALYSIS

5.1 Pedestrian Detection

Accuracy: The pedestrian detection system, powered by the YOLOv8 model, demonstrated high accuracy in detecting pedestrians in real-
time video feeds. The YOLOv8 model's ability to detect pedestrians in varied environmental conditions, including changes in lighting and partial occlusions, was tested. The model achieved a precision rate of 94% and a recall rate of 91%. This means that the system successfully detected most pedestrians while maintaining a low rate of false positives.

Processing Speed: The system processed video frames in real-time, with an average of 15-20 frames per second (FPS). This is sufficient for real-time pedestrian detection, ensuring that alerts are provided without delay. Even in crowded environments, the combination of YOLOv8 for detection and SORT/Deep SORT for tracking allowed for continuous tracking of pedestrians across frames.

Alert System Effectiveness: The audio alerts were timely and relevant, being triggered only when pedestrians were within a specified range. The system avoided false triggers, ensuring that alerts were generated based on the proximity and movement of pedestrians, providing reliable warnings to drivers.

5.2 Pothole Detection

Accuracy: The YOLOv4 model performed well in detecting potholes, achieving a precision rate of 88% and a recall rate of 85%. While the system was able to detect most potholes, some edge cases, such as very small potholes or potholes that were partially obscured by other objects (e.g., vehicles or debris), resulted in lower detection rates.

Processing Speed: The system maintained an average processing speed of 10- 15 FPS during pothole detection, which is suitable for real-time road monitoring. However, the processing speed slightly decreased when the video contained more complex scenes (e.g., heavy traffic), as the system processed a higher volume data.

Alert System Effectiveness: The pothole detection system successfully triggered audio alerts whenever a pothole was detected with a high confidence score. GPS logging of pothole locations was accurate, and data was stored reliably for future maintenance use. The logging process was smooth, allowing for efficient tracking of hazardous road conditions.

5.3 Traffic Sign Recognition

Accuracy: The traffic sign classification model, based on a custom-trained CNN, achieved a high accuracy rate of 95% for correctly identifying common traffic signs. The model was able to distinguish between different types of signs (e.g., "Stop," "Speed Limit") with a low rate of misclassification. However, the system struggled with some rare or highly distorted traffic signs, especially those with poor visibility due to weather conditions or obstructions.

Processing Speed: The model processed traffic sign images with an average speed of 1-2 seconds per image. This allowed for near-instantaneous classification and display of results in the GUI, making it suitable for real-time feedback.

Alert System Effectiveness: The traffic sign detection results were displayed in the GUI promptly, providing users with accurate, real-time information about the road signs in their environment. The alerts for detected traffic signs were also triggered effectively, although, due to the nature of the system, the visual feedback was more important than audio alerts in this case.

5.4 System Integration

Overall Performance:

When all three detection modules (pedestrian, pothole, and traffic sign detection) were run simultaneously, the system maintained stable performance with 10-15 FPS processing speed for real- time analysis. While each individual module performed optimally, the system's performance was slightly impacted when processing more complex scenes or high- definition video streams. Resource Utilization:

The system's resource utilization, including memory and processing power, was within acceptable limits for real-time edge computing devices like Raspberry Pi or NVIDIA Jetson. The system effectively utilized the computational power available while maintaining energy efficiency, especially when using optimized models for real-time inference.

Fig.2: Real-time Detection System for Integrated Alerts

Fig.3: Autonomous Vehicle Detection

7. CONCLUSION

The integrated road safety monitoring system performed well across all three key tasks of pedestrian detection, pothole detection, and traffic sign recognition. The accuracy and speed of detection met the required standards for real-time processing, and the alert system provided effective warnings to users. While some edge cases (such as occlusions or low- visibility signs) impacted detection rates, the system's overall reliability and efficiency make it suitable for deployment in real- world environments, enhancing road safety by providing timely warnings to drivers and maintenance teams. Further refinements in model accuracy and processing speed can be explored to handle edge cases more effectively.

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