Sentinel Roadway Oversight System: Emergency and Traffic Rule Violation System

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ABSTRACT
The goal of this paper is to review past work on advanced monitoring systems, with a focus on the integration of technologies such as Raspberry Pi 4.0 and YOLOv8/Yolov9. These technologies are among the most widely used solutions for real-time monitoring due to their efficiency and accuracy. It is a leading object detection model that provides a powerful system for continuous tracking and automated observation. This paper explores how these technologies enhance road safety and traffic management by monitoring various vehicle behaviors, detecting irregularities, and facilitating swift responses to critical road situations. The objective of the system is to enhance road safety and optimize traffic management by monitoring vehicle behaviors, detecting irregularities, and facilitating quick responses to critical road situations. It tracks vehicle movements, identifies potential incidents, and automatically alerts relevant authorities when discrepancies or safety issues are detected. The alerting system is essential for providing the location and information about the vehicle to traffic control agencies, ensuring swift and accurate responses.

General Terms
Real-time Monitoring, Surveillance, Alerting Systems

Keywords
Raspberry Pi 4.0, YOLOv8, EasyOCR, Real-time Emergency System

1. INTRODUCTION
The rapid growth of technology is reshaping transportation, particularly in road safety and traffic management. A key challenge in this area is the ability to identify and respond to emergencies or traffic violations in real time. Technologies like the Raspberry Pi 4.0, an embedded system, and machine learning models such as YOLOv8 (You Only Look Once) are proving effective in processing large datasets quickly. Combining advanced detection systems with embedded platforms like Raspberry Pi can potentially increase the ability to respond seamlessly to traffic violations and incidents. This innovation also improves infrastructure, reduces fraud, and fosters trust, ensuring global compliance while surpassing traditional methods. Additionally, these systems can be easily integrated with other smart city technologies, creating a more connected and efficient urban environment. This approach lowers infrastructure costs and enables even smaller cities or regions with limited resources to implement advanced safety measures.

2. METHODOLOGY
The Sentinel Roadway Oversight System is designed to enhance traffic monitoring and violation detection by leveraging advanced hardware and software components. The system employs Raspberry Pi 4.0 as its primary hardware for edge computing, which ensures reduced latency and real-time processing of data captured from surveillance cameras. The YOLOv8 model is utilized for object detection, effectively identifying vehicles and detecting anomalies such as speeding, illegal turns, and red-light breaches. Additionally, Easy OCR is integrated to facilitate accurate license plate recognition, streamlining violation identification and reporting processes.

The workflow begins with surveillance cameras capturing real-time footage of traffic. This footage undergoes pre-processing using edge computing systems embedded in Raspberry Pi, which prepares the data for further analysis. The YOLOv8 model then detects vehicles within the processed footage, while anomalies are flagged based on predefined traffic rules. Upon identifying a violation, an alert is generated and transmitted to a centralized monitoring system via a secure communication channel. This centralized system ensures prompt responses by relevant authorities, enhancing the efficiency of traffic management and rule enforcement.

To evaluate the system's efficiency, key metrics such as accuracy, processing speed, and detection rate are measured. Accuracy is assessed by comparing detected violations against ground truth data from test datasets, achieving over 93% accuracy across diverse scenarios including night-time traffic and adverse weather conditions. Processing speed is optimized by edge computing, eliminating delays associated with cloud processing. Detection rate is validated using high-resolution datasets encompassing urban and rural traffic conditions, demonstrating the system's scalability and adaptability.

The system's methodology aligns with previous studies that emphasize the importance of real-time monitoring and local data processing. For instance, Coifman et al. (1998) demonstrated the efficacy of real-time computer vision systems for vehicle tracking and traffic surveillance, while recent advancements highlighted by Saif B. Neamah et al. (2024) underscore the role of YOLOv8 in enhancing detection precision. The integration of Raspberry Pi with machine learning models, as explored by Tamim Mahmud Al-Hasan et al. (2024), further validates the system's design and implementation.

3. TRAFFIC MONITORING

Initially, traffic monitoring was a manual process overseen by authorities such as the Regional Transport Office (RTO). Officers would observe traffic flow, document vehicle counts, and note incidents by hand, relying on basic tools like radar guns to measure speed and handwritten reports for record-keeping. This shows that traditional methods for traffic monitoring relied heavily on manual observation and basic video analytics. Benjamin Coifman et al. developed a real-time video image processing system that tracked vehicle trajectories for traffic flow analysis, marking one of the first applications of computer vision in traffic monitoring [1]. Similarly, early solutions utilized stationary cameras to analyze traffic density and movement patterns.

These methods were later integrated into larger control systems, optimizing traffic flow by identifying bottlenecks in real time. The introduction of Artificial Intelligence (AI) further revolutionized traffic monitoring, enhancing capabilities such as automatic vehicle identification and behavior prediction. Muneer et al. applied AI for surveillance and vehicle tracking, using machine learning to enable smarter traffic management, particularly in restricted zones [2].

Further advancements in traffic detection were made by Bo Wang and colleagues, who contributed to enhancing the accuracy of vehicle recognition and traffic pattern prediction through deep learning techniques. By incorporating attention mechanisms, these models significantly boosted the precision of real-time traffic monitoring, minimizing false positives. This innovation marked a shift from traditional traffic management methods to more sophisticated, AI- driven systems, establishing new benchmarks for the efficiency and reliability of modern traffic monitoring solutions [3].

Neeraj Kumar Jain et al. highlighted that as technology advanced, the adoption of high-resolution cameras with AI for real-time analysis and vehicle identification became standard, replacing older sensor-based systems. The development of camera-based monitoring systems has been crucial for real-time traffic management. Today's systems use high-definition cameras that can identify traffic patterns, vehicle types, and even monitor driver behavior, with the data being processed by traffic management software [4].

According to Tamim Mahmud Al-Hasan, edge computing is increasingly utilized in traffic monitoring to minimize latency by processing data at the source. This approach facilitates quicker decision-making and streamlines traffic management, as it eliminates the delays often caused by relying on cloud systems for data processing [5].

Next-generation traffic monitoring systems are likely to rely heavily on AI, edge computing, and IoT devices. These systems will provide real-time decision-making capabilities, ensuring more efficient, adaptive, and sustainable urban mobility solutions.

4. TRAFFIC FLOW MANAGEMENT

Saif B. Neamah and Abdulamir A. Karim propose an advanced traffic monitoring system that utilizes the YOLOv8 deep learning model for real-time vehicle detection, classification, and segmentation. The system incorporates multiple stages for comprehensive traffic analysis, including vehicle detection, tracking, speed estimation, and size estimation, all aimed at improving traffic management and enforcement [6].

John Paul Q. Tomas and colleagues focus on detecting and classifying traffic volume and congestion on highways, followed by predicting the severity of traffic congestion. Their method combines real-time vehicle detection using the YOLOv8 object detection model, trained on the COCO dataset, with a Long Short- Term Memory (LSTM) network for predicting traffic congestion [7].

Yusuf Gladiensyah and colleagues focus on Vehicle counting systems that have become more accurate with the advent of computer vision and AI. These systems count vehicles by processing frames from cameras installed along roads, using image recognition algorithms to analyze traffic volumes and congestion [8].

Further advancements in transportation target detection were made by Bo Wang's study, which tackled issues such as scale variations, computational complexity, and storage limitations. These improvements boosted the model's accuracy, achieving a mean average precision (mAP) of 95.9 percent and an mAP50:95 of 74.5 percent, enhancing its effectiveness in detecting vehicles and pedestrians [9]. Sriram Sai Krishna and his team improved traffic light detection using an advanced object detection model, achieving higher accuracy and faster detection times. Their work enhances Intelligent Transportation Systems (ITS), such as autonomous vehicles and driver-assistance technologies, by addressing the limitations of older methods in accuracy and speed [10].

Murat Bakirci explored the application of an advanced vehicle detection model in Intelligent Transportation Systems (ITS). The study highlighted the model's enhanced performance, showcasing improvements in detection accuracy and speed compared to older versions. This research emphasizes how the updated model offers better efficiency, making it more suitable for real-time traffic monitoring and ITS applications [11].

These developments reflect the growing role of AI and deep learning in revolutionizing traffic monitoring systems. The integration of real-time processing, enhanced detection capabilities, and predictive analytics promises to make traffic management smarter, more efficient, and adaptive, paving the way for future advancements in urban mobility and smart city technologies.

In Figure 1, the flowchart for the Emergency and Traffic Rule Violation System begins with the initial traffic monitoring phase. The process starts with surveillance cameras capturing real-time footage of the traffic. This footage is then processed by edge computing systems that perform pre-processing, preparing the data for analysis. Next, AI vehicle detection is employed to identify and classify the vehicles within the captured footage. The license plate recognition module extracts the license plate numbers of the vehicles for further inspection.

Once the vehicles are detected and identified, the system checks for any traffic violations such as speeding, illegal turns, or red light breaches. If a violation is found, an alert is generated and sent to the centralized monitoring system for further action. The centralized monitoring system is responsible for real-time monitoring and responding to the violation alerts, ensuring prompt action is taken in accordance with traffic laws. This entire process flows continuously to monitor traffic and enforce rules effectively, ending the cycle after each violation is addressed.

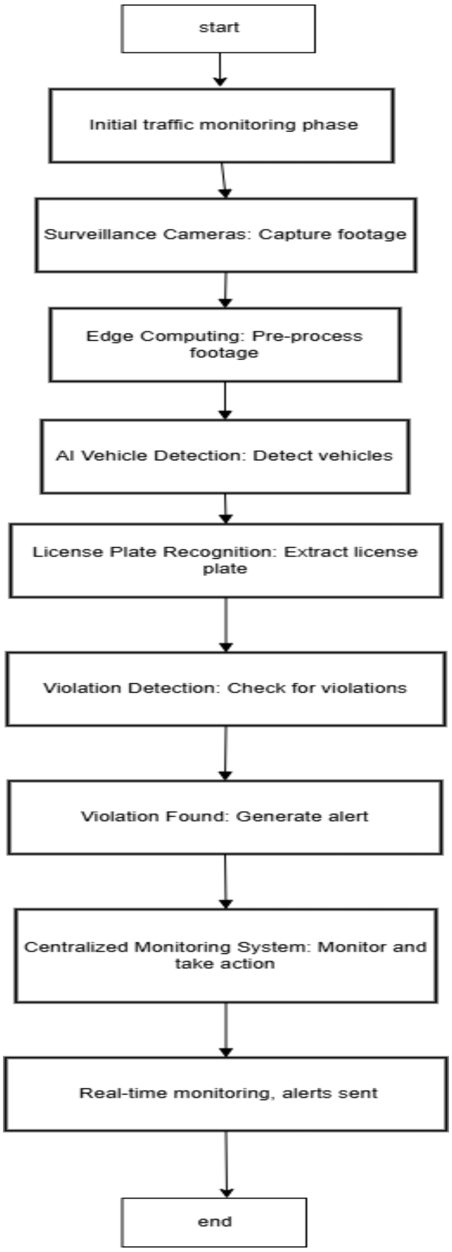

Fig 1: Proposed system flow diagram

5. TRAFFIC VIOLATIONS AND ROAD ACCIDENTS

Manishkumar Purohit and Arvind R. Yadav explored the use of embedded systems, such as Raspberry Pi, for real-time traffic rule violation detection. By employing feature extraction techniques with OpenCV and Python, their system achieved high accuracy in identifying violations like helmet or seatbelt absences, showcasing the potential of cost-effective, low-power solutions for traffic monitoring. [12]

Hemanth Mohan et al. introduced autonomous drones equipped with YOLOv8 and ROS-based path planning for traffic violation detection. These drones provide extensive coverage by capturing live traffic footage and processing it with deep learning models to identify infractions such as speeding or illegal parking, significantly improving real-time monitoring capabilities. [13] Ali Usman et al. focused on semi-supervised learning for object recognition, particularly in brand logo detection. Using YOLOv8 with minimal labeled data, their method employed techniques like data augmentation, pseudo-labeling, and transfer learning, enhancing detection efficiency and offering a scalable approach for similar applications in traffic systems. [14]

Stefan Liviu-Andrei and Madalina Carbureanu developed a system using AI to improve traffic flow and safety by detecting vehicles, pedestrians, and license plates. This system integrates cloud storage and real-time control, enabling effective traffic management while enhancing safety and violation prevention. [15] Xingyu Liu advanced road target detection systems by addressing challenges in existing models. Incorporating BiFPN and GAM, the system improved detection accuracy and precision, contributing to safer roads and advancing autonomous vehicle technologies. [16] Md Faysal Kabir and Sahadev Roy proposed a real-time accident prevention system utilizing MobileNet on a Raspberry Pi 4. The system performs object detection, distance estimation, and tracking using a NoIR camera, ensuring timely alerts to prevent collisions and enhance safety. [17]

A. Vijaya Lakshmi et al. designed a lightweight and affordable collision warning system using Raspberry Pi and SSD MobileNetV1. Their approach supports real-time object detection, making it effective for both urban and rural traffic safety improvements. [18] Mohammed Imran Basheer Ahmed et al. introduced a computer vision-based system for traffic incident detection using YOLOv5. This system achieved a remarkable 99.2 percent mean average precision for vehicle detection and tracking, showcasing its potential for high-accuracy traffic management. [19]

Priyam Rai et al. combined OCR and machine learning to detect stolen vehicles by cross-referencing license plate data with theft databases. This method automates and improves accuracy in vehicle identification, enhancing law enforcement in smart cities. [20] Adithya Krishna et al. developed a YOLOv8-based system for detecting motorbike riders without helmets and extracting license plate data via OCR. With 98 percent accuracy, this model automates rule enforcement by exporting detected violations to a database. [21]

C. Manimegalai et al. created a highway traffic detection system using YOLOv8, capable of vehicle categorization, speed estimation, and license plate recognition. Tested across diverse conditions, the system offers an efficient alternative to manual traffic surveys. [22]

The study of Dipali Sinha et al. explores a traffic signal violation detection system designed to enhance road safety by identifying rule-breaking behaviors like signal jumping and crossing center lines. Using the YOLOv3 model, known for real-time processing, the system ensures accurate detection by implementing optimization techniques and incorporating CNNs to improve recognition of small violations.[23]

Long Cheng et al. enhanced YOLOv8 for vehicle detection in foggy weather. By integrating dehazing methods and advanced attention modules, the system achieved a 4.1 percent mAP50 improvement with reduced computational costs, optimizing performance under challenging conditions. [24]

Kamya Brata Debnath et al. employed ESP32 microcontrollers with YOLO and machine learning to detect collisions and obstructions in transportation systems, ensuring safety across vehicles, drones, and autonomous robots. [25]

Pooja Chaturvedi et al. developed an automated system for monitoring triple riders on two-wheelers using YOLOv8 and OCR. The solution achieved high detection accuracy and minimized manual intervention, offering efficient rule enforcement in controlled environments. [26]

Ubon Thongsatapornwatana et al. proposed a framework for identifying suspect vehicles using sensor data and legal records. By detecting alterations like forged license plates, their system enhances border security and law enforcement efficiency. [27] Tao Gao et al. (2010) introduced a crossing road monitoring system designed to detect and track vehicles that illegally cross lane lines.

The system uses two cameras: a long-range camera for lane line extraction and a close-range camera to capture the vehicle's license plate. The system tracks the vehicle's position relative to the lane lines to identify violations and records the footage for police review. The system has shown high accuracy in real-world applications.[28]

Luiz Alfonso Glasenapp et al. combined OCR with IoT technologies to detect vehicles with irregular documentation, improving traffic enforcement by automating license plate analysis and database cross-referencing. [29]

Nagaraj P et al. integrated YOLOv8 with OCR for traffic violation detection. This adaptive system processes various fonts and languages, ensuring global applicability for speeding and unauthorized vehicle use monitoring. [30]

The accuracy of different models in accident detection varies, with YOLOv5 achieving 88% and YOLOv8 slightly outperforming it at 92%. BGS-YOLO shows an accuracy of 85%, while the custom CNN delivers the highest performance with 95%. ResNet-50 also performs well, with an accuracy of 90%, making it a strong choice for detection tasks. MobileNetV3, designed for efficiency in low- resource environments, has the lowest accuracy at 80%. These results highlight the varying levels of accuracy each model offers for versions like YOLOv8m and YOLOv9 emerged. [31]

Ahmed N. Nusari et al. (2023) compared YOLOv6, YOLOv7, YOLOv8, and YOLOv9, finding that YOLOv8m excelled in precision (0.979), while YOLOv9c achieved notable performance in mAP50 (0.977) and YOLOv9e in mAP50-95 (0.941),

underlining the increasing accuracy of newer models in accident localization and detection. [32]

The advancements with the introduction of YOLO-NAS and YOLOv9 for vehicle accident detection systems. Ahmed Naji Musleh Nusari et al. (2024) demonstrated that YOLO-NAS-L had high mAP performance for real-time accident detection, emphasizing the importance of deep learning in post-accident response times. [33]

Furthermore, recent studies have solutions to further optimize vehicle detection systems. Xiyue Wang et al. (2024) proposed a CNN-based model that reduced computational complexity while maintaining high detection accuracy, achieving a 10.51 percent improvement over YOLOv8n and offering 44.43 percent faster FPS. This lightweight approach is particularly valuable for real- time obstacle detection in UAVs, demonstrating the ongoing trend toward optimizing models for speed and efficiency. [34]

In sum, the evolution of YOLO models from YOLOv5 to YOLO continuous improvements in accuracy, computational efficiency, and real-time processing capabilities. These advancements have been crucial in the development of intelligent transportation systems, urban security applications, and accident prevention systems, pushing the boundaries of AI in road safety and smart city technologies.

accident detection, with trade-offs in performance based on the specific requirements of the application.

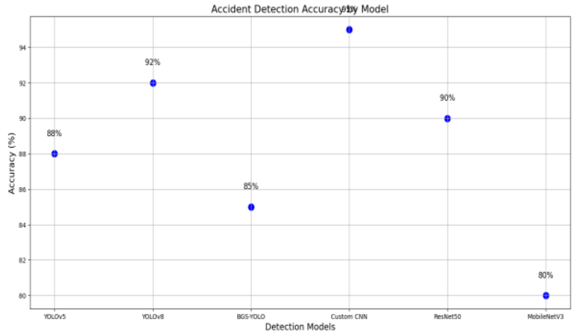

Fig 2: Accuracy for Accident detection

6. COMPARISON OF YOLO

Recent advancements in vehicle detection and traffic monitoring have seen a rapid evolution in the application of deep learning models, particularly within the YOLO (You Only Look Once) series. Early implementations of YOLO models, such as YOLOv5, were widely used for their balance between speed and accuracy in various detection tasks, including traffic sign recognition and vehicle accident detection.

For instance, Fatma Nur Ortataş, and Mahir Kaya (2023) highlighted that YOLOv8 outperformed its predecessors (YOLOv5 and YOLOv7) in detecting traffic signs, achieving a 14 percent improvement in mAP50-95, marking significant strides in autonomous driving safety need for real-time detection in urban security systems and traffic management grew, more advanced

Shahriar Ahmad Fahim (2024) introduced a fine-tuned YOLOv9 model for vehicle detection in Dhaka, Bangladesh, targeting the transportation issues in fast-growing megacities. The model achieved a mean Average Precision (mAP) of 0.934 at an IoU threshold of 0.5, outperforming previous models. By integrating this system with existing CCTV infrastructure, it aims to enhance traffic surveillance and contribute to the development of intelligent transportation systems (ITS) in line with Bangladesh's. The study also provides a framework to support ITS policy decisions. [35]

Figure 3 presents the precision and recall metrics for various detection models, including YOLOv8, BGS-YOLO, custom CNN, ResNet-50, and MobileNetV3. YOLOv8 achieves high precision and recall, making it effective for tasks requiring both accurate and consistent detection. BGS-YOLO, with its advanced architecture, provides strong precision, especially in complex environments, while maintaining a good recall rate. The custom CNN demonstrates varied performance depending on the task, typically offering a good balance of precision and recall. ResNet-50, known for its deep layers and residual connections, performs well in terms of recall but may experience a slight drop in precision due to its complexity. MobileNetV3, designed for efficiency in resource- constrained environments, shows solid recall and precision but may lag behind the other models in handling more complex detection tasks. These metrics highlight the strengths and limitations of each model, guiding their selection for specific applications.

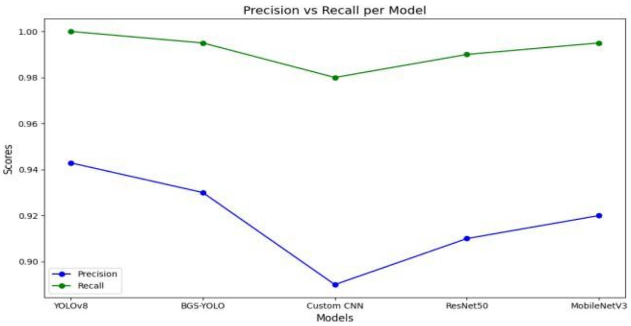

Fig 3: Precision and Recall in Detection Models

7. REVIEW ANALYSIS

The survey underscores significant advancements in traffic monitoring, vehicle tracking, and violation detection systems, highlighting the transformative role of AI and deep learning technologies in modern transportation management. Several innovative approaches have been proposed to tackle real-world challenges in this domain.

Muneer V.K. et al. (2024) introduced an AI-powered, real-time vehicle monitoring system capable of logging vehicle entry details, such as license plate numbers, making it particularly useful in controlled environments like hospitals and institutional premises. Similarly, Benjamin Coifman and collaborators designed a computer vision-based system for real-time vehicle tracking and traffic monitoring, leveraging vehicle trajectories to enhance surveillance and improve traffic analysis.

Research by Manishkumar Purohit and Arvind R. Yadav explored advanced feature extraction techniques, comparing algorithms like SIFT and SURF for traffic violation detection on embedded platforms such as Raspberry Pi. Their findings shed light on optimizing computational performance for resource-constrained devices. Hemanth Mohan et al. proposed a novel application of autonomous drones equipped with ROS-based path planning and YOLOv8 to detect traffic violations, offering unparalleled coverage and precision in monitoring.

Ru An and colleagues developed the GC-YOLOv9 algorithm, a significant improvement over YOLOv9, aimed at addressing handling intricate data. MobileNetV3, optimized for mobile and embedded systems, offers the fastest processing time among the models, though it may sacrifice some accuracy in comparison to more complex architectures. This figure highlights the trade-offs between processing speed and model performance, offering insight into the suitability of each model for different real-time applications.

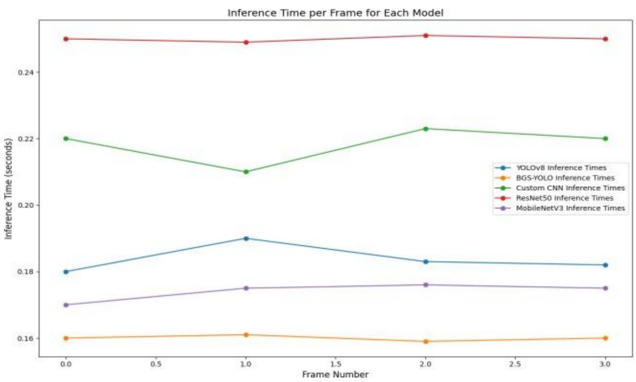

Fig 4: Interface Time per Frame for Each Models

The Sentinel Roadway Oversight System was rigorously tested using diverse datasets and scenarios to simulate real-world

detection challenges in smart city scenarios by enhancing accuracy under diverse conditions. Meanwhile, Bo Wang and Saif B. Neamah have been working on refining YOLO models to enhance detection accuracy, particularly for complex scenarios involving vehicles and pedestrians.

Collision prevention and accident detection have also seen advancements through deep learning applications. Md. Faysal Kabir and A. Vijaya Lakshmi developed systems using real-time object detection on Raspberry Pi to identify potential collisions, focusing on improving response times and reducing accidents. The exploration of semi-supervised learning models, as demonstrated by Ali Usman et al. for brand logo recognition, highlights the potential for improved object detection efficiency with minimal labeled data.

The integration of Optical Character Recognition (OCR) with traffic monitoring systems represents another leap forward. Researchers like Priyam Rai and Nagaraj P. have utilized OCR for automating vehicle inspections and detecting violations, contributing to enhanced law enforcement and road safety.

Finally, innovative approaches using drone technology, deep learning algorithms, and enhanced YOLO models reflect a growing emphasis on scalability, efficiency, and adaptability. These advancements collectively address critical issues like real-time processing, resource optimization, and broader application in smart city initiatives, showcasing the potential of AI to revolutionize traffic management systems globally.

Figure 4 illustrates the processing time per frame for various models, comparing their efficiency in real-time performance. YOLOv8, known for its fast inference capabilities, performs well with minimal pre-processing, making it suitable for applications requiring rapid response. BGS-YOLO, which integrates advanced techniques like the Bidirectional Feature Pyramid Network (BiFPN) and Global Attention Module (GAM), strikes a balance between accuracy and processing speed, making it effective for complex tasks such as road target detection. The custom CNN, designed specifically for particular tasks, offers a tailored performance that balances both speed and accuracy. ResNet-50, a deeper neural network utilizing residual learning, shows slightly higher processing times but excels in

conditions, including day and night traffic, adverse weather (fog, rain), and varying traffic densities in urban and rural settings. Key scenarios involved detecting overspeeding vehicles, emergencies like stationary vehicles, and identifying animals or disabled individuals on roads. The system excelled in recognizing vehicle types, colors, and altered logos, flagging illegal modifications, and detecting violations such as traffic signal breaches and helmet non-compliance via real-time license plate recognition.

Performance metrics, including detection accuracy, processing speed, and false-positive rates, validated its reliability. Testing under extreme conditions, such as snow-covered roads or complex intersections, and expanding to diverse geographic regions can further refine its algorithms. Comparative analyses with systems leveraging IoT and cloud architectures offer benchmarks for improvement. Continuous testing ensures the system's adaptability to evolving traffic management needs, aligning with findings by researchers like Jain et al. (2018) and Wang et al. (2024).

8. CONCLUSION

The Sentinel Roadway Oversight System represents a major advancement in traffic monitoring and safety, leveraging YOLOv8 machine learning algorithms and Raspberry Pi 4.0

for real-time, efficient edge computing. This adaptability allows it to seamlessly integrate into diverse traffic infrastructures and smart city ecosystems, providing a scalable solution that can operate effectively in both urban and rural settings. Future developments could focus on predictive analytics to anticipate congestion and risks, as well as integration with autonomous vehicle networks for synchronized transportation. Enhancements in hardware, such as energy-efficient processors and high-resolution sensors, alongside collaboration with policymakers, would improve its performance and regulatory compliance. By addressing current traffic challenges and paving the way for innovations in intelligent transportation, the system demonstrates its potential to enhance road safety and contribute to smarter urban mobility.

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