



YOLOv8-Based Automatic Vehicle Counting and Classification for Traffic Optimization

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KEYWORDS	ABSTRACT
YOLOv8, Vehicle Detection, Vehicle Counting, Traffic Monitoring, Deep Learning, Intelligent Transportation Systems.	Efficient traffic management has become a major challenge in rapidly growing urban areas due to the continuous increase in the number of vehicles on roads. Traditional manual traffic monitoring methods are time-consuming, less accurate, and unable to provide real-time insights required for modern smart city applications. This paper presents an automated vehicle detection, counting, and classification system based on the YOLOv8 deep learning model. The proposed system processes real-time or recorded traffic video streams to accurately identify and classify vehicles into categories such as cars, motorcycles, buses, and trucks. YOLOv8 provides high detection accuracy, improved object localization, and fast processing speed, making it highly suitable for real-time traffic analysis. The system automatically counts vehicles passing through a defined region and records traffic statistics that can be used to evaluate traffic density, identify peak hours, and analyze vehicle movement patterns. These insights can assist traffic authorities in optimizing signal timings, reducing congestion, and improving road safety. The proposed approach minimizes human effort, reduces monitoring errors, and enables scalable deployment in smart transportation infrastructure. Experimental evaluation demonstrates that the system performs reliably under different lighting conditions, camera angles, and traffic scenarios, making it a practical solution for intelligent traffic monitoring and management.

INTRODUCTION

Rapid urbanization and the continuous growth in the number of vehicles have created significant challenges for traffic management in modern cities. Traffic

congestion, increased travel time, fuel consumption, and environmental pollution are some of the major problems faced by transportation authorities. Traditional traffic monitoring methods such as manual vehicle counting or

basic sensor-based systems are often inefficient, costly, and prone to human error. Recent advancements in intelligent transportation systems and Internet of Things (IoT) technologies have enabled more efficient monitoring of road infrastructure and traffic behavior [1].

Modern communication technologies, including edge computing and distributed systems, have further enhanced the capability of real-time traffic monitoring systems by enabling faster data processing and decision-making near the data source [2]. In addition, the integration of advanced networking technologies such as 5G supports large-scale deployment of smart traffic systems with low latency and improved reliability [3]. These technologies provide a strong foundation for intelligent traffic monitoring solutions that rely on computer vision and deep learning.

Computer vision has become one of the most effective approaches for analyzing traffic scenes from surveillance cameras. Several studies have explored object detection and video analysis techniques for monitoring vehicles and road activity [18], [19]. Recent developments in deep learning-based object detection models, particularly the You Only Look Once (YOLO) family, have significantly improved detection accuracy and processing speed. A comprehensive review of YOLO architectures highlights their strong performance in various real-world applications including transportation monitoring [8]. These models are capable of detecting multiple objects simultaneously in real time, making them suitable for vehicle detection and classification tasks.

Intelligent transportation systems also rely on advanced sensing technologies such as 3D sensing, multiple camera tracking, and automated surveillance to collect accurate traffic data [9], [10]. These systems allow authorities to monitor traffic flow, analyze vehicle patterns, and optimize signal control strategies. Furthermore, recent research has demonstrated the importance of automated monitoring systems in applications such as parking management and smart city infrastructure [17].

In this work, a YOLOv8-based vehicle detection and counting system is proposed to automatically monitor traffic from video streams. The system detects different categories of vehicles such as cars, motorcycles, buses, and trucks, and calculates traffic statistics that can support better traffic management decisions. The

proposed system aims to improve the accuracy and efficiency of traffic monitoring while reducing the dependency on manual observation.

The overall workflow of the proposed intelligent traffic monitoring system is illustrated in Fig. 1. The architecture includes video acquisition, vehicle detection using YOLOv8, vehicle classification, and traffic data analysis for optimization of transportation systems.



Figure 1: Overall architecture of the proposed YOLOv8-based vehicle detection, counting, and traffic analysis system.

RELATED WORK

The rapid development of intelligent transportation systems has led to significant research in traffic monitoring, vehicle detection, and automated analysis using sensors, computer vision, and deep learning techniques. Various studies have explored different technologies to improve road infrastructure monitoring and traffic management.

IoT-based sensing technologies have been widely used for monitoring transportation systems and road environments. Micko et al. [1] presented a comprehensive review of IoT sensor systems used in road infrastructure monitoring, highlighting their role in collecting traffic and environmental data. Similarly, wireless sensor networks have been applied for smart monitoring applications including energy systems and urban infrastructure [7]. These sensor-based systems provide valuable data but often lack the capability to accurately classify and track multiple vehicles in complex traffic environments.

Advancements in edge computing and distributed processing have further enhanced real-time data analysis in transportation systems. Zakarya et al. [2] proposed an efficient resource management technique for multi-access edge computing that improves system

performance and energy efficiency. Hassan et al. [3] discussed the importance of edge computing in 5G networks, emphasizing its ability to support large-scale intelligent applications such as smart transportation and traffic monitoring.

Several research efforts have also explored sensing technologies and multi-camera systems for traffic data collection. Wen et al. [9] highlighted the role of 3D sensing technologies in intelligent transportation systems, while Subedi and Tang [10] developed a multi-camera vehicle tracking system capable of collecting traffic data at road intersections. Other sensing methods such as depth cameras and laser scanners have been investigated for monitoring structural and environmental changes [11]. These approaches improve data acquisition but often require expensive hardware and complex system configurations.

Video-based monitoring has become an increasingly popular approach due to the availability of surveillance cameras and advances in image processing. Background modeling and motion detection techniques have been widely used to extract moving vehicles from video streams [18]. Yasir and Ali [19] reviewed various real-time background extraction models and discussed their applications in surveillance and traffic monitoring. However, traditional image processing methods often struggle in complex environments with varying lighting conditions, occlusions, and heavy traffic.

Recent progress in deep learning has significantly improved object detection accuracy in traffic monitoring applications. The YOLO family of models has become one of the most widely used frameworks for real-time object detection. Terven et al. [8] provided a comprehensive review of YOLO architecture from YOLOv1 to YOLOv8, demonstrating their effectiveness in computer vision tasks including vehicle detection and surveillance. These models can detect multiple objects simultaneously while maintaining high speed and accuracy.

In addition, intelligent monitoring systems have been applied to several smart city applications such as automated parking systems and surveillance platforms. Elfaki et al. [17] developed a smart real-time parking monitoring system that improves parking management and traffic flow in urban areas. Tian et al. [20] presented a survey on hierarchical vehicle surveillance systems in

intelligent transportation environments, emphasizing the importance of automated monitoring for efficient traffic control.

Although significant progress has been made in traffic monitoring technologies, many existing systems still face challenges related to scalability, accuracy, and real-time performance. Therefore, this work focuses on implementing a YOLOv8-based vehicle detection, counting, and classification system that provides an efficient and accurate solution for modern traffic analysis and optimization.

PROPOSED SYSTEM ARCHITECTURE

The proposed system is designed to automatically detect, classify, and count vehicles from traffic video streams using the YOLOv8 deep learning model. The architecture integrates video acquisition, preprocessing, object detection, vehicle classification, and traffic analysis modules to generate useful traffic statistics. The system can operate on both real-time camera feeds and recorded traffic videos, making it suitable for deployment in smart city traffic monitoring systems.

Initially, traffic video is captured using roadside surveillance cameras or existing traffic monitoring systems. The captured video frames are processed and prepared for analysis through preprocessing steps such as resizing, normalization, and noise reduction. These steps ensure that the input data is compatible with the deep learning model and improves detection accuracy.

The processed frames are then passed to the YOLOv8 object detection model. YOLOv8 is capable of identifying multiple objects in a single frame and locating them using bounding boxes. In this work, the model is trained to recognize different categories of vehicles including cars, motorcycles, buses, and trucks. Once vehicles are detected, the system classifies them based on the learned features and assigns appropriate labels.

After detection and classification, the system performs vehicle counting by tracking vehicles that pass through a pre-defined region of interest (ROI) or virtual counting line. This enables the system to estimate traffic density, vehicle flow rate, and peak traffic hours. The collected data is stored and can be further analyzed to support traffic signal optimization, congestion monitoring, and transportation planning.

The proposed architecture provides several advantages including automation, real-time processing, high detection accuracy, and scalability. It can also be integrated with intelligent transportation systems to support data-driven traffic management decisions



Figure 2: Block diagram of the proposed YOLOv8-based vehicle detection, classification, and traffic analysis system.

METHODOLOGY

The proposed system utilizes a deep learning-based object detection framework to automatically detect, classify, and count vehicles from traffic video streams. The methodology consists of several stages including data acquisition, preprocessing, vehicle detection using YOLOv8, vehicle classification, and traffic data analysis. The overall workflow enables accurate monitoring of traffic flow and vehicle patterns.

Data Acquisition

Traffic video data is collected either from real-time surveillance cameras or pre-recorded traffic videos. The video streams are converted into individual frames which serve as input to the detection model. Continuous frame extraction ensures that the system can analyze traffic movement in real time.

Preprocessing

Before feeding the frames into the detection model, preprocessing steps are applied to improve detection performance. These include resizing the frames to match the input size required by the YOLOv8 network,

normalization of pixel values, and removal of noise. These steps help the model perform consistently across different lighting and environmental conditions.

Vehicle Detection Using YOLOv8

The core component of the system is the YOLOv8 object detection model. YOLO (You Only Look Once) is a single-stage detector that predicts bounding boxes and class probabilities directly from an image in one pass. The model divides the input image into grids and detects vehicles based on learned features from training data. Each detected object is assigned a bounding box and class label such as car, motorcycle, bus, or truck.

Vehicle Tracking and Counting

After detection, vehicles are tracked across consecutive frames. A virtual counting line or region of interest (ROI) is defined in the frame. Whenever a detected vehicle crosses this line, the system increments the corresponding vehicle counter. This allows the system to estimate traffic density and traffic flow.

Traffic Data Analysis

The collected vehicle counts and classifications are stored for further analysis. The system calculates traffic statistics such as total vehicle count, category-wise distribution, and peak traffic periods. These insights can be used by traffic authorities to optimize signal timings and improve road management strategies.

Algorithm for Vehicle Detection and Counting

Algorithm 1 YOLOv8-Based Vehicle Detection and Counting

- 1: Initialize YOLOv8 trained model
- 2: Start video stream or load traffic video
- 3: Extract frames from the video
- 4: **for** each frame **do**
- 5: Preprocess the frame (resize, normalize)
- 6: Input frame into YOLOv8 model
- 7: Detect vehicles with bounding boxes
- 8: Classify detected vehicles (car, bike, bus, truck)
- 9: Track vehicles across frames
- 10: **if** vehicle crosses counting line **then**
- 11: Increment vehicle counter
- 12: **end if**
- 13: Store detection results
- 14: **end for**
- 15: Compute traffic statistics
- 16: Display results and traffic analysis =0

RESULTS AND DISCUSSION

The proposed YOLOv8-based vehicle detection and counting system was implemented and tested using traffic video datasets containing multiple types of vehicles such as cars, motorcycles, buses, and trucks. The experiments were conducted using Python and the YOLOv8 deep learning framework. The system processes each video frame, detects vehicles, classifies them into predefined categories, and counts them when they cross a predefined region of interest.

The trained model demonstrated strong performance in detecting multiple vehicles simultaneously under different traffic densities and lighting conditions. YOLOv8 effectively localized vehicles using bounding boxes and provided class labels with high confidence scores. Fig. 3 shows a sample output of the detection process where multiple vehicles are identified and classified in a traffic scene.

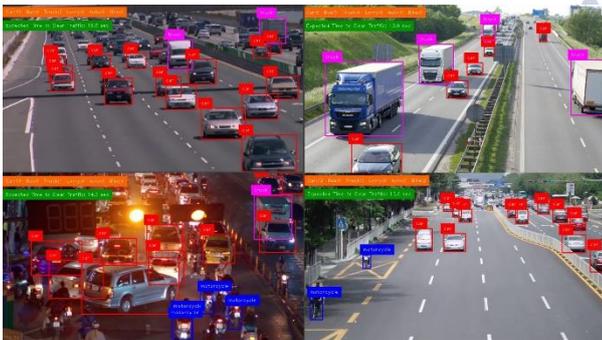


Figure 3: Simulation output showing vehicle detection and classification using YOLOv8.

The system also performs automatic vehicle counting using a predefined virtual line. Each vehicle crossing the line is counted and stored in the traffic database. This enables the system to estimate traffic flow and congestion levels in real time. Fig. 4 illustrates the counting mechanism where vehicles are tracked and counted as they move across the monitoring region.

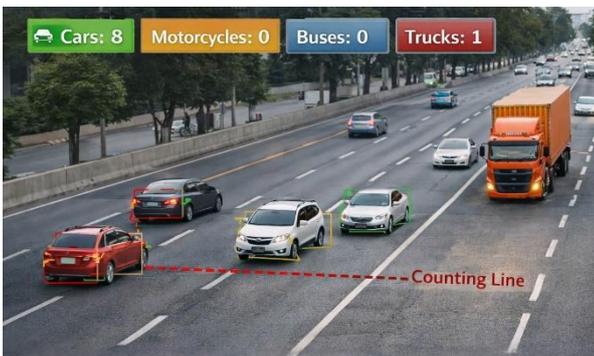


Figure 4: Vehicle counting using a virtual counting line in the traffic monitoring system.

The proposed system provides useful traffic statistics such as total vehicle count, category-wise distribution, and vehicle movement patterns. These results can assist traffic authorities in understanding traffic behavior and optimizing signal timing. The system also reduces manual effort and minimizes errors associated with traditional traffic monitoring methods.

Furthermore, the model maintained reliable detection accuracy in different scenarios including moderate traffic, heavy traffic, and varying illumination conditions. Fig. 5 presents the final traffic analysis dashboard generated by the system, which summarizes vehicle counts and traffic flow information.



Figure 5: Traffic analysis results showing vehicle count statistics and monitoring information.

Overall, the experimental results demonstrate that the proposed YOLOv8-based system is capable of performing real-time vehicle detection, classification, and counting with high efficiency. The system can be deployed in intelligent transportation environments to support smart traffic management and data-driven decision making.

CONCLUSION

This paper presented a YOLOv8-based automated vehicle detection, classification, and counting system designed for intelligent traffic monitoring. The proposed approach utilizes deep learning and computer vision techniques to analyze traffic video streams and accurately detect different types of vehicles such as cars, motorcycles, buses, and trucks. By integrating real-time detection with vehicle counting mechanisms, the system provides valuable traffic statistics including vehicle flow, density, and category-wise distribution.

The experimental results demonstrate that the YOLOv8 model is capable of achieving reliable detection

performance under various traffic conditions and lighting environments. The system successfully automates the traffic monitoring process, reduces the need for manual observation, and minimizes errors associated with traditional traffic counting methods. Furthermore, the generated traffic data can assist transportation authorities in optimizing traffic signal control, improving road safety, and reducing congestion in urban areas.

Overall, the proposed system contributes to the development of intelligent transportation systems and smart city infrastructure. In future work, the system can be enhanced by incorporating multi-camera integration, real-time cloud-based monitoring, advanced vehicle tracking algorithms, and predictive traffic analysis using machine learning techniques. Such improvements would further increase the scalability, accuracy, and practical applicability of the system in real-world traffic management scenarios.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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