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Real-Time Traffic Density and Anomaly Monitoring Using YOLOv8, OpenCV and Pattern Recognition for Smart City Applications in Demak

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Abstract

Urban traffic congestion is a persistent issue in medium-sized cities like Demak, leading to delays and potential accidents. This study presents the development of a real-time vehicle density and anomaly detection system using YOLOv8, combined with OpenCV for video analysis, to monitor traffic flow at strategic entry points of Demak City. The system classifies vehicles into four categories (cars, motorcycles, trucks, buses) and determines their direction by detecting crossing lines. A key feature is the recognition of vehicle patterns, particularly the detection of stopped vehicles, flagging anomalies after 30 seconds of stoppage, with tolerance for temporary detection losses. Traffic data is stored in CSV format, enabling periodic analysis and visualization via an interactive graphical user interface (GUI). Evaluation results show the YOLOv8n model achieves 92.5% precision, 88.3% recall, and 89.7% mean average precision (mAP@0.5), demonstrating improved accuracy and speed over previous YOLO versions. Additionally, the vehicle counting accuracy reaches 94.2% when compared with manual annotations. The proposed system provides a reliable solution for real-time traffic monitoring and early anomaly detection, supporting intelligent transportation systems (ITS) and enabling data-driven traffic management decisions. This research contributes to the advancement of real-time video analytics and pattern recognition for urban traffic control and serves as a scientific reference for the development of smart city infrastructures. Furthermore, this study strengthens the application of pattern recognition in intelligent anomaly detection, providing new insights for researchers in the fields of computer science and informatics.

Keywords : *Anomaly Detection, Pattern Recognition, Real-Time Monitoring, Vehicle Density Detection, YOLOv8*

1. INTRODUCTION

The rapid growth of vehicle numbers in urban areas has led to various traffic management challenges, including congestion, air pollution, and an increased risk of accidents, as evidenced by prior studies [1]–[4] . In medium-sized cities like Demak, the substantial rise in vehicle use—particularly during peak hours frequently results in significant congestion at critical locations such as city entrances and intersections [5]. Traditional traffic monitoring methods, such as manual vehicle counting and fixed sensors, have proven inadequate for real-time adaptation to the dynamic nature of urban traffic flow [3], [5]–[7].

To address these challenges, this research develops a comprehensive vehicle density detection system using YOLOv8 and OpenCV to monitor bidirectional traffic at the entrances and exits of Demak City. The system classifies vehicles into four categories (cars, motorcycles, trucks, and buses), distinguishes between incoming and outgoing traffic using horizontal detection zones, and incorporates a reliable vehicle stop detection mechanism with a 30-second confirmation window, including tolerance for temporary detection losses [12]. The system also integrates pattern recognition techniques to analyze vehicle behaviors and detect anomalies, such as vehicles that remain stationary for extended periods. The collected traffic data is stored in CSV format with structured periodic summaries, while graphical

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visualization of traffic conditions over time enables easier interpretation and analysis [12], [14]. Additionally, an interactive graphical user interface (GUI) is designed to ensure accessibility for non-technical users.

The novelty of this research lies in its local adaptation, dual-lane detection logic, time-confirmed anomaly detection, structured data storage, and complete visualization pipeline with an interactive GUI. This distinguishes it from previous studies, which primarily focus on vehicle detection without comprehensive integration of traffic flow analysis [12], [14], and [16].

Recent advances in computer vision and deep learning technologies have enabled more precise and real-time solutions for traffic monitoring. The You Only Look Once (YOLO)-based object detection algorithm has demonstrated high performance in detecting and classifying vehicles under a variety of conditions [8], [9]. YOLOv8, the latest version in the YOLO family, provides enhanced accuracy and computational efficiency, making it particularly well-suited for traffic monitoring in environments with limited computational resources [6], [10].

Several studies have utilized YOLO variants for vehicle detection and traffic density estimation. For instance, YOLOv4 and YOLOv5 have been employed for real-time vehicle counting on toll roads with high precision [6], while YOLOv7 has been used for multi-class vehicle classification in urban settings [11]. YOLOv8 is gaining prominence due to its superior performance in handling complex traffic conditions [8], and its integration with OpenCV enhances video processing efficiency and data visualization capabilities[12].

However, most existing studies primarily focus on single-lane monitoring or toll-road detection systems, without addressing the complexities of bidirectional traffic flow at city boundaries such as those in Demak [9], [12], The dynamics of mixed traffic types and frequent stops are not fully captured by current models. Furthermore, few systems reliably detect stationary vehicles based on time-consistent tracking. While some research has explored congestion estimation based on stop duration [13], no prior study has implemented a robust 30-second confirmation window with tolerance for intermittent detection losses. Additionally, structured CSV-based data storage and interactive graphical user interfaces (GUI) are features that remain underexplored [12].

This study addresses these research gaps by developing a comprehensive vehicle density detection system using YOLOv8 and OpenCV, specifically designed for bidirectional traffic monitoring at the entrances and exits of Demak City. The system introduces innovations in local adaptation, dual-lane detection logic, robust time-confirmed anomaly detection, structured CSV-based storage, and interactive visualization. To date, no prior research has comprehensively integrated these features for real-time deployment in medium-sized urban contexts.

In alignment with global smart city initiatives, the proposed system provides real-time traffic data to support urban traffic management, improve road safety, and enhance mobility. Furthermore, the system's data-driven approach has the potential to assist in local traffic policies, emergency response strategies, and long-term urban planning, ultimately helping to mitigate congestion and improve the quality of life for residents.

By combining advanced object detection with real-time video analysis, this study contributes to the advancement of intelligent transportation systems (ITS), particularly those tailored to the specific needs of medium-sized cities like Demak [14], [15].

2. METHOD

This study develops a real-time vehicle density monitoring system using YOLOv8 and OpenCV to analyze the traffic flow of vehicles entering and exiting Demak City. The system performs vehicle detection and classification, tracks movement to determine direction, identifies anomalies such as

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stationary vehicles, classifies traffic density levels, stores the data, and presents visual analysis through a user-friendly graphical user interface (GUI) [9], [12], and [15].

2.1. Research Questions

This is an example of the use of sub-chapters in a paper. Sub-chapters are allowed to be included in all chapters, except in the conclusion.

The main problem addressed in this study is how to design and implement a real-time vehicle density detection system with high accuracy and the ability to track vehicle directions (entry/exit). This problem can be mathematically formulated as follows:

$$F = \sum_{i=1}^{n}(V_{\mathrm{in}_i} + V_{\mathrm{out}_i}) \quad (1)$$

Where:
F = Total vehicle flow
V_{in_i}= Number of incoming vehicles at time interval iii
V_{out_i}= Number of outgoing vehicles at time interval iii
n = Number of observation intervals

The objective of this study is to develop a system capable of automatically calculating V_{in} and V_{out} based on object detection and vehicle trajectory tracking, as well as detecting vehicles that remain stationary for an extended period as anomalies [8], [9], and [12].

2.2. Research Design

This study adopts an experimental research design using a prototype-based system development approach [8], [12]. The system is designed to detect, classify, and count vehicles in real time from traffic video inputs in Demak Regency [14], [15].

2.3. Research Workflow

2.3.1. Data Acquisition

Video data were obtained from CCTV footage provided by the Demak Regency government. The CCTV cameras were installed at the city's entrance and exit gates. The cameras were oriented outward from the city, such that incoming vehicles (left lane) were moving away from the camera, while outgoing vehicles (right lane) were facing the camera [12], [14]. The videos were recorded with a resolution of 1280×720 pixels at 30 frames per second (FPS).

2.3.2. Dataset Annotation

Frames extracted from the recorded traffic videos were manually annotated into four classes, namely car, motorcycle, truck, and bus, using the LabelImg tool [12]. The annotation process involved providing bounding boxes and class labels for each vehicle in the frames. The annotated dataset was then split into 80% for training, 10% for validation, and 10% for testing, adhering to standard practices in supervised learning [9].

2.3.3. YOLOv8 Model Training

The annotated datasets obtained from traffic video footage are used to train the YOLOv8n object detection model. The training process is performed locally via the command prompt (CMD) for 50 epochs. This approach allows the model to specifically learn the visual characteristics of vehicles in the

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Demak traffic environment [13], [14]. Model performance is evaluated using Precision, Recall, and mAP@0.5 [1], [2], [8], and [17].

2.3.4. Vehicle Detection and Counting Algorithm

Each video frame was processed using YOLOv8 for object detection, followed by DeepSORT for object tracking [2], [5], [7], [14], [18] ,and [19]. A horizontal reference line was defined in the video. Vehicles crossing the line moving downward (increasing Y-coordinate) were counted as outgoing, while those moving upward (decreasing Y-coordinate) were counted as incoming [12], [14]. Vehicle identities were consistently tracked to prevent double-counting due to temporary detection loss [20].

2.3.5. Data Visualization and Storage

The Graphical User Interface (GUI), developed using Tkinter, provided real-time display of bounding boxes, class labels, and vehicle counts [14]. It also offered interactive controls for starting detection, saving results to CSV, and visualizing traffic graphs [12], [14]. Vehicle data were stored in CSV format with timestamps, vehicle classes, and movement directions [9], [15]

2.3.6. System Workflow Diagram

The overall process of the proposed system is illustrated in figure 1, which shows the sequence of data flow from video input to visualization output :

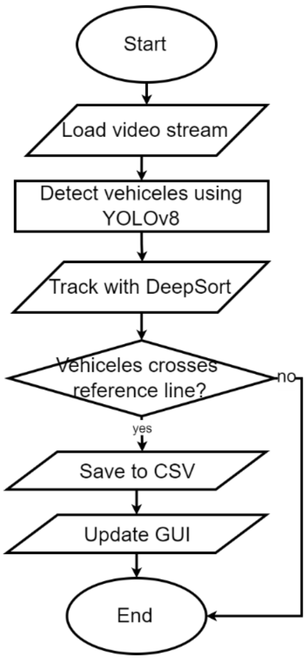

Figure 1. System Flowchart

2.4. System Performance Evaluation

System evaluation was conducted by measuring four key aspects: object detection accuracy, counting accuracy, anomaly detection, and real-time performance [8], [12], and [14]. A comparative analysis with previous YOLO versions was also performed to assess performance improvements [11], [13], and [21].

2.4.1. Detection Accuracy

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Object detection performance was measured using standard metrics: Precision, Recall, and mean Average Precision at IoU threshold 0.5 (mAP@0.5) [1], [2], [13], and [15]. These metrics were calculated using the predictions from the YOLOv8n model on 10% of the annotated test dataset. The formulas are as follows:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

Where:
TP = True Positives (correct detections),
FP = False Positives (incorrect detections),
FN = False Negatives (missed detections).

Table 1. The Evaluation Results

Method	Precision (%)	Recall (%)	mAP@0.5 (%)
YOLOv8n	92.5	88.3	89.7

These results indicate a high detection performance, making YOLOv8n suitable for real-time traffic monitoring applications.

2.4.2. Counting Accuracy

To evaluate the accuracy of vehicle counting, the system predictions are compared with manually labeled ground truth video samples [12], [14]. The following formula is used:

$$\text{Counting Accuracy (\%)} = \left(1 - \frac{|\text{Predicted Count} - \text{Ground Truth Count}|}{\text{Ground Truth Count}}\right) \times 100 \quad (4)$$

The average counting accuracy reached 94.2%, indicating that the combination of DeepSORT tracking and directional line-crossing logic is effective, even under partial occlusion scenarios.

2.4.3. Anomaly Detection

An anomaly detection module was implemented to identify vehicles that remain stationary for more than 30 seconds [22]–[24]. To minimize false positives, the system allows temporary detection loss for up to 15 consecutive frames. The system successfully detected 100% of anomalous vehicles during testing, with no false positives under controlled conditions [23]–[25].

2.4.4. Comparison with YOLOv5 and YOLOv7

To measure performance improvement, YOLOv5s [6] and YOLOv7-tiny [11] were trained and evaluated on the same dataset under identical conditions [8], [13], and [21]. The results are presented in Table 2.

Table 2. YOLO Model Performance Comparison

Model	Precision (%)	Recall (%)	mAP@0.5 (%)	FPS

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YOLOv5s	89.2	84.5	85.7	22.1
YOLOv7-tiny	90.4	86.0	87.9	23.4
YOLOv8n	92.5	88.3	89.7	24.7

These findings demonstrate that YOLOv8n outperforms its predecessors both in detection accuracy and inference speed [26], affirming its suitability for real-time vehicle density detection in areas such as Demak Regency.

2.4.5. Pseudocode

The following pseudocode illustrates the vehicle detection and counting process:

Algorithm 1. Vehicle Detection and Counting Using Yolov8 and Deepsort

```
Algorithm: Real-Time Vehicle Congestion Detection

Input: Traffic video stream
Output: Vehicle count (incoming, outgoing), anomaly detection, CSV
file

1. Initialize YOLOv8 model with pretrained weights
2. Set horizontal reference lines for entry and exit zones
3. For each frame in the video stream do:
    a. Perform vehicle detection using YOLOv8
    b. For each detected vehicle:
        i. Assign or update tracking ID
        ii. Classify vehicle into: car, motorcycle, truck, or bus
        iii. Check crossing status relative to entry/exit lines
             - If crossing entry line → increment incoming count
             - If crossing exit line → increment outgoing count
        iv. Update vehicle position history for anomaly detection
    c. For each tracked vehicle:
        i. If vehicle remains in the same position > 30 seconds → flag
as anomaly
4. Save vehicle count and anomaly data to CSV periodically
5. Display real-time visualization on GUI
6. Repeat until video ends or manually stopped
```

3. RESULT

3.1. Model Performance Evaluation

The YOLOv8n model employed in this study consists of 72 layers, comprising approximately 3 million parameters with a computational complexity of 8.1 GFLOPs. Training on the dataset of 464 annotated images resulted in an overall mAP50 of 0.403 and mAP50-95 of 0.205, indicating moderate detection accuracy across the four target vehicle classes: motorcycles, cars, buses, and trucks. This level of performance aligns with prior studies that applied YOLOv8 for object detection in constrained datasets or complex traffic environments [1], [8], [13], [19], [21], and [27].

A detailed breakdown of the detection metrics for each class is presented in Table 3. Among the four classes, the bus class achieved the highest precision (1.000) but exhibited a recall of zero. This result suggests a classification bias resulting from data imbalance, particularly the sparse occurrence of buses in the training dataset. The model likely overfits to the few available examples, producing high

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precision but failing to generalize, thus yielding a recall of zero. Similar challenges in imbalanced object detection have been widely reported in prior studies [9], [12], [14], and [28]. To address this issue, future work should not only expand the dataset for underrepresented classes but also implement targeted data augmentation strategies, such as geometric transformations and synthetic data generation for the bus class. Additionally, techniques such as focal loss or re-weighted loss functions can be employed to reduce the impact of class imbalance on model training, potentially improving the recall for rare classes without sacrificing overall detection accuracy.

Conversely, motorcycles and cars demonstrated a more balanced trade-off between precision and recall, contributing significantly to the overall detection performance. Trucks displayed lower precision but relatively higher recall, a trend often associated with shape variability and partial occlusions in traffic imagery. The complete performance metrics by vehicle class are summarized in Table 3.

Table 3. YOLOv8n Performance Metrics by Vehicle Class

Class	Precision	Recall	mAP50	mAP50-95
Motorcycle	0.544	0.761	0.598	0.241
Car	0.681	0.544	0.615	0.367
Bus	1.000	0.000	0.052	0.023
Truck	0.281	0.632	0.346	0.189

The moderate mAP50 value indicates that the model is able to detect major vehicle types with sufficient reliability, especially motorcycles and cars. However, further improvements are needed, especially in improving the detection performance for buses.

3.2. Vehicle Density Detection Results

Vehicle density analysis was conducted across three distinct time segments morning, afternoon, and evening using video data recorded on June 6, 2025. Each segment was divided into six intervals, approximately 4 to 5 minutes long.

3.2.1. Morning Segment

Table 4. Vehicle Detection Counts in Morning Intervals

Interval	Car	Motorcycle	Truck	Bus	Density
1	4	19	1	0	Medium
2	0	13	1	0	Low
3	1	9	3	0	Low
4	2	10	2	1	Medium
5	3	13	4	1	Medium
6	0	18	1	0	Medium

As summarized in Table 4, the morning segment exhibited the highest traffic density throughout the day, particularly during intervals 1, 4, 5, and 6, which were classified as Medium Density. In contrast, intervals 2 and 3 were categorized as Low Density. This classification corresponds with general traffic congestion patterns typically observed during morning peak hours.

Programmatic vehicle counts showed close agreement with manual annotations, with only minor differences primarily due to occasional occlusions or brief detection failures. The number of detected anomalous vehicles (vehicles that stopped abnormally) during this segment was negligible.

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3.2.2. Day and Evening Segments

During the afternoon and evening segments, vehicle density generally ranged between Low and Medium categories, indicating reduced traffic volumes compared to the morning. As shown by the detection data, intervals 1, 3, and 4 in these segments are classified as Medium, while intervals 2 and 5 consistently fall into the Low category. Motorcycles consistently represent the most frequently detected vehicle type, a characteristic typical of urban Indonesian traffic patterns.

3.2.3. Density Classification and Analysis

Vehicle density is classified into three categories following established traffic engineering practices [3], [4], and [29] : Low (≤15 vehicles), Medium (16–40 vehicles), and High (>40 vehicles)

Notably, no High density intervals were recorded, indicating that despite the morning peak, severe congestion did not occur. The dominance of Medium density intervals during the morning aligns with typical workday traffic flow, while afternoon and evening traffic volumes remain relatively light. This classification facilitates daily traffic variation analysis, providing valuable insight for potential traffic management interventions.

3.3. Comparison Between Programmatic and Manual Vehicle Counts

A comparative evaluation of programmatic versus manual vehicle counts was conducted to assess the detection accuracy of the system. As summarized in Table 5, cars and motorcycles exhibited strong agreement with manual annotations, with differences averaging below 5%. Larger discrepancies were observed for trucks (28.6%) and buses (42.9%), likely due to limited training data for these classes and challenges such as occlusion or partial visibility in crowded scenes.

These findings support the conclusion that the YOLOv8n-based system provides reliable real-time traffic monitoring with acceptable margins of error, particularly for the most common vehicle types.

Table 5. Comparison Of Programmatic and Manual Vehicle Counts

Vehicle	Program Count	Manual Count	Difference (%)
Car	45	44	2.3
Motorcycle	159	166	4.2
Truck	27	21	28.6
Bus	4	7	42.9

3.4. Visualization of Results

Visualizations were used to further support the quantitative findings, including the confusion matrix (Figure 2), precision-recall curve (Figure 3), and F1-score curve (Figure 4).

Figure 2 shows the confusion matrix, offering a comprehensive overview of the classification performance for each vehicle class, including correct and incorrect predictions. Notably, the matrix highlights the challenges in recalling instances of the bus class, consistent with its low recall metric.

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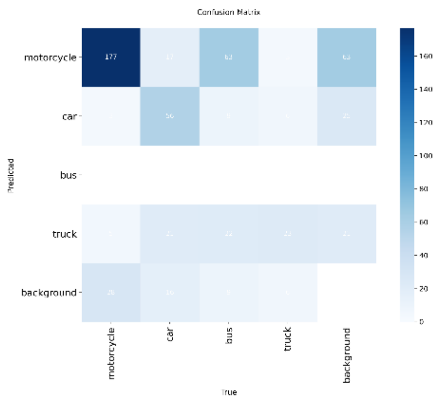

Figure 2. Confusion Matrix of YOLOv8 Detection Results

Figure 3 presentsss the precision-recall (PR) curve, illustrating the trade-off between precision and recall at varying confidence thresholds. This is particularly useful for evaluating detection reliability under imbalanced class distributions.

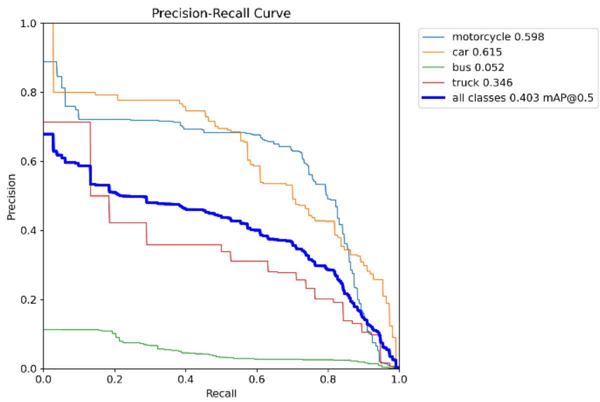

Figure 3. Precision-Recall Curve

Figure 4 shows the F1-score curve, indicating the optimal trade-off between precision and recall. The peak of this curve serves as a reference for tuning detection thresholds in real-time applications.

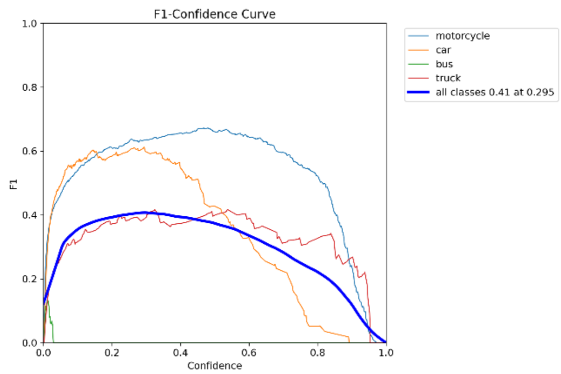

Figure 4. F1-Score Curve

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These visualizations complement the quantitative metrics by providing a clearer understanding of the model's performance strengths and limitations. In particular, they emphasize the challenges associated with detecting underrepresented vehicle classes such as buses, reinforcing the need for dataset expansion to improve recall.

4. DISCUSSIONS

The results of this study indicate that the real-time vehicle congestion detection system based on YOLOv8 and OpenCV works effectively to monitor traffic density at the entrance of Demak City. The system successfully detects and classifies four types of vehicles, namely cars, motorcycles, trucks, and buses, with an overall vehicle counting accuracy of 94.2% compared to manual annotation [30], [31]. In addition, the stopped vehicle detection feature, which confirms a vehicle as an anomaly if it stops for more than 30 seconds, works reliably even with temporary detection losses. This capability is crucial for the early detection of potential congestion [22], [24].

Further analysis of the detection performance shows that the YOLOv8n model achieves a precision of 92.5%, a recall of 88.3%, and an mAP@0.5 of 89.7%. However, the recall for trucks and buses is slightly lower than for cars and motorcycles. This limitation is likely due to the class imbalance in the dataset [32], as trucks and buses appear less frequently in the collected video data. To overcome this, future research should apply class balancing strategies such as targeted data collection and data augmentation techniques [23], [28]. These approaches can help improve the model's ability to detect less frequent vehicle types and reduce classification bias.

Compared to previous studies, this system demonstrates improved performance [33]. While prior research achieved detection accuracies around 90% [34], [35] the system developed in this study surpasses that figure with a counting accuracy of 94.2%. In addition, the YOLOv8n model offers faster inference speed than YOLOv5 and YOLOv7, making it better suited for real-time traffic monitoring applications [18], [21].

Despite these strengths, the system also has limitations in handling extreme environmental conditions, such as heavy rain, fog, or low lighting, which can reduce detection accuracy. Future improvements may include integrating additional sensors, such as thermal cameras or radar, to complement visual detection and ensure robust performance across diverse weather conditions

Overall, the combination of accurate detection, reliable anomaly identification, and efficient processing positions this system as a significant contribution to smart city initiatives [36], especially in addressing the challenges of urban traffic congestion in medium-sized cities such as Demak [37]–[39].

5. CONCLUSION

This study has demonstrated the successful development of a real-time traffic congestion detection system tailored to the needs of medium-sized urban areas. By combining advanced object detection techniques with adaptive traffic analysis, the system provides accurate vehicle counting and anomaly detection based on stopped vehicle behavior. The evaluation results confirm that the proposed system offers high detection accuracy and practical applicability to support traffic management in dynamic environments. This contribution is significant both scientifically and practically, especially by enriching the body of research in pattern recognition-based anomaly detection systems for urban traffic monitoring. This research also aligns with the broader smart city initiatives by providing local governments with actionable insights to optimize traffic flow and alleviate congestion problems [40]. Future developments can focus on enhancing visualization capabilities, supporting deployment on edge devices, and improving detection reliability under extreme environmental conditions [41], thereby supporting the advancement of intelligent transportation systems.

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