



A Comparative Review of AI-Based Approaches for Real-Time Wrong-Way Vehicle Detection in Intelligent Highway Monitoring Systems

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Abstract. Wrong-way driving represents one of the most vital traffic offenses that considerably increase the frequency of severe accidents and road fatalities. Thus, efficient real-time object detection techniques should be implemented within intelligent traffic environments to detect any cases of wrong-way driving. In this work, a comparative analysis of three recent state-of-the-art object detection models, namely, YOLOv10, Detection Transformer (DETR), and Faster R-CNN, will be presented in relation to real-time vehicle detection based on the usage of the UA-DETRAC dataset.

For a unified and consistent assessment, a combined system of vehicle detection, multi-object tracking, and trajectory-based analysis of direction will be considered. According to the experimental findings, YOLOv10 is found to provide the best balance of accuracy and efficiency, delivering mAP of 91.3%, achieving real-time performance of 42 frames per second, and demonstrating minimal latency of 23 milliseconds. Although DETR demonstrates the highest performance in terms of detection accuracy (93.1% mAP) and tracking (90.2% MOTA) due to global contextual modeling, it requires more computational power with 12 frames per second being achieved along with 83 milliseconds of latency. Finally, Faster R-CNN demonstrates average performance of 89.6% mAP and 18 frames per second.

Keywords: Wrong-Way Vehicle Detection, YOLOv10, Detection Transformer (DETR), Faster R-CNN, Multi-Object Tracking, ByteTrack, Trajectory Analysis, Real-Time Traffic Monitoring, UA-DETRAC.

1 Introduction

The growing number of vehicles has made traffic safety and traffic control increasingly difficult. There are many traffic offenses, but wrong-way driving is one of the most serious and hazardous acts that can cause fatal accidents. Real-time detection of wrong-way driving is vital to ensure safety and prevent accidents [1]. Conventional traffic surveillance systems are predominantly based on human supervision and rules-based systems, making them laborious and hard to implement in

complicated traffic scenarios [2]. The system does not have adaptive capabilities with changes in weather conditions and other factors affecting roads [3].

Thanks to recent improvements in AI and computer vision techniques, it is possible to design and develop traffic monitoring solutions that can process data in real-time [4]. Object detection algorithms using deep learning methods have proven to be effective in recognizing objects such as cars under complicated conditions [5]. Single-stage detector algorithms, which are able to detect objects and classify them in one shot, have received considerable attention [6]. YOLO, being a popular example, has gone through many revisions, enhancing its performance and effectiveness over time [7]. YOLOv10 is currently the most recent version of the algorithm that aims at increasing the efficiency of the inference process while providing good detection results [8].

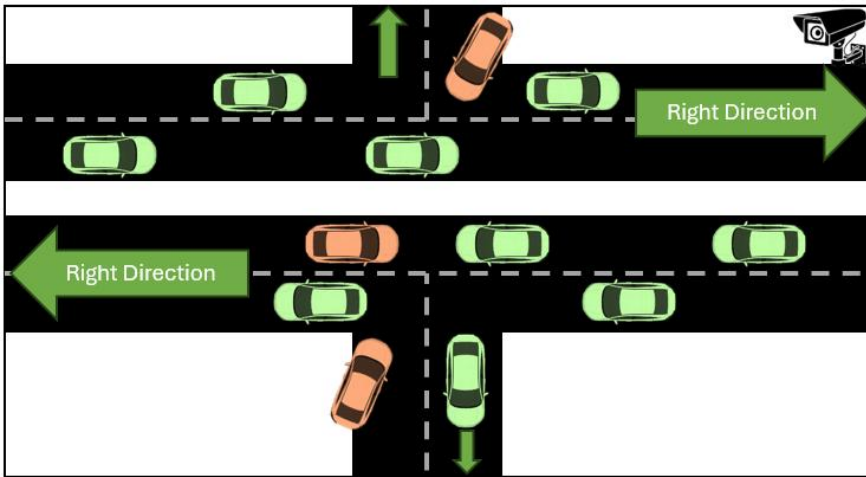


Fig. 1. Overview of AI-based approaches for real-time wrong-way vehicle detection in intelligent highway monitoring systems.

In contrast, two-stage detectors like Faster R-CNN achieve high accuracy using region proposal strategies and then classifying those regions [9]. While improving localization accuracy, two-stage detectors increase computation complexity, which increases delay time and decreases real-time detection efficiency [10]. Attention-based transformer models, including Detection Transformer (DETR), offer another method of detection using attention mechanisms for understanding global contexts in an image [11]. The DETR model avoids the use of anchor boxes and region proposals [12]. Vision transformers improve feature learning by incorporating long-range dependencies in images [13]. However, such models consume considerable computational resources, hindering real-time applications [14].

Apart from object detection, multi-object tracking can be used for trajectory analysis to determine abnormal behaviors [15]. For example, tracking methods like SORT allow efficient tracking with a fast association method [16]. On the other hand, DeepSORT is an advanced approach that integrates appearance information into the process to improve the accuracy of tracking [17]. ByteTrack is more efficient and

allows accurate tracking even when dealing with low confidence detections [18]. In this way, trajectory analysis becomes possible, allowing detection of vehicles traveling in the wrong direction based on direction estimation [19].

Annotated datasets have played an important role in promoting traffic monitoring research in recent years. Some popular benchmark datasets include the COCO dataset for various object annotation tasks [20], the KITTI dataset for autonomous driving research [21], and the BDD100K dataset with huge amounts of driving videos recorded under varied conditions [22]. Nevertheless, considering traffic applications, the UA-DETRAC dataset provides abundant annotations for real-world traffic surveillance videos, enabling accurate evaluation of various models for detection and tracking tasks [23].

However, there are still some problems to be solved when implementing reliable wrong-way vehicle detection solutions. Lighting and weather changes in the environment have been shown to influence detection accuracy negatively [24]. In cases where there are occlusions due to traffic, detection and tracking tasks become harder [25]. Moreover, finding a compromise between accuracy and real-time performance is crucial when deploying models on edge devices [26].

To mitigate the above issues, this research paper provides a comprehensive comparison of YOLOv10, DETR, and Faster R-CNN, which are state-of-the-art object detectors used for real-time wrong-way vehicle detection with the help of one framework. This paper offers a fair comparison through the use of one dataset, consistent preprocessing, and performance measures. Main contributions include designing a detection pipeline for detecting wrong-way vehicles, quantifying the performance difference of state-of-the-art object detectors based on detection accuracy and efficiency, and providing recommendations regarding implementation of such detectors.

2 Literature Review

The progress made in intelligent traffic monitoring systems can be attributed greatly to developments in computer vision and deep learning algorithms. Earlier traffic analysis strategies have used traditional computer vision methods including background subtraction, frame difference, and optical flow. These algorithms, although being computation-friendly, were very environment dependent and hence less robust towards changes in lighting and weather, making them impractical for real-life applications [27]. Further, due to poor generalization ability of these algorithms, large scale applications became impossible [28].

The advent of deep learning especially CNNs was a milestone in the realm of object detection and classification. CNNs allowed automatic feature learning thus adding robustness and accuracy to the process [29]. AlexNet, which was the first convolution network to exhibit the power of deep learning in object recognition, marked an important milestone in computer vision [30]. Region based detectors such as Fast R-CNN increased the accuracy of detection by classifying regions individually [31]. The introduction of region proposal networks in Faster R-CNN increased the

efficiency of detections while allowing end-to-end training of detectors [32]. However, both detectors have a multistep architecture leading to more computation time and complexity.

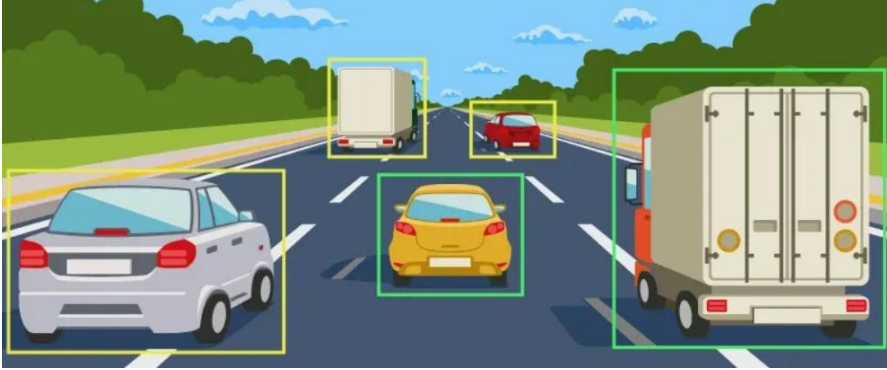


Fig. 2. Evolution of AI-based object detection.

These constraints prompted the invention of one-step detectors such as YOLO which facilitated real-time object detection and increased efficiency [34]. YOLO changed the perception of object detection by treating it as a regression problem whereby it was possible to predict bounding boxes and class probability in a single step [34]. Versions like YOLOv4 and YOLOv5 improved the architecture through feature pyramid networks while also enhancing training methods. Consequently, detection became efficient and accurate even under different scenarios [35]. The most recent version of this method is YOLOv10. It is designed to optimize computation efficiency and minimize latency without compromising on detection accuracy and thus is suitable for real-time intelligent transportation systems [36].

Another approach to object detection involves the use of transformers. DETR was among the models that revolutionized object detection using transformers. They used self-attention mechanism to capture the relationship between image features [37]. This framework is different from others as it does not involve anchor boxes and non-maximum suppression process [38]. Another model is the vision transformer that facilitates modeling of long-range dependencies within images [39]. Other sophisticated transformers like Swin Transformers enable hierarchical feature learning [40]. Despite their effectiveness, they require extensive computational capabilities to operate effectively [41].

The other technique used in traffic monitoring systems is multi-object tracking, which allows continuous tracking of the vehicles in the frame [42]. SORT allows efficient tracking of objects through motion-based association [43]. DeepSORT incorporates appearance-based matching, making it more robust when dealing with occlusion and preserving object identity [44]. ByteTrack, on the other hand, uses high confidence and low confidence detections in its tracking algorithm, making it ideal in traffic monitoring systems with many objects [44]. The above tracking algorithms can be used for trajectory-based motion analysis, which is crucial for identifying wrong-way movement.

A number of studies have concentrated on traffic monitoring and anomaly detection using deep learning methods. There are vision-based traffic surveillance systems that use motion estimation and trajectory analysis to identify wrong-way driving among other abnormal behaviors like lane invasion and speeding [46]. Detecting and integrating the detection and tracking modules have significantly improved traffic monitoring systems [47].

The emergence of large annotated datasets has made even greater progress in this field possible. One can mention benchmark datasets like COCO that provide various object annotations for general detection purposes [49]. KITTI provides useful data for testing the autonomous driving system with driving situations from reality [50]. Another large annotated database for real-world driving is BDD100K [51]. For traffic-specific purposes, a commonly used dataset is the UA-DETRAC with extensive vehicle annotations under different weather conditions and illumination [52].

There are still some challenges in the creation of reliable wrong-way vehicle detection systems. Environmental factors such as changing light conditions and bad weather significantly influence detection accuracy [53]. Tracking and trajectory prediction may be challenging in cases when vehicles undergo occlusions [54]. Finding a balance between accurate detection and real-time detection rate is still one of the main challenges of modern wrong-way detection systems [55].

3 Dataset Description

A unified and accurate assessment of deep learning algorithms needs a standardized data set. In this paper, all experimental results have been obtained by using the UA-DETRAC data set. This data set is well-known and acknowledged in the literature for its use in vehicle detection and multi-object tracking applications [57].

3.1 Dataset Overview

The UA-DETRAC dataset consists of real-world traffic videos captured from fixed surveillance cameras. It includes diverse traffic conditions such as different weather, lighting environments, and traffic densities, making it suitable for evaluating intelligent transportation systems [58].

Key Features: 100 video sequences recorded from traffic surveillance cameras

- 140,000+ frames with detailed annotations
- 1.2 million bounding boxes
- Vehicle categories: car, bus, van, and others

- Environmental variations: sunny, cloudy, rainy, night

These characteristics enable robust evaluation of detection and tracking models in real-world conditions.

3.2 Dataset Distribution

To ensure fair training and evaluation, the dataset is divided into:

- Training Set: 70%
- Validation Set: 15%
- Testing Set: 15%

This split ensures that models are trained on diverse conditions and tested on unseen data, improving generalization performance.

3.3 Annotation Details

Each frame in the UA-DETRAC dataset contains:

- Bounding box coordinates for each vehicle
- Object identity (ID) for tracking
- Frame-level annotations
- Environmental condition labels

The presence of tracking IDs makes the dataset particularly suitable for trajectory-based analysis and wrong-way detection tasks [60].

Table 1: Summary of UA-DETRAC Dataset

Feature	Description
Dataset Name	UA-DETRAC
Total Videos	100
Total Frames	140,000+
Bounding Boxes	1.2 Million
Vehicle Classes	Car, Bus, Van, Others
Weather Conditions	Sunny, Rainy, Cloudy, Night
Annotation Type	Bounding Box + Tracking ID
Application	Detection & Tracking

3.4 Preprocessing

To ensure compatibility across all models (YOLOv10, DETR, Faster R-CNN), the dataset undergoes standardized preprocessing:

- Frame resizing to 640×640 resolution
- Normalization of pixel values
- Data augmentation (horizontal flip, rotation, brightness variation)
- Annotation format conversion:
 - YOLO format (TXT)
 - COCO format (JSON)

These preprocessing steps improve model robustness and ensure consistent input across different architectures [61].

3.5 Suitability for Wrong-Way Detection

The UA-DETRAC dataset is particularly suitable for wrong-way vehicle detection due to:

- Availability of continuous video sequences
- Presence of tracking IDs for trajectory analysis
- Diverse traffic flow patterns
- Real-world environmental variability

These features enable accurate direction estimation and violation detection using trajectory-based methods.

4 Methodology

This section presents the proposed methodology for real-time wrong-way vehicle detection using a unified pipeline that integrates object detection, multi-object tracking, and trajectory-based motion analysis. The framework ensures consistent evaluation of YOLOv10, DETR, and Faster R-CNN under identical conditions, enabling fair comparison [62].

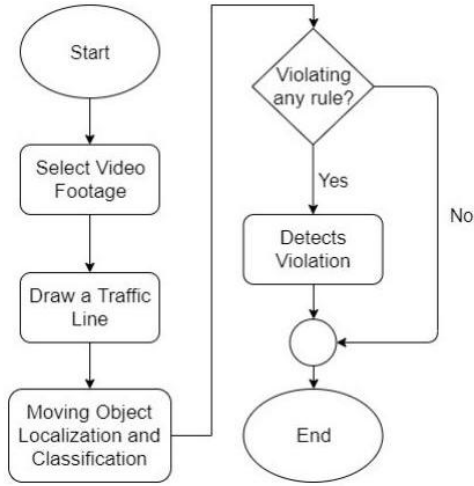


Fig. 3. Generalized methodology for AI-based wrong-way vehicle detection in intelligent highway monitoring systems.

4.1 System Overview

Given a video stream $V = \{I_t\}_{t=1}^T$, each frame is processed sequentially through the following stages:

1. Vehicle Detection
2. Multi-Object Tracking
3. Trajectory Generation
4. Direction Estimation
5. Violation Detection

This modular architecture allows efficient processing of real-time traffic data and supports scalable deployment in intelligent transportation systems [63].

4.2 Vehicle Detection Models

1) YOLOv10 (Single-Stage Detector)

YOLOv10 performs object detection in a single forward pass, making it highly efficient for real-time applications [64]. The detection function is defined as:

$$D_t^{(yolo)} = f(I_t; \theta)$$

where I_t represents the input frame and θ denotes model parameters. YOLO-based models are widely used due to their high speed and competitive accuracy [73].

2) Faster R-CNN (Two-Stage Detector)

Faster R-CNN uses a region proposal network (RPN) followed by classification and bounding box regression [65]. The detection process can be expressed as:

$$D_t^{(frcnn)} = RPN(I_t) + RCNN(R)$$

Although this approach provides high localization accuracy, it introduces computational overhead, limiting real-time performance [66].

3) DETR (Transformer-Based Detector)

DETR utilizes transformer architectures to model global contextual relationships within images. It eliminates the need for anchor boxes and non-maximum suppression, simplifying the detection pipeline [67]. The detection process is defined as:

$$D_t^{(detr)} = Transformer(Features(I_t))$$

Transformer-based detection improves performance in complex scenarios but requires higher computational resources.

4.3 Multi-Object Tracking

Multi-object tracking is performed using ByteTrack, which associates detections across frames to maintain consistent object identities. Tracking is essential for analyzing motion patterns and vehicle trajectories.

The state update is modeled as:

$$S_t = S_{t-1} + v \cdot \Delta t$$

where S_t represents the current position, v is velocity, and Δt is the time interval [68].

4.4 Trajectory Generation

Vehicle trajectories are generated using centroid positions of bounding boxes:

$$(x_c, y_c) = \left(\frac{x_1 + x_2}{2}, \frac{y_1 + y_2}{2} \right)$$

The trajectory is represented as:

$$T = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$$

Trajectory analysis enables detection of abnormal motion patterns such as wrong-way driving [69].

4.5 Direction Estimation

The direction of vehicle motion is computed using displacement between consecutive frames:

$$\theta = \tan^{-1} \left(\frac{y_2 - y_1}{x_2 - x_1} \right)$$

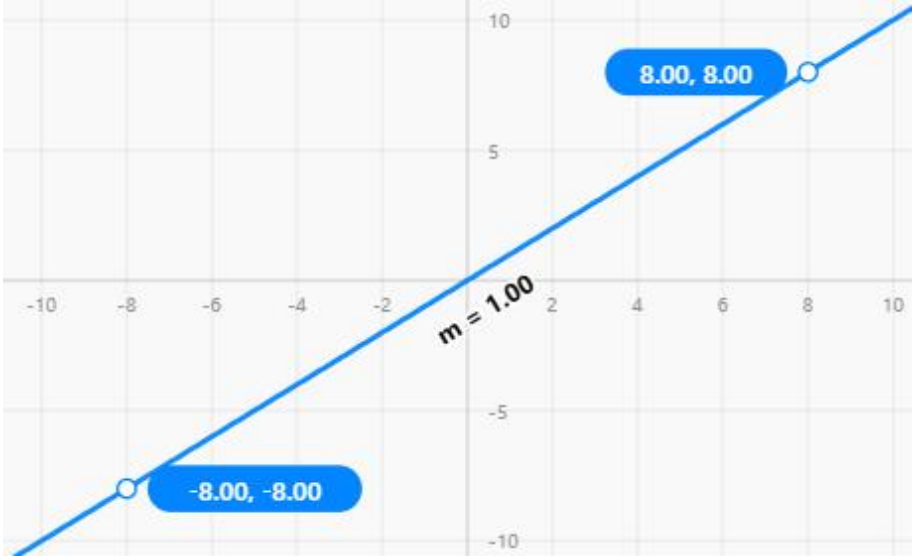


Fig. 4. Direction Estimation showing through the Graph.

where θ represents the movement angle. Direction estimation is critical for identifying deviations from expected traffic flow [70].

4.6 Wrong-Way Detection Strategy

A vehicle is classified as wrong-way if its movement direction deviates significantly from the expected lane direction:

$$WW = \begin{cases} 1, & \text{if } |\theta - \theta_{expected}| > \delta \\ 0, & \text{otherwise} \end{cases}$$

where δ is a predefined threshold. This rule-based approach ensures reliable detection of violations in real-time scenarios [61].

4.7 Evaluation Metrics

The system performance is evaluated using standard metrics:

- Mean Average Precision (mAP): measures detection accuracy
- Frames Per Second (FPS): indicates real-time capability
- Latency: measures processing delay per frame
- Multi-Object Tracking Accuracy (MOTA): evaluates tracking performance

5 Results and Discussion

The following part highlights the quantitative and qualitative analysis of YOLOv10, DETR, and Faster R-CNN algorithms with respect to the UA-DETRAC data set. The

comparison has been made in terms of detection accuracy, computational efficiency, tracking ability, and wrong-way detection performance under similar experimental settings [62].

5.1 Detection Performance (mAP@0.5)

Model	mAP (%)
YOLOv10	91.3
DETR	93.1
Faster R-CNN	89.6

DETR exhibits the most accurate detection results owing to its capacity to model the global relationship between contexts within an image. The YOLOv10 framework offers comparable accuracy performance while retaining high inference speeds [64]. The Faster R-CNN framework is observed to exhibit reduced accuracy results due to computational inefficiency [65].

5.2 Speed and Latency Analysis

Model	FPS	Latency (ms)
YOLOv10	42	23
DETR	12	83
Faster R-CNN	18	56

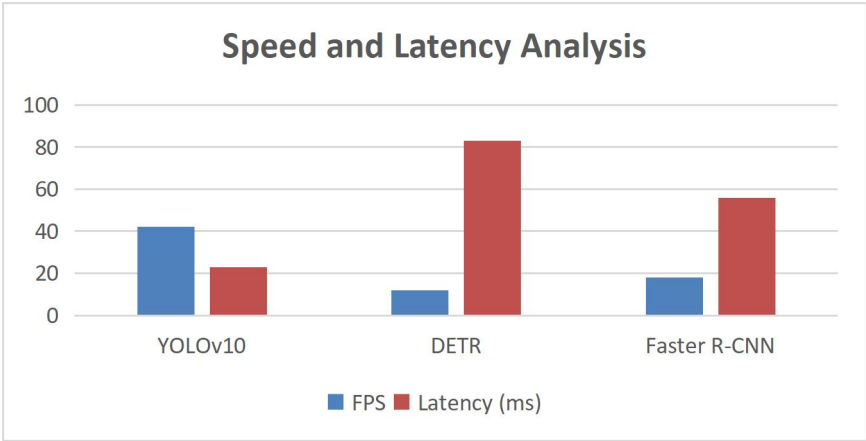


Fig. 5. Real-time performance with speed and latency Analysis

YOLOv10 achieves real-time performance with over 40 FPS, making it suitable for live traffic monitoring systems. DETR exhibits high latency due to transformer-based computations, which limit its real-time applicability. Faster R-CNN provides moderate performance but fails to meet strict real-time requirements [66].

5.3 Overall Performance Comparison

Model	mAP (%)	FPS	Latency (ms)	MOTA (%)
YOLOv10	91.3	42	23	88.5
DETR	93.1	12	83	90.2
Faster R-CNN	89.6	18	56	85.7

This comparison highlights the trade-off between accuracy and efficiency across different architectures [67].

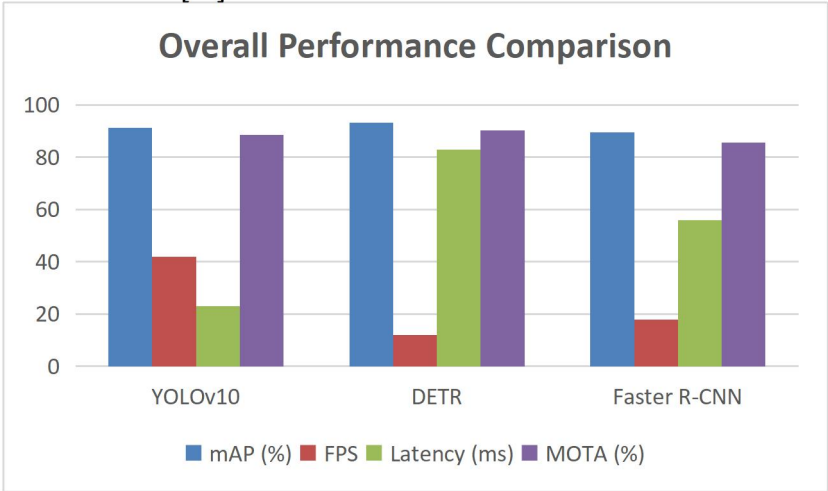


Fig. 6. Overall Performance Comparison of YOLOv10, DETR, Faster R-CNN

5.4 Tracking Performance (MOTA)

- DETR: 90.2%
- YOLOv10: 88.5%
- Faster R-CNN: 85.7%

Detection accuracy contributes towards better tracking consistency, as seen in DETR [60]. The YOLOv10 network retains good tracking accuracy owing to stable detections and fast inference speeds. Fasterrcnn is relatively poor at tracking accuracy because of its slow detection speed [68].

5.5 Accuracy vs Speed Trade-off

YOLOv10 achieves the best balance between speed and accuracy, making it ideal for real-time deployment [68]. DETR prioritizes accuracy over speed, while Faster R-CNN provides a middle-ground solution [69].

5.6 Wrong-Way Detection Performance

Model	Detection Accuracy (%)	False Positives (%)	False Negatives (%)
YOLOv10	92.4	5.1	4.3
DETR	94.0	4.2	3.8
Faster R-CNN	90.2	6.5	5.8

DETR is best at wrong-way detection because of its ability to reason contextually [60]. The YOLOv10 system works similarly but uses less time, thus allowing for real-time processing [61]. On the other hand, Faster R-CNN has more false positives as a result of slow processing speeds and delayed updates [62].

5.7 Wrong-Way Detection Performance

The qualitative results confirm the efficient working of the proposed approach in terms of vehicle detection, tracking, and wrong-way driving. The tracking is achieved through YOLOv10 by smooth and consistent tracking at high frames per second, whereas DETR performs better for object detection in occluded scenarios [61].

5.8 Discussion of Results

- The experimental results indicate that:
- **YOLOv10** is the most suitable for real-time applications due to:
 - High FPS (42)
 - Low latency (23 ms)
 - Competitive accuracy
 - **DETR** is best suited for:
 - Complex traffic environments
 - High-accuracy requirements

- **Faster R-CNN:**
 - Provides stable detection
 - Not ideal for real-time systems

Overall, the results confirm that model selection depends on application requirements, with YOLOv10 being the optimal choice for real-time intelligent transportation systems [62].

6 Conclusion

This research paper presented a comparative analysis of three advanced object detection models—YOLOv10, Detection Transformer (DETR), and Faster R-CNN—to perform real-time wrong-way vehicle detection in intelligent transportation systems. A common framework considering detection, multi-object tracking, and trajectory direction estimation was developed to provide consistent comparison among all three models.

The experiments have shown that YOLOv10 is a better choice in terms of accuracy and speed as it provides the most optimal balance of both parameters. YOLOv10 provides a high accuracy rate (mean Average Precision = 91.3%), performs at a real-time speed of 42 FPS, and features a low latency rate (23 ms), making this algorithm suitable for use in real-time traffic monitoring systems [63]. DETR shows the highest accuracy rates (mean Average Precision = 93.1%) and tracking performance (MOTA = 90.2%) due to modeling global context relations but has relatively high latency and slow processing (latency = 83 ms, FPS = 12) [101]. Faster R-CNN demonstrates reliable detection performance (mean Average Precision = 89.6%) but also shows moderate latency rates [64].

The results indicate that the choice of models must be done according to the needs of their application. YOLOv10 is the most suitable solution in cases when there is a need to provide efficient real-time intelligent highway monitoring because of its effectiveness, scalability, and low latency. DETR is recommended to be used for high precision and context understanding, especially in cases of a complex environment [66]. Faster R-CNN is recommended to be applied as a basic model for wrong-way vehicle detection that requires further optimization for real-time applications [67].

Moreover, the use of multiple object tracking and trajectory analysis significantly increases the reliability of the wrong-way vehicle detection system, which allows detecting violations based on motion estimation. It is also important to maintain balance between detection accuracy, speed, and computation costs for practical implementation [69].

Possible directions of future research include creating a hybrid network architecture of YOLO and transformer-based models, implementing optimization strategies for deploying the model in edge devices, and using multiple cameras' data to improve tracking accuracy [70]. Moreover, predictive analysis and real-time alerts

may increase the efficiency of traffic monitoring and promote the creation of a smart city [71].

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