Dynamic Polygon-Based Reverse Driving Detection Technique for Enhanced Road Safety

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***Abstract*—Reverse driving and lane collapse pose serious risks to road safety, especially on complex infrastructures such as multi-lane highways, intersections, and roundabouts. Existing detection systems often depend on rigid lane configurations and struggle to adapt to varied road geometries and environmental conditions. Prior works are typically limited to straight, multi-lane roads and rely on automated boundary extraction, making them unsuitable for irregular traffic layouts. To address this gap, the objectives of this research paper is to propose a vision-based detection system that combines the YOLOv8 object detector with a dynamic polygon-based zone management strategy. The system aims to detect reverse driving and lane collapse incidents in real time using CCTV footage, without requiring additional sensors. Its key novelty lies in manually configurable zones and the integration of ByteTrack for robust vehicle tracking across complex scenes. The system was tested under diverse real-world parameters, including different road types (single-lane, multi-lane, roundabouts), lighting conditions (day and night), and traffic behaviors (normal flow, reverse, and collapse) and visual evaluations highlight consistent and logically coherent results across scenarios, highlighting its practical effectiveness for real-time intelligent traffic monitoring.**

***Keywords*—Reverse driving detection; lane collapse detection; polygon zones; object detection; YOLOv8**

I. Introduction

Preventing traffic accidents and maintaining efficient traffic flow are critical challenges of modern transportation infrastructure [1]. Although wrong-way driving incidents account for only 3% of global traffic accidents, they result in a disproportionate 22% of traffic-related fatalities [2], highlighting their severe impact. This underscores the urgent need for effective detection and prevention systems to mitigate the risks associated with dangerous driving behaviors, particularly reverse driving and lane collapse incidents [3], [4], [5].

Recent advances in intelligent transportation systems have played a crucial role in enhancing road safety and traffic management. However, the increasing complexity of modern road networks, diverse driving behaviors, and unpredictable environmental conditions pose significant challenges to existing solutions. Traditional countermeasures, including physical barriers and static signage, provide some deterrence but often prove inadequate in dynamic traffic environments that require rapid response. Although emerging detection technologies, including sensor-based and artificial intelligence AI-driven methods, offer promising alternatives, they face limitations in scalability, adaptability, and cost-effectiveness.

To address these challenges, this study proposes a novel AI-driven detection system for identifying wrong-way driving and lane collapse incidents in real-world traffic scenarios. Using advanced computer vision techniques, the proposed method enhances detection accuracy and robustness across various road environments, including intersections, highways, and roundabouts, making it well-suited for intelligent traffic management systems.

The proposed approach integrates the state-of-the-art You Only Look Once, version 8 (YOLOv8) [6] object detection model with a dynamic polygon-based zone management system, offering several key advantages:

1) Adaptive configuration: Dynamic polygon-based zones adjust to various road configurations, enabling deployment across diverse infrastructure environments.

2) Real-time processing: The lightweight architecture of YOLOv8, combined with efficient zone management, enables real-time detection and response.

3) Robust scene adaptability: The combination of polygonal zones and ByteTrack enables reliable detection across intersections, roundabouts, and complex traffic scenes.

4) Cost-effectiveness: The vision-based system requires minimal additional infrastructure, making it accessible to transportation authorities with varying resources.

Through the comprehensive evaluation of diverse datasets, our approach demonstrates superior performance in detecting reverse driving and lane collapse scenarios across various road configurations. The system maintains high accuracy while minimizing computational overhead, ensuring its suitability for widespread deployment.

Objectives of the Paper:

- To conduct an in-depth literature review of diverse driving behavior detection techniques proposed in prior research, with a focus on identifying limitations related to adaptability, road type constraints, and deployment cost in existing systems;
- To propose a novel vision-based methodology for detecting reverse driving and lane collapse behaviors using CCTV surveillance. The purpose is to provide

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a lightweight and infrastructure-independent system capable of adapting to a variety of real-world road layouts, including intersections and roundabouts. The novelty of the proposed system lies in its manually configurable polygon-based zone management and integration with YOLOv8 and ByteTrack for precise object detection and multi-object tracking in complex scenes;

- To test and validate the system's performance across varied traffic scenarios using visual assessments under different lighting conditions (day and night), road types (single-lane, multi-lane, roundabout), and behavioral patterns (normal flow, reverse driving, and lane collapse);
- And, to validate the proposed system in real-time system responsiveness to detect and update reverse-driving incidents immediately within video stream processing.

The remainder of this paper is organized as follows. The literature review section analyzes existing detection methods and their limitations. The methodology section details the system architecture. The implementation details section summarizes the steps of the algorithm, illustrating the logical workflow. The result section discusses the experimental results across various road configurations, demonstrating the effectiveness of the system. Finally, the discussion concludes with insights into future research directions and potential applications.

II. Literature Review

Research highlights the significant impact of wrong-way driving and lane collapse incidents on road safety. The AAA Foundation reported a 34% increase in driving against the traffic flow incidents over the past five years, particularly on highways and divided roads [7]. In the United States, annual economic losses from such incidents exceed $5.2 billion, encompassing direct damage, emergency response costs, and productivity losses. Lane collapse incidents account for 18% of highway accidents, with heightened risks under adverse weather conditions and reduced visibility [8], [9].

Traditional countermeasures, including signage and physical barriers, have been widely implemented, yet their effectiveness remains limited, preventing only 65% of wrong-way entries [10], [11]. Electronic detection systems, such as roadside cameras and automated warnings, can improve response times but suffer from high false-positive rates (15–20%) and incur high maintenance costs, averaging $50,000 annually per installation [12]. Sensor-based solutions, including radar, lidar, and GPS tracking, have also been explored [13], [14], [15], [16], [17]. However, radar systems exhibit reduced accuracy in adverse weather, lidar presents high deployment costs, and GPS-based approaches require vehicle-mounted units, which hinders scalability in public infrastructure applications.

Artificial intelligence (AI)-based systems, particularly those utilizing convolutional neural networks (CNNs), have demonstrated high accuracy in detecting traffic anomalies in controlled environments. Studies report over 95% accuracy in detecting lane violations and reverse movement under ideal conditions [18], [19], [20], [21]. Nevertheless, real-world deployment remains challenging due to lighting variation, complex road geometries, and occlusions. Camera-based detection approaches, including dashcam footage and surveillance systems, also require adaptation to varied environmental conditions [22], [23], [24], [25]. Moreover, these methods often struggle with performance in intersections, roundabouts, and irregular traffic zones [26], [27].

Recent advances have sought to combine multiple techniques to address these challenges. Hybrid systems integrating vehicle detection, motion tracking, and infrastructure feedback have improved robustness. Vehicle-to-infrastructure (V2I) methods offer real-time alerts, but remain costly and dependent on specific installations [28]. Grouping-based vehicle detection enhances classification accuracy but is vulnerable to changes in weather, traffic density, and road layout [29]. Loop-type detectors such as those from Sumitomo Electric require precise calibration and suffer from false activations in dense traffic areas [30].

Among recent contributions, the work by Suttiponpisarn et al. [18] presents an enhanced system combining YOLOv4-Tiny with FastMOT [31] and a road boundary extraction algorithm (RLB-CCTV). This method achieves high accuracy using embedded-suitable components, and replaces manual boundary marking with automated lane detection based on edge and line detection. However, it remains limited to straight roads. The system's dependency on statistical estimation for directional flow and sensitivity to environmental conditions constrain its applicability in complex or non-linear road structures such as roundabouts or intersections.

These observations highlight the need for a flexible and generalizable detection system that performs reliably across diverse road conditions. Our study addresses this gap by introducing a polygon-based zone framework integrated with YOLOv8 for real-time detection and tracking. The proposed approach allows users to manually configure detection zones for arbitrary road layouts, enabling robust performance in environments where automated methods or fixed detectors fail to generalize.

III. Methodology

The proposed system is designed to detect reverse driving and lane collapse incidents using video streams from roadside CCTV cameras. The overall architecture is composed of four primary modules: video input processing, dynamic zone setup, movement detection and analysis, and real-time monitoring. A visual overview of the framework is presented in Fig. 1.

A. Video Input and Frame Processing

Each video stream is processed frame-by-frame. Frames are extracted in real time and passed to the object detection and tracking module. This ensures the system can maintain temporal continuity of vehicle movement and associate detection results across time.

B. Object Detection and Vehicle Tracking

To detect vehicles, we use YOLOv8 [6], a state-of-the-art object detection model known for its accuracy and efficiency,

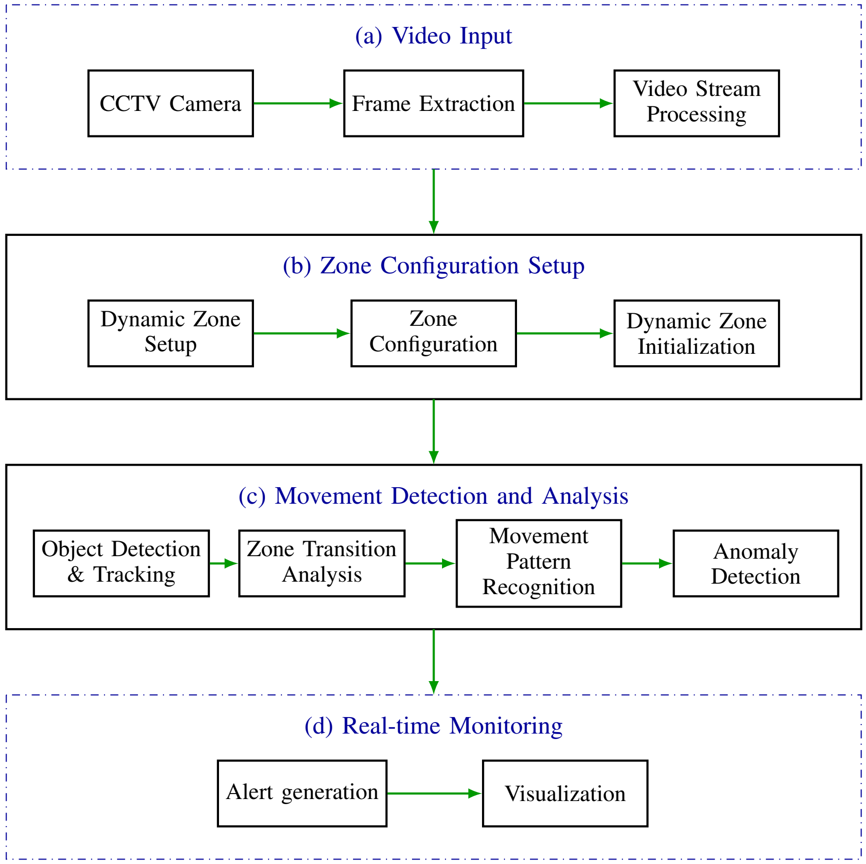

Fig. 1. Overview of the proposed traffic monitoring system architecture. (a) Video input module processes CCTV streams. (b) Configuration defines dynamic detection zones. (c) Movement detection analyzes object transitions and detects anomalies. (d) Real-time monitoring generates alerts and visual output.

particularly in complex scenes. Each detected vehicle is represented by a bounding box and class label (e.g., “car”, “truck”). The detection results are then passed to the ByteTrack multi-object tracker [32], which assigns a unique tracker ID to each vehicle.

ByteTrack in Section III-G operates by associating detections across frames using Intersection-over-Union (IoU) matching. It follows multiple steps which helps maintain trajectory consistency even when detections are temporarily uncertain or occluded.

C. Dynamic Zone Configuration

In the initial frame of the video, polygonal zones are manually defined using OpenCV [33]. For a two-lane road, four zones are created: in-zone-0, out-zone-0, in-zone-1, and out-zone-1. These zones represent logical boundaries of entry and exit for each lane (as shown in Fig. 2 and 3).

Each vehicle’s bounding box is evaluated in every frame to check whether it intersects any of these predefined zones. The result is stored as a binary occupancy value for that zone (1 = inside, 0 = outside). Each tracker ID maintains a zone presence vector over time.

D. Illustrative Example

Consider vehicle ID #3 on a single-lane road in Fig. 2:

- It enters in-zone-0 and later exits through out-zone-0.
- Its zone vector becomes (1,1,0,0), matching the first row in Table I.
- Therefore, the reverse value is set to 0 (reverse driving within the same lane).

By contrast, if a vehicle enters both `in-zone-0` and `in-zone-1`, but never exits correctly, its vector becomes (1,0,1,0) and is assigned a reverse value of 1 (violation or lane collapse) as shown in Fig. 3.

E. Real-Time Output and Monitoring

Once the reverse status is determined for a tracker ID, the label is visualized in real time using bounding boxes and zone overlays. Vehicles are annotated with their ID and reverse status (e.g., “car (reverse: 1)”), enabling immediate visual confirmation and alerting.

This modular pipeline ensures the system can operate reliably across varied road configurations, including intersections and roundabouts, without retraining. The manual polygon zone setup provides flexibility, while YOLOv8 and ByteTrack ensure accurate detection and persistent identity tracking.

F. Reverse Driving Judgement

The algorithm, outlined in Table I, employs a zone-based configuration with four distinct monitoring areas—in-zone-0

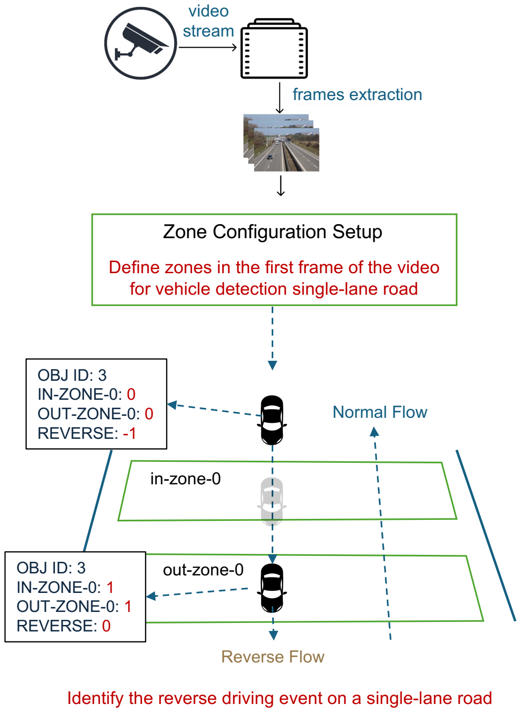

Fig. 2. Zone configuration for single-lane road monitoring.

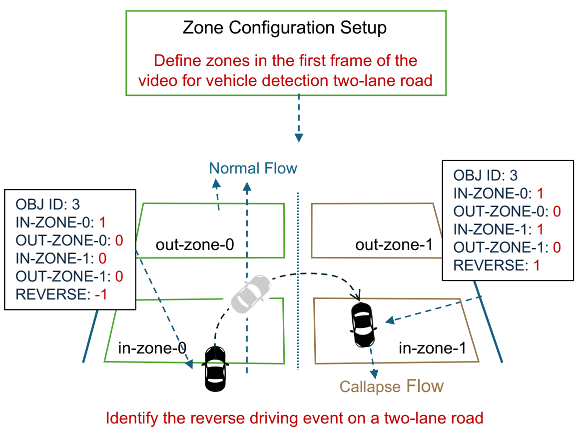

Fig. 3. Zone configuration for two-lane road monitoring.

TABLE I. ZONE TRANSITION STATES AND THEIR CORRESPONDING REVERSE VALUES. THE 'REVERSE' COLUMN INDICATES WHETHER A VEHICLE IS IN AN UNKNOWN STATE (-1), REVERSE WITHIN ITS LANE (0), AND COLLAPSE ON OTHER LANES (1)

in-zone-0	out-zone-0	in-zone-1	out-zone-1	reverse
1	1	0	0	0
0	0	1	1	0
1	0	0	1	1
0	1	1	0	1
1	0	1	0	1
0	1	0	1	1
else				-1 (unknown)

and out-zone-0 for the left lane, and in-zone-1 and out-zone-1 for the right lane, as depicted in Fig. 3. The occupancy of each zone is binary (0 or 1), enabling precise vehicle movement tracking and directionality assessment. The algorithm evaluates all possible combinations of zone occupancies to detect reverse driving incidents. The 'reverse' column in Table I represents the detection outcome, where 0 indicates reverse driving within the same lane, 1 signifies cross-lane reverse driving or lane collapse, and -1 indicates ambiguous cases requiring further analysis. This six-row approach effectively identifies and assesses vehicle movements, enhancing detection accuracy for traffic anomalies on two-lane roads. This approach provides a robust framework for automated reverse driving detection, improving traffic safety by identifying potentially hazardous situations.

The implementation, illustrated in Fig. 3, demonstrates both normal traffic flow and lane collapse scenarios, with corresponding zone transition states documented in Table I. This comprehensive method ensures accurate monitoring and timely detection of reverse driving events, contributing to traffic safety.

G. Vehicle Tracking

ByteTrack [32] is employed as a robust multi-object tracking algorithms that effectively track objects, including vehicles, by utilizing both high-confidence (D_{high}) and low-confidence (D_{low}) detection. This algorithm serves as the starting point of Algorithm 1, which analyzes the movements of tracked vehicles and assigns each one a unique `tracker_id`, as defined in Algorithm 1.

The ByteTrack tracking mechanism involves the following main steps:

1) Detection set division: At each frame t, the detections are divided into:

$$D_t = D_{\text{high},t} \cup D_{\text{low},t}, \tag{1}$$

where:

- $D_{\text{high},t}$: comprises detections with confidence $c > \tau$, where τ is a high confidence threshold.
- $D_{\text{low},t}$: include detections with confidence $\tau_{\text{low}} < c \leq \tau$, where τ_{low} is a lower confidence threshold.

2) Matching with high-confidence detections: High-confidence detections are matched to existing tracks T_t using the intersection over union (IoU) metric:

$$\text{IoU}(d_i, T_j) = \frac{|b_i \cap b_j|}{|b_i \cup b_j|}, \tag{2}$$

where b_i and b_j are the bounding boxes of detection d_i and track T_j, respectively. The Hungarian algorithm is used to find the optimal matching:

$$T_{\text{matched}} = \text{Hungarian}(T_t, D_{\text{high},t}, \text{IoU}). \tag{3}$$

3) Incorporation of low-confidence detections: To prevent track loss, unmatched tracks from the high-confidence step are matched with low-confidence detections:

$$T_{\text{low-matched}} = \{(t, d) \mid \tag{4}$$
$$\text{IoU}(t, d) \geq \tau_{\text{low}},$$
$$t \in T_{\text{unmatched}},\ d \in D_{\text{low},t}\} \tag{5}$$

4) Track update: Matched tracks are updated using Kalman filtering [34] to refine the bounding box predictions:

$$b_{\text{updated}} = K(b_{\text{predicted}}, b_{\text{new}}), \tag{6}$$

where $b_{\text{predicted}}$ is the predicted state of the track, b_{new} is the observed detection, and K represents the Kalman filter.

5) New track initialization: Unmatched high-confidence detections are initialized as new tracks:

$$T_{\text{new}} = \{b_i \mid b_i \in D_{\text{high},t},\ b_i \notin T_{\text{matched}}\}. \tag{7}$$

6) Track termination: Tracks are terminated if they remain unmatched for k consecutive frames:

$$T_{\text{terminated}} = \{t \mid \Delta t > k,\ t \notin T_{\text{updated}}\}. \tag{8}$$

IV. Implementation Details

Algorithm 1 is designed to detect reverse driving by processing object detections with their associated `tracker_id` and bounding boxes. The algorithm's primary goal is to update `reverse_conditions` for each detection, which stores information about tracked objects.

Algorithm 1 Detecting Reverse Driving and Lane Collapse

Input: Detections with `tracker_id` and bounding boxes
Output: Detections with updated `reverse_conditions`
`tracker_id`: An object being tracked
`reverse_conditions`: Stores values related to tracked objects (as in Table I) Initialize `reverse_conditions` for all detections **ForEach** *detection in* `detections`
  Extract `tracker_id` and bounding box Initialize `reverse_conditions[tracker_id]`
end
ForEach *zone in* `zones`
  ForEach `tracker_id` *in zone*
    Update zone information for `tracker_id` Check if `tracker_id` moved in or out of the zone **If** *reverse driving is detected*
      `reverse_conditions[tracker_id]` ← `true`
  end
end
Return `detections` *with updated* `reverse_conditions`

It begins by initializing `reverse_conditions` for all detections in the input data. The process then iterates through each detection, extracting the `tracker_id` and bounding box information, and initializes the corresponding `reverse_conditions` entry for that `tracker_id`. The core detection logic operates by examining each zone and the `tracker_ids` within them. For each `tracker_id` present in a zone, the algorithm updates the zone information and monitors whether the tracked object has moved in or out of the zone. When reverse driving behavior is detected, the algorithm sets the `reverse_conditions` for the corresponding `tracker_id`.

After processing all zones and their associated `tracker_ids`, the algorithm concludes by returning the complete set of detections with their updated value of `reverse_conditions` as shown in 'reverse' column in Table I, providing a comprehensive record of any reverse driving incidents detected during the analysis.

V. Results

To validate the proposed system, we present qualitative results using real-world video footage across various scenarios. Fig. 4 to 7 demonstrate the system's ability to detect normal and reverse driving behavior in single-lane, multi-lane, nighttime, and roundabout road conditions. These case studies confirm the robustness and practical performance of the system, even in complex or low-visibility environments.

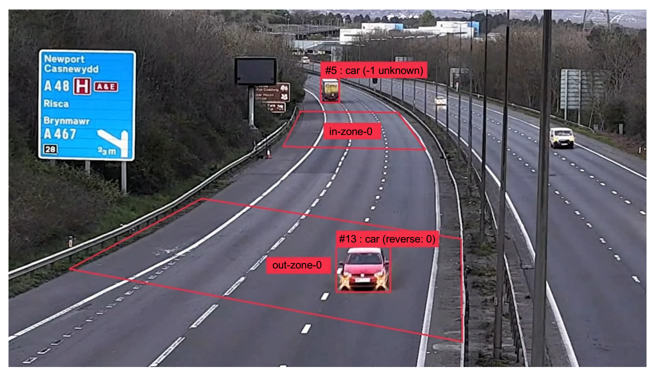

Fig. 4. Result of monitoring on single-lane road configuration.

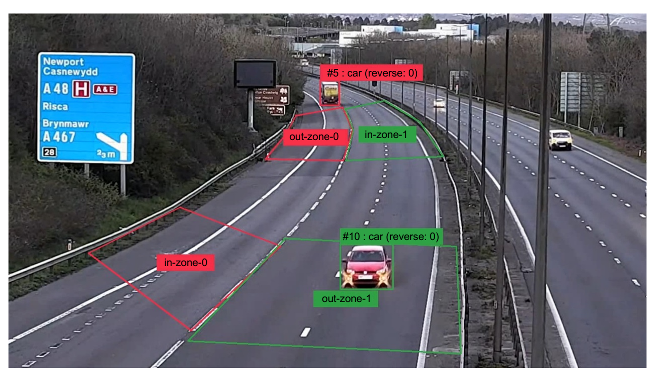

Fig. 5. Result of monitoring on double-lane road configuration.

The real-world implementation demonstrates the effectiveness of the reverse driving detection algorithm on single-lane road segments. As shown in Fig. 4, the system successfully

TABLE II. COMPARISON BETWEEN THE PROPOSED METHOD AND SUTTIPONPISARN ET AL. [18]. THE TABLE HIGHLIGHTS DIFFERENCES IN DETECTION FLEXIBILITY, DEPLOYMENT SCOPE, AND CORE ALGORITHMIC CHOICES

Aspect	Suttiponpisarn et al	Proposed Method
Detection Model	YOLOv4-Tiny	YOLOv8
Tracking Algorithm	FastMOT	ByteTrack
Zone Definition	Automated rectangular zones via edge detection	Manual polygonal zones for flexible layout
Supported Road Types	Straight, unobstructed multi-lane roads	Multi-lane, intersections, roundabouts
Lighting Adaptability	Requires brightness correction	Works under day/night
Object Focus	Motorcycle detection in 4 test locations	All vehicles across diverse traffic scenarios
Evaluation Type	Quantitative (96.61% accuracy)	Qualitative visual validation
False Positive Handling	Measured and reported	Acknowledged; future work planned

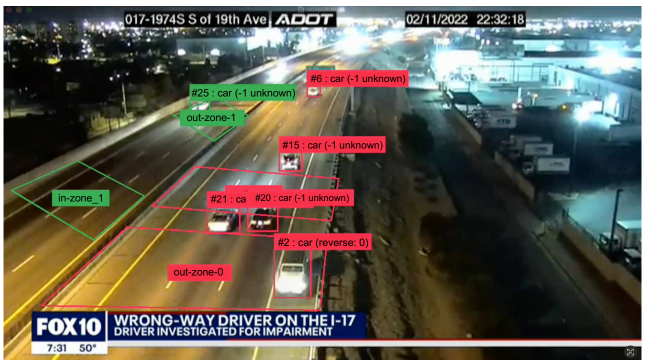

Fig. 6. Result of monitoring at night condition.

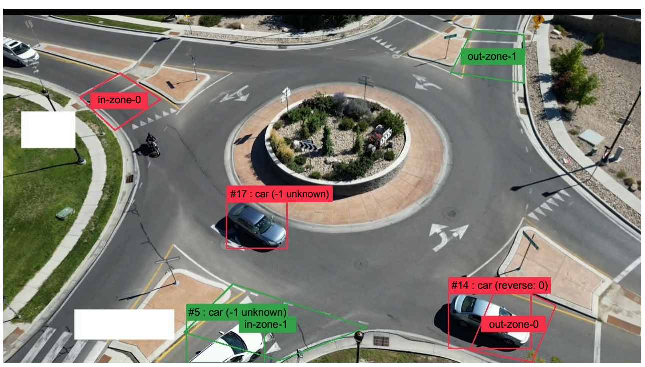

Fig. 7. Result of monitoring on roundabout road configuration.

monitors vehicle movement through defined zones on a primary road. A test case with vehicle #13 demonstrated normal forward motion. The vehicle traversed through in-zone-0 and out-zone-0, with the algorithm correctly assigning reverse: 0 based on the zone transition states in Table I. This corresponds to the first row of the transition table, where the activation of both zones in a single lane (1,1,0,0) indicates proper directional flow. Additionally, the system simultaneously tracks multiple objects. For instance, vehicle #5 was detected in an unknown state (-1), aligning with the undefined state conditions of the table. These results validate the capability of the algorithm to differentiate normal and reverse driving patterns in real-time monitoring scenarios. The clear zone demarcation enables reliable movement classification.

The monitoring capabilities of the system were further tested in multi-lane scenarios, where multiple vehicles were tracked simultaneously. As shown in Fig. 5, the algorithm correctly classifies vehicle #5 in out-zone-0/in-zone-0 and vehicle #10 in in-zone-1/out-zone-1 with reverse: 0. This aligns with the zone transition states of Table I, where the simultaneous occupation of zones (0,0,1,1) indicates normal directional flow in the right lane. Clear zone delineation between lanes (red for lane 0 and green for lane 1) enables accurate vehicle tracking and classification. These results validate the effectiveness of the algorithm in complex multi-vehicle, multi-lane monitoring scenarios.

Fig. 6 presents results from nighttime highway monitoring. Vehicles are detected and annotated with bounding boxes and labels. Vehicle #2, labeled 'car (reverse: 0)', indicates it is traveling against the flow of traffic in out-zone-0.

The reverse driving detection algorithm can monitor roundabout scenarios, where dynamic polygonal zone setups present unique challenges. Fig. 7 demonstrates the performance of the system at a roundabout intersection, where multiple vehicles are tracked simultaneously. Detected vehicles include vehicle #14 in out-zone-0 (reverse: 0), indicating normal flow and vehicles #17 and #5 in unknown states (-1) due to movement through zones that do not conform to the standard transition patterns in Table I. The system effectively monitors multiple entrance and exit points, although the increased complexity of roundabout navigation results in a higher frequency of unknown state classifications compared to straight road segments.

A. Analysis

To further evaluate the strengths and limitations of the proposed system, we conducted a comparative analysis with a closely related work by Suttiponpisarn et al. [18]. Their method combines YOLOv4-Tiny for object detection, FastMOT [31] for tracking, and an automated road boundary extraction algorithm (RLB-CCTV) that utilizes edge detection and Hough transforms to define lane boundaries. The system is designed for embedded devices and achieves high accuracy (96.61%) for detecting wrong-way motorcycles on straight, well-lit roads.

However, their approach presents several constraints. It is restricted to straight, unobstructed multi-lane roads and depends on brightness correction and predefined geometric assumptions. It does not support curved roads, roundabouts, or intersections—scenarios which are common in urban traffic environments.

In contrast, our method uses manually defined polygonal zones that can be flexibly adapted to any road geometry. The system is validated qualitatively across multiple complex real-world scenarios, including intersections and roundabouts, and performs reliably under both day and night conditions. Moreover, we adopt YOLOv8 for object detection, which has demonstrated superior accuracy and generalization over YOLOv4-Tiny in benchmark evaluations, particularly in detecting small or partially occluded objects [6]. Table II summarizes the key differences between the two approaches.

This comparative analysis underscores the broader applicability and deployment flexibility of our method, particularly in urban environments where roads are non-linear and traffic conditions are more dynamic.

VI. Conclusion and Future Work

The research paper proposes a novel system for detecting reverse driving and lane collapse using CCTV-based video monitoring. The system integrates YOLOv8 for object detection, ByteTrack for vehicle tracking, and manually defined polygonal zones for flexible configuration across different road layouts. The novelty of the method lies in its adaptability to intersections, roundabouts, and non-linear road geometries without relying on additional sensors or automated boundary extraction. Experimental results show consistent visual performance across day, night, single-lane, multi-lane, and roundabout scenarios. However, the evaluation remains qualitative due to the absence of labeled datasets.

In the near future, it is planned to focus on developing dynamic zone adjustment mechanisms that extend beyond straight road detection. In contrast to prior approaches that rely on automated boundary extraction limited to linear lane structures, the proposed direction will aim to support adaptive zone generation for complex geometries such as roundabouts, intersections, and curved roads. This advancement is expected to reduce manual configuration effort and improve generalizability. In addition, the work will include quantitative evaluation using annotated datasets to assess detection accuracy, false detection rates, and latency. These improvements can further enhance the system's robustness and scalability for real-world intelligent traffic surveillance.

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