DATASET CONSTRUCTION AND IMAGE PERSPECTIVE ANALYSIS FOR LANE DETECTION UNDER VIETNAMESE ROAD CONDITIONS

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Abstract

This article presents the construction of a dataset for lane detection research under Vietnamese road conditions along with an evaluation of some of the best state-of-the-art lane detection models at the moment, as well as an analysis of image perspective effects on detection performance. A custom dataset is collected from real-world road scenes in Vietnam, covering diverse traffic scenarios and lane marking conditions. Multiple pretrained state-of-the-art lane detection models are then evaluated on the proposed dataset using precision, recall, and F_1-score metrics. To study perspective sensitivity, perspective modification was applied to the input images, shifting the vanishing-line (road horizon) from 20% to 80% of the image's height. The results indicate a clear dependence on image perspective, with the best overall performance achieved (F_1-score peaks at 73.4%) when the vanishing-line position is 37% of the image height. The dataset, perspective analysis, and benchmarking results together provide practical guidance for dataset design, perspective normalization, and the deployment of pretrained lane detection models in real-world Vietnamese traffic environments.

Keywords: *Lane detection; vanishing-line optimization; ADAS.*

1. Introduction

Lane detection is a core component of advanced driver assistance systems (ADAS) and autonomous driving technology [1]. Despite significant progress driven by deep learning models, real-world deployment remains challenging due to strong domain dependence on road structure, traffic behavior, and sensor configuration. Lane detection remains challenging due to factors such as long-range perception limitations, complex road topologies, semantic ambiguities from non-lane markings, occlusions, and varying visual conditions. These challenges are further exacerbated in Vietnamese traffic environments, where lane markings are often degraded, occluded, or non-standard. Such issues motivate the need for a dedicated dataset and a systematic analysis of perspective effects.

Beyond data diversity, camera installation parameters play a critical role in perception performance. The camera pitch angle determines the image perspective and,

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consequently, the vertical location of the vanishing-line line. Although lens distortion can affect the apparent convergence of lane markings, its impact is limited due to the moderate field-of-view and the focus on the central image region. In the context of lane detection, the vanishing-line is defined as the horizontal line (Fig. 1) that represents the maximum height (minimum y-coordinate value) that lane markings can reach in the image. Visually, this corresponds to the "vanishing-line" of the road, where parallel lane markings converge to a vanishing point. The vanishing-line position is critical because it defines the upper boundary of the road surface and determines the perspective geometry of lane markings. This vanishing-line position directly influences the spatial distribution of lane features in the image and affects both feature extraction and geometric reasoning in lane detection models.

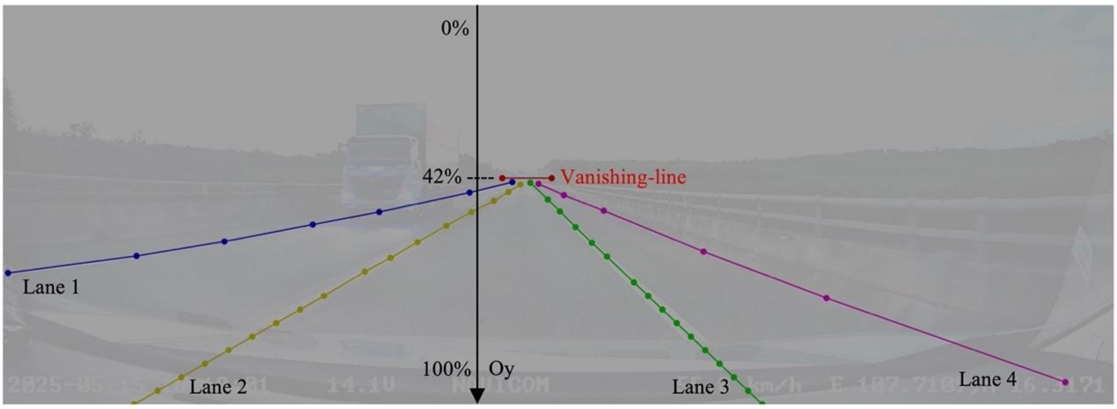


Fig. 1. Visual representation of vanishing-line and lane lines.

The vanishing-line position in captured images is influenced by multiple factors:

• Camera settings and mounting (fixed for a given camera installation):

- Camera tilt angle (pitch).
- Camera height above ground.
- Field of view settings.

• Terrain variations:

- Beginning of uphill roads: Vanishing-line appears higher in the image (lower y-coordinate percentage).
- Beginning of downhill roads: Vanishing-line appears lower in the image (higher y-coordinate percentage).
- Flat terrain: Vanishing-line position remains relatively constant.

This article addresses two closely related objectives:

- To construct a dedicated lane detection dataset reflecting Vietnamese road conditions, intended for testing, benchmarking, training, and model improvement.
- To systematically optimize the vanishing-line (perspective) parameter and study its influence on lane detection precision, recall, and F1-score.

By combining dataset statistics with controlled vanishing-line (perspective) optimization experiments, an insight into how camera perspective should be selected or normalized for robust lane detection was provided.

2. Related work

Lane detection methods have evolved along three main paradigms according to lane representation: segmentation-based, anchor-based, and parameter-based approaches, as summarized in recent diffusion-based lane detection studies.

Segmentation-based methods formulate lane detection as a pixel-wise classification problem. Spatial Convolutional Neural Network introduced directional message passing to capture long-range spatial dependencies along rows and columns, significantly improving lane continuity modeling [2]. Subsequent approaches further enhanced global context aggregation while maintaining real-time performance. Although segmentation-based methods are robust to appearance variations, they often require complex post-processing to group pixels into lane instances and may struggle with thin, heavily occluded, or degraded lane markings.

Anchor-based methods detect lanes by refining a predefined set of lane anchors. Ultra Fast Lane Detection introduced row-wise anchors for efficient inference, while later methods employed dense or learnable anchors combined with region-based feature extraction to achieve high accuracy [3], [4]. Despite their efficiency, anchor-based approaches are sensitive to dataset bias, particularly variations in road geometry and image perspective, which can degrade generalization when the input distribution changes.

Parameter-based methods describe each lane using compact parametric forms such as polynomials or splines. These methods provide smooth and interpretable lane representations but are sensitive to initialization and perspective distortion, especially when the apparent geometry of the road changes due to viewpoint variation.

According to [5], diffusion-based models have emerged as a new paradigm for structured lane detection. Diffusion-based lane detectors reformulate lane prediction as an iterative denoising process in a continuous parameter space, enabling robust modeling of lane topology and uncertainty. DiffusionLane demonstrates improved robustness under distribution shifts by sampling lane anchors from a Gaussian distribution and progressively refining them through a reverse diffusion process. However, existing diffusion-based studies primarily focus on network architecture and denoising strategies, while the influence of image perspective variation remains largely unexplored.

In parallel, several large-scale datasets have been proposed to benchmark lane detection under challenging conditions such as shadows, night scenes, and occlusions [6]. Nevertheless, these datasets are collected in limited geographic regions (most of them are in the United States of America, South Korea or China) [7] and do not fully reflect the heterogeneous traffic, irregular markings, and mixed vehicle flows typical of Vietnamese roads, which will be mentioned in the next chapter. Moreover, most existing benchmarks implicitly assume a fixed input perspective, without systematically analyzing how image-space perspective variation affects detection performance.

In contrast to prior work, this study explicitly investigates image perspective as an independent factor by applying controlled image-space transformations that shift the vanishing line. By combining dataset construction with perspective analysis, the complementary insights that extend beyond model-centric improvements and are directly applicable to real-world deployment under Vietnamese road conditions were provided.

3. Challenges of lane detection

Across diverse driving environments worldwide, lane detection remains challenging due to a combination of perceptual, geometric, and semantic factors. First, many lane detection models inherently emphasize near-field lane segments, where visual cues are stronger and more consistent, as demonstrated later in this article. This bias often limits long-range perception, reducing the ability to anticipate lane curvature, merges, splits, or topology changes at greater distances.

Second, complex road topologies are common in both urban and inter-urban settings globally (Fig. 2(a)). Short lanes, lane merges and splits, temporary markings, and intersecting lane boundaries can create ambiguous or overlapping lane structures, complicating the separation and consistent tracking of individual lanes (Fig. 2(b)).

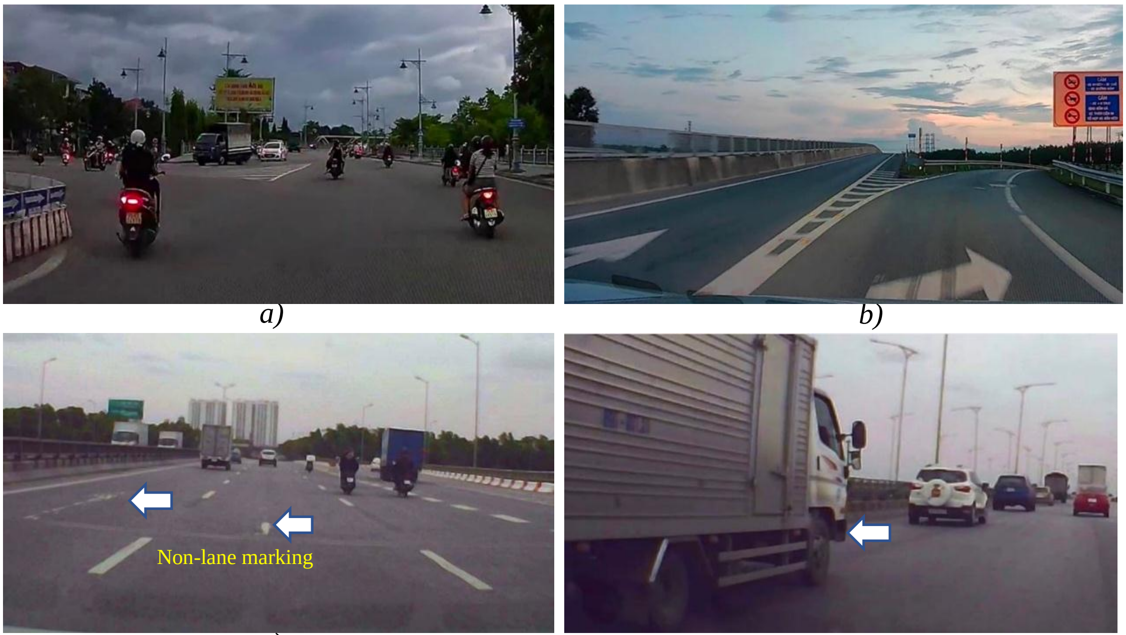
Third, non-lane road markings frequently introduce semantic confusion. Traffic direction arrows, textual markings, or symbols painted within lanes may be mistakenly interpreted as lane boundaries, particularly when their color, width, or orientation resembles standard lane markings (Fig. 2(c)).

Fourth, special-purpose markings such as emergency lanes, shoulder boundaries, and diagonal hatched regions (e.g., chevrons or cross-hatched patterns, Fig. 2(a) and (b) are often underrepresented in training data and are therefore poorly recognized, despite their importance for driving assistance and safety.

Fifth, vehicle maneuvers such as turning, lane changing, or traversing intersections induce rapid variations in camera viewpoint and perspective (Fig. 2(b)). These changes shift the apparent vanishing-line (perspective) position and distort lane geometry in the image, frequently leading to unreliable lane estimation.

Sixth, frequent occlusions caused by surrounding traffic - particularly large vehicles such as trucks, buses, or trailers - temporarily obscure lane markings or overwrite them visually, depriving perception systems of critical cues (Fig. 2(d)).

Finally, adverse visual conditions including nighttime driving, motion blur, and sensor degradation further exacerbate detection difficulty.



a) b) c) d)

Fig. 2. Common challenges of lane detection: (a) Complex road topology; (b) Road splitting; (c) Non-lane marking confusion; (d) Lane marking occlusion by large vehicle.

Lane detection in Vietnam also presents a set of unique challenges that differ substantially from those commonly addressed in standard benchmark datasets. These challenges directly motivate the need for a dedicated dataset and a careful analysis of camera perspective effects.

First, lanes located near sidewalks or outermost road edges are often encroached upon by roadside activities, including street vendors (Fig. 3(a)), temporary constructions, vegetation, soil, or debris (Fig. 3(b)). This issue is particularly severe for lanes dedicated to non-motorized or mixed traffic, where lane markings are frequently faded, broken, or completely obscured.

Adverse visual conditions such as blurred camera lenses, worn or faded lane markings (Fig. 3(c)), nighttime driving, and insufficient illumination (Fig. 3(d)) significantly degrade detection performance. Under such conditions, even advanced deep learning models struggle to extract reliable lane features.

a)

b)

c)

d)

Fig. 3. Challenges of lane detection in Vietnam: (a) Lane encroached by roadside activities; (b) Lane encroached by soil and debris; (c) Faded lane marking; (d) Insufficient illumination.

Together, these factors highlight the need for datasets and evaluation protocols that explicitly account for perspective variation, occlusion, and non-standard lane semantics [8].

They also motivate vanishing-line analysis as a principled approach to stabilizing image geometry and improving robustness across diverse global driving conditions.

4. Dataset construction for Vietnamese road conditions

The proposed dataset consists of 1,109 road images captured under real traffic conditions in Vietnam. Data were collected from forward-facing monocular camera mounted on passenger vehicles. The dataset covers a wide range of scenarios, including urban, suburban and highway roads with different image perspectives; daytime and nighttime conditions with varying illumination; roads with clear, worn, or partially missing lane markings and mixed traffic involving cars, motorcycles, and bicycles.

Lane markings were manually annotated in LabelMe using polyline (linestrip) representations, where points are placed along the centerline of visible lane markings while following their curvature. A key preprocessing step involved estimating the vanishing-line (Fig. 4) position as a percentage of image height, enabling both statistical analysis and controlled experimentation. The dataset contains a total of 4,679 annotated lane polylines, with an average of 4.22 lanes per image, ranging from 0 to 8 lanes per image. Only 6 images contain no visible lanes, while 1,103 images contain at least one lane.

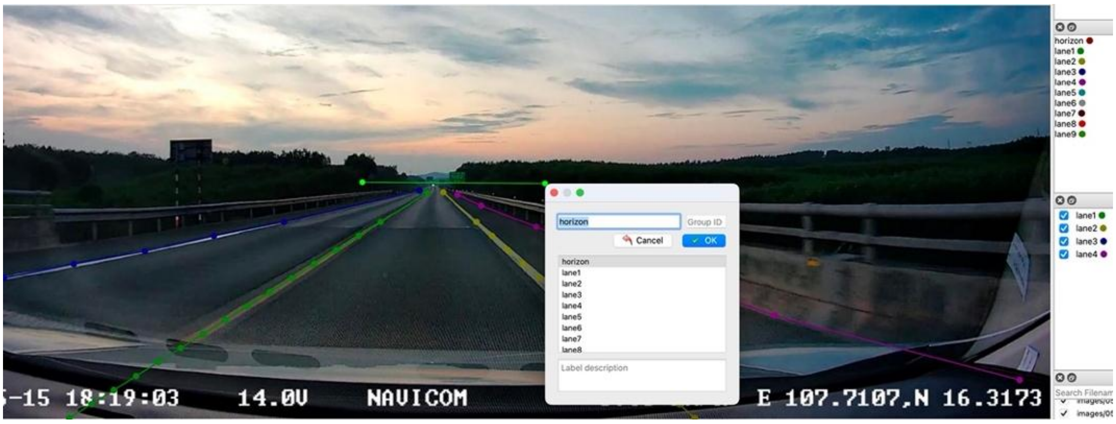


Fig. 4. Process of labeling the lanes (lane1, lane2, lane3, lane4) and vanishing-line (horizon).

The distribution of vanishing-line positions in the dataset ranges from 12% to 53.9% of image height, with a mean value of 34.2%, standard deviation of 6.9% and a median of 35.4% (Fig. 5). The mean value $\bar{h}$ (1) and standard deviation σ_h (2) of N vanishing-lines with height h_i are calculated as following:

$$\bar{h} = \frac{\sum_{i=1}^{N} h_i}{N} \tag{1}$$

$$\sigma_h = \sqrt{\frac{\sum_{i=1}^{N}\left(h_i - \bar{h}\right)^2}{N-1}} \tag{2}$$

The distribution reflects realistic camera mounting angles as well as everyday driving condition (uphill and downhill). Importantly, the dataset statistics suggest a natural concentration of vanishing-line positions around one-third of the image height, motivating further performance-driven analysis. The significant variation in vanishing-line positions also demonstrates the importance of camera angle optimization for real-world deployment scenarios with varying terrain.

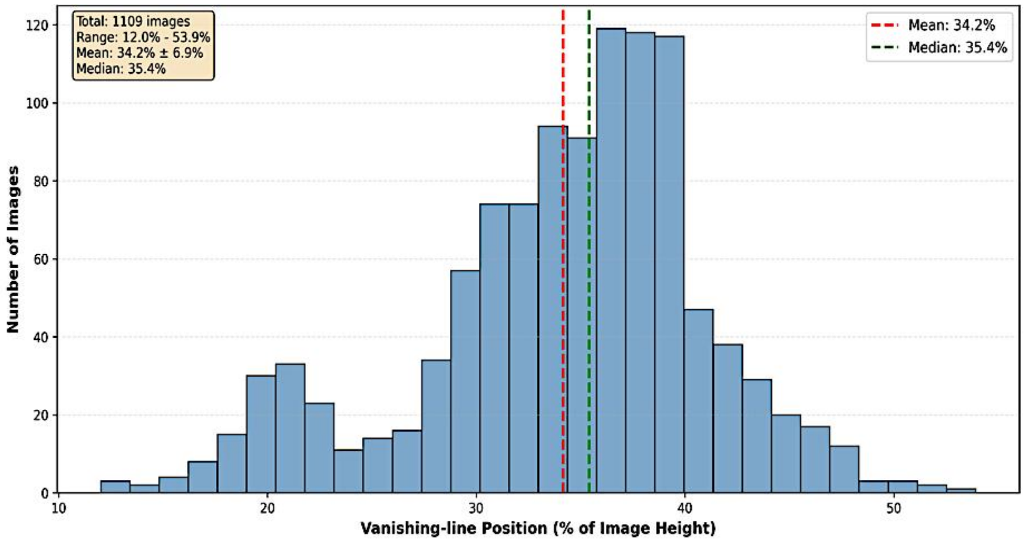


Fig. 5. Distribution of vanishing-line positions in dataset.

5. Model selection

Lane detection models' performance is evaluated using precision *P* (3), recall *R* (4) and F_1-score (5):

$$P = \frac{TP}{TP + FP} \tag{3}$$

$$R = \frac{TP}{TP + FN} \tag{4}$$

$$F_1 = \frac{2 \cdot P \cdot R}{P + R} \tag{5}$$

where *TP* is true positive, *FN* is false negative, *FP* is false positive. A detected lane is considered a *TP* if its IoU (intersection over union) with the corresponding ground truth exceeds threshold value. The IoU in lane detection is defined by following formula:

$$IoU = \frac{|\mathrm{Pr} \cap Gt|}{|\mathrm{Pr} \cup Gt|} \tag{6}$$

where *Pr* is predicted lane region and *Gt* is ground truth region. Therefore, IoU quantifies the degree of overlap between predicted region and ground truth. This metric produces a value ranging from 0 to 1, where 0 indicates no overlap and 1 represents a perfect match between prediction and the reality [9].

To evaluate the applicability of existing state-of-the-art lane detection models to Vietnamese road conditions, three pretrained models were benchmarked on the dataset, following recent evaluation practices in confidence-aware and attention-guided lane detection studies [10], [11]. At the end of 2025, those diffusion-based models achieved favorable performance compared to the existing lane detectors [5], following the CLRNet detection framework but differ in backbone architecture and training data [11], enabling an analysis of both architectural capacity and cross-dataset generalization.

The evaluated models include: (i) CLRNet with a ResNet34 backbone trained on CULane, (ii) CLRNet with a ConvNeXt backbone trained on CULane, and (iii) CLRNet with a ResNet34 backbone trained on TuSimple. All models were evaluated using the official evaluation protocol, the IoU threshold of 0.5 and lane width of 30 pixels were used to determine *TP* [5].

The benchmarking results indicate that models trained on the CULane dataset generalize more effectively to Vietnamese road conditions than those trained on TuSimple. This trend is closely related to the scale and diversity of the training data. TuSimple, introduced in 2017, contains approximately 3,626 annotated training images and 2,728 test images, recorded mainly on the United States of America highways with relatively simple 2-4 lane layouts, good weather conditions, and limited scene variability [7]. In contrast, CULane is a large-scale dataset comprising 133,235 annotated images collected across urban streets, rural roads, and highways, with substantial variations in traffic density, illumination (including nighttime scenes), and complex lane topologies, as well as explicit annotation of occluded lanes [6], [7]. The significantly larger size and richer scene diversity of CULane enable models trained on it to learn more robust and transferable lane representations. As a result, CULane-trained models – particularly the ConvNeXt-based CLRNet – achieve higher F1-scores on the Vietnamese dataset by maintaining stronger recall without sacrificing precision, whereas the TuSimple-trained model exhibits noticeable performance degradation due to limited exposure to complex geometries, occlusions, and heterogeneous lane markings during training (Tab. 1).

Tab. 1. Benchmark of diffusion-based models

Model (based dataset)	**F_1-score**	**Precision**	**Recall**	**F_1-score on based dataset**
ResNet34 (TuSimple)	61.48%	78.92%	50.17%	*96.64%*
ResNet34 (CULane)	69.79%	85.21%	58.91%	*78.99%*
ConvNeXt (CULane)	71.47%	86.32%	61.04%	*80.21%*

6. Results and discussion

The original dataset was modified to shift the position of vanishing-line from 20% to 80% with 1% increments in the 30–40% range and 5% increments elsewhere. The vanishing-line position is adjusted by modifying image perspective through vertical cropping and resizing, effectively shifting the vanishing-line to the desired position. Correspondingly, ground truth lane annotations are transformed using the same geometric mapping to maintain consistency. The modified dataset then fed to the model to run the inference and benchmark metrics were recorded. At very low or very high vanishing-line values, performance degraded significantly due to distorted perspective and reduced visibility of relevant lane features. The optimization demonstrated a clear optimal region between 35% and 40% vanishing-line position, with the peak F_1-score (73.37%) achieved at 37% position (Fig. 6).

At this point, the model achieved a balanced trade-off between precision and recall. While recall also peaked of 63.47% at 37% position, the precision continues to increase beyond the F_1-optimal position, reaching its peak of 86.93% at 40% position. This occurred because as the vanishing-line position increases (moves down in the image), the model became more conservative, producing fewer *FP* but also missing more true lanes.

Precision measures the correctness of predictions. As vanishing-line position increases (moves down), the model becomes more conservative, fewer *FP* are generated, increasing precision. However, this conservatism also leads to more missed lanes (*FN* increases).

Recall measures the completeness of detection. At 37%, the model achieved the best balance between detecting lanes, avoiding *FP*. Beyond 37%, the model became too conservative, missing more true lanes (*FN* increased faster than *FP* decreased).

Both precision and recall performed better at optimal vanishing-line position in comparison with original dataset. For applications prioritizing precision (fewer false alarms), 40% vanishing-line may be preferred. For applications requiring balanced performance, 37% provides optimal F_1-score.

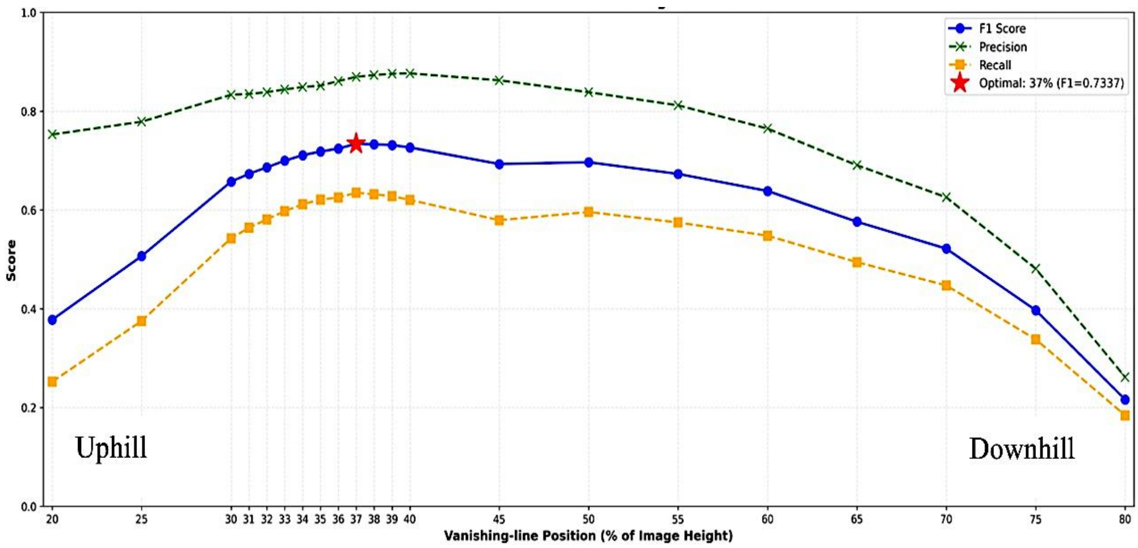


Fig. 6. Results of optimization for the position of the vanishing-line in the dataset.

The experimental results provided several important insights into the role of image perspective in lane detection. First, the dependency of precision, recall, and F_1-score on the vanishing-line position confirms that perspective mismatch is a fundamental source of performance degradation, rather than a secondary implementation detail, as visualized in Fig. 7. When the vanishing-line is positioned too high or too low in the image, lane features are either overly stretched or excessively compressed, leading to unstable feature extraction and degraded geometric consistency, missing the top of the lanes (Fig. 7(a)).

Second, the observation that the optimal vanishing-line position aligns closely with the mean and median values of the dataset distribution suggests that pretrained models implicitly adapt to the dominant perspective present in the training data. When evaluated under perspectives that deviate from this dominant configuration, the models exhibit reduced recall or increased false positives. This finding highlights a form of implicit perspective bias embedded in data-driven lane detection models.

Third, the results indicate that vanishing-line optimization can act as a lightweight model robustness enhancement. Unlike architectural modifications or retraining, perspective normalization can be applied as a preprocessing step, making it particularly attractive for deployment scenarios where retraining is impractical or computational resources are limited. For example, the authors' advanced driver assistance system using the vanishing-line optimization to enhance the system performance is currently under development (Fig. 8).

Moreover, the differing sensitivities of precision and recall to perspective variation reveal an important trade-off. Lower vanishing-line positions tend to favor precision by emphasizing near-field lane segments, while higher positions improve recall by expanding long-range visibility at the cost of increased ambiguity. The optimal perspective therefore represents a balance between geometric stability and semantic completeness.

a)

b)

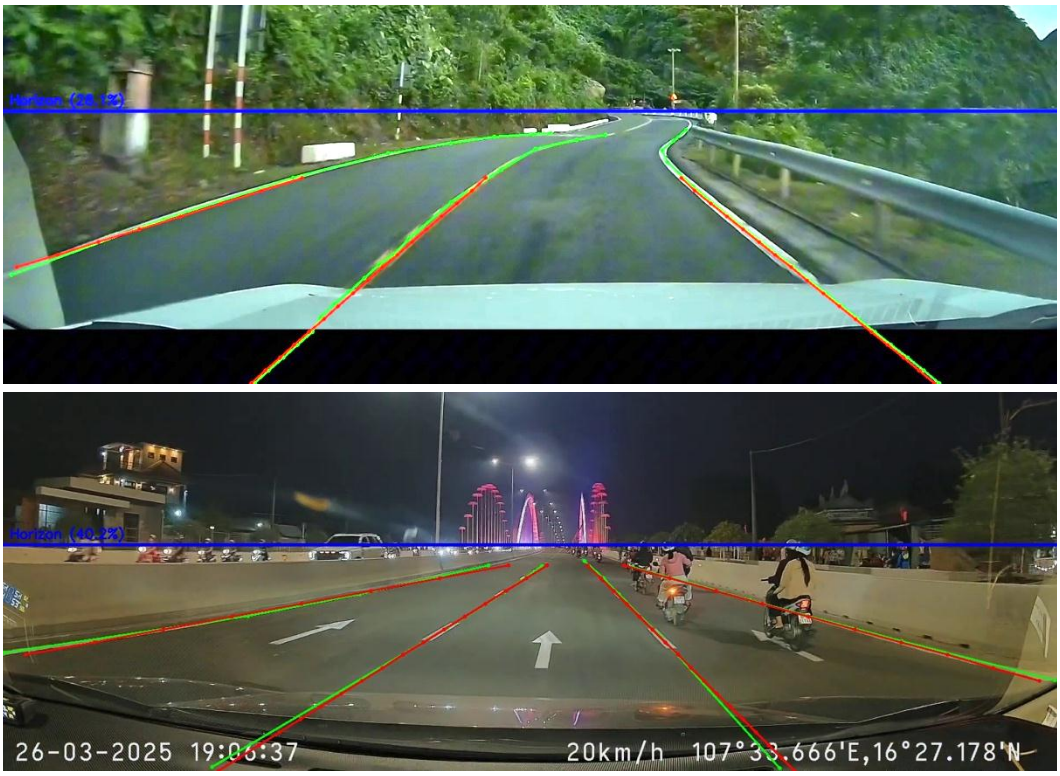


Fig. 7. Different model's performance on different position of vanishing-line:

(a) High vanishing-lane position (28.13%) while vehicle is uphill.

(b) Normal vanishing-line position (40.2%) in the city.

Red line = predicted lane. Green line = ground truth. Blue line = Vanishing-line.

Finally, these findings have broader implications beyond Vietnamese road conditions. Since camera mounting height and pitch vary across vehicle platforms and manufacturers, uncontrolled perspective variation can significantly hinder cross-vehicle generalization. Explicit modeling or normalization of the vanishing-line may therefore be a key factor in improving the robustness and transferability of lane detection systems across diverse deployment environments.

The findings have several practical implications:

- Dataset design: Training data should reflect realistic vanishing-line distributions to ensure generalization.

- Camera calibration: Camera pitch and mounting height should be carefully selected or compensated for via image normalization.

• Model robustness: Horizon augmentation during training may further improve robustness across vehicles and mounting configurations.

For Vietnamese road conditions, a vanishing-line range centered around 37–40% of image height is recommended for both dataset construction and deployment.

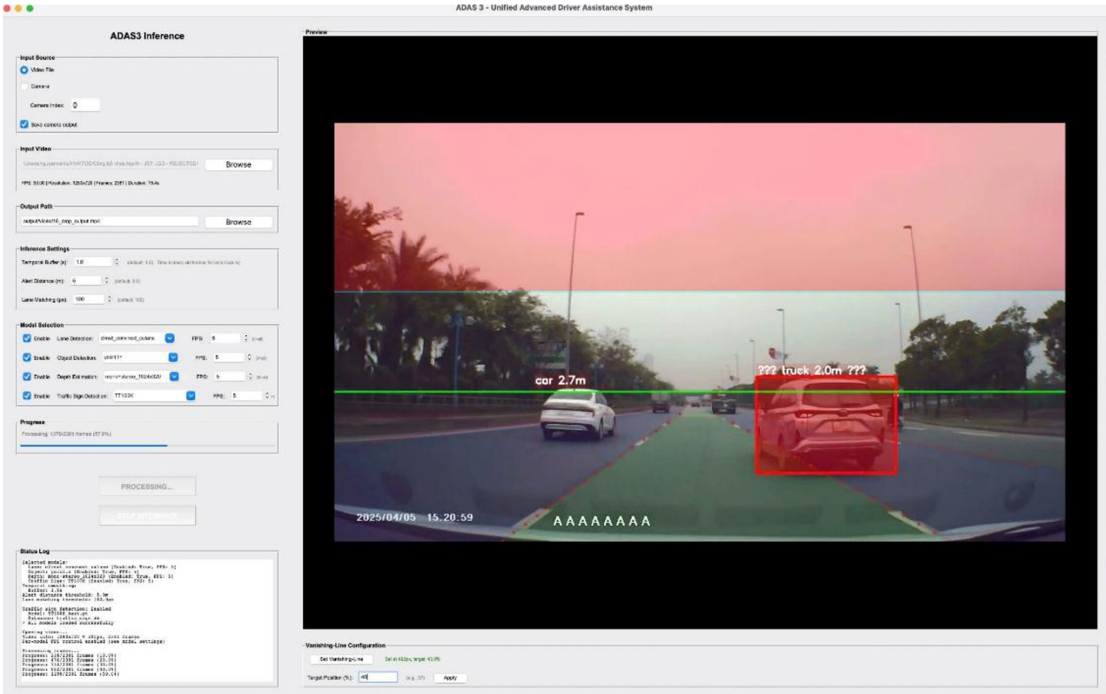


Fig. 8. Application of vanishing-line optimization in developing ADAS.

7. Conclusion

This article presented a custom lane detection dataset tailored to Vietnamese road conditions and a systematic study on vanishing-line parameter optimization. By analyzing both dataset statistics and model performance, it was demonstrated that the vanishing-line position plays an important role in lane detection accuracy. An optimal vanishing-line at 37% of image height was identified, yielding the highest F_1-score and aligning well with real-world camera configurations.

Future work will explore dynamic vanishing-line estimation, vanishing-line-aware network architectures, and cross-dataset generalization to further enhance lane detection robustness in diverse traffic environments.

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XÂY DỰNG BỘ DỮ LIỆU VÀ PHÂN TÍCH PHỐI CẢNH ẢNH CHO BÀI TOÁN PHÁT HIỆN LÀN ĐƯỜNG TRONG ĐIỀU KIỆN GIAO THÔNG VIỆT NAM

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Tóm tắt: Nghiên cứu này trình bày việc xây dựng bộ dữ liệu phục vụ nghiên cứu phát hiện làn đường trong điều kiện giao thông Việt Nam, kết hợp với đánh giá một số mô hình phát hiện làn đường tiên tiến hiện nay, đồng thời phân tích ảnh hưởng của phối cảnh ảnh đến hiệu năng của mô hình. Một bộ dữ liệu nhận diện làn đường được xây dựng từ thực tế giao thông tại Việt Nam, gồm nhiều kịch bản giao thông và tình trạng vạch kẻ đường khác nhau. Trên cơ sở đó, một số mô hình phát hiện làn đường tiên tiến hiện nay được đánh giá trên bộ dữ liệu này, dùng các chỉ số độ chính xác (precision), độ thu hồi (recall) và F_1-score. Để nghiên cứu mức độ nhạy cảm đối với phối cảnh một cách độc lập, các phép điều chỉnh phối cảnh được áp dụng trực tiếp lên ảnh đầu vào, trong đó vị trí đường hội tụ làn đường được dịch chuyển trong khoảng từ 20% đến 80% chiều cao ảnh. Kết quả thực nghiệm cho thấy hiệu năng phát hiện phụ thuộc rõ rệt vào phối cảnh ảnh, với hiệu năng tổng thể tốt nhất đạt được (F_1-score đạt cực đại 73,4%) khi vị trí đường hội tụ làn đường nằm tại khoảng 37% chiều cao ảnh. Bộ dữ liệu, phân tích phối cảnh và các kết quả đánh giá mô hình thu được cung cấp những chỉ dẫn thực tiễn cho việc thiết kế bộ dữ liệu, chuẩn hóa phối cảnh và triển khai các mô hình phát hiện làn đường đã huấn luyện sẵn trong môi trường giao thông thực tế tại Việt Nam.

Từ khóa: *Phát hiện làn đường; tối ưu đường hội tụ; ADAS.*

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