Performance Evaluation of Advanced YOLO Models for Road Marking Detection

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Abstract: Road marking identification is a highly essential part of intelligent transportation systems and autonomous vehicles, as it directly influences route guidance and road safety. However, due to varying light sources, weather conditions, faded paint, and complex road geometry, their identification is a challenging task for computers and machines to perform precise analysis and deduction. This work conducts a comparative analysis of some new YOLO-based techniques for tracking and identifying objects, YOLOv8, YOLOv9, YOLOv10, and YOLOv11, on a road marking identification dataset containing varied real-time situations on roads. The experiment on all techniques is conducted under similar settings for consistent analysis and comparison. The performance evaluation criteria for assessing their efficiency include precision, recall, F1-score, mAP value with a 0.5 IoU requirement, and accuracy. The accuracy for road marking identification reaches 93% with YOLOv11, which has notably superseded its predecessors by significant margins, thanks to improvements in architecture, the use of anchor-free techniques, new learning methods, and end-to-end testing and analysis for enhanced accuracy and precision. This analysis clearly predicts that YOLO-based techniques, especially YOLOv11, are exceptionally efficient and well-suited for real-time, precise road marking identification in advanced driver assistance systems, automated vehicles, and other road vehicles, thereby enhancing road safety and efficiency.

Keywords: Road Safety, Machine Learning, Deep Learning, YOLO, Lane Detection.

Introduction

Efficient and well-maintained transportation infrastructure is cardinal to economic development, road safety, and seamless mobility. Among its critical components, lane markings paint the roads for drivers and support advanced driver-assistance systems and autonomous vehicles. However, lane markings deteriorate over time due to environmental exposure, heavy traffic, inconsistent maintenance practices, and poor lighting [1]. These factors degrade lane visibility and reliability to a great extent, hence challenge the effective regulation of traffic flow and intelligent transportation systems. Traditional lane inspection methods, mostly based on manual surveys or simple white-line detection, are labor-intensive, time-consuming, and prone to human error; as a result, they cannot meet modern transportation network demands at scale and in real time.

Most traditional lane detection methods, which rely solely on visible lane markings, fail in real-world scenarios where markings are faded, occluded, or even completely missing [2]. In this respect, a vehicle-clustering-based lane detection strategy using mobile cameras has demonstrated improved performance in developing regions with dense, heterogeneous traffic conditions, where white-line detection is conventionally unreliable [3]. This point underscores the need for alternative lane-estimation strategies beyond explicit road markings. A multitask learning architecture that coupled vehicle detection, tracking, and lane-change violation detection using the Fast YOLO framework, highlighting synergy between lane detection and automated traffic enforcement [4].

Monocular 3D lane detection is one of the most promising research directions for enhancing spatial understanding. As Ma et al. have noted, lane estimation in 3D provides more informative geometric cues, such as lane elevation, curvature, and topology, which are crucial for autonomous navigation. However, even with these merits, monocular 3D lane detection faces many challenges due to depth ambiguity, scene complexity, and robustness under diverse road and environmental conditions [5]. Recent advances in deep learning have dramatically enhanced lane detection performance in degraded visual conditions. A region-based CNN approach that detected lane boundaries on noisy, low-contrast, and deteriorated road surfaces using region proposals and discriminative feature extraction [6]. Complementary to vision-based approaches, IR-based lane-line detection systems, as explored by [7], offer enhanced robustness in low-light and other unfavorable weather conditions, enabling reliable lane monitoring from both autonomous and non-autonomous vehicles.

In real driving scenarios, it often benefits from temporal information across frames [8]. To handle problems such as occlusion, motion blur, and sudden illumination changes, PHNet, an online video lane-detection framework that uses adaptive routing and cross-frame attention mechanisms to recover missing lane information via temporal context [9]. On the other hand, for actual implementations, there is an increasing interest in embedded real-time solutions. A framework using YOLOv8 that integrates lane and vehicle detection to achieve robust performance in challenging lighting, shadowing, and partial occlusion conditions, suitable for ADAS applications in real time [10], [11]. Beyond lane structure identification, modern intelligent transportation systems require comprehensive scene understanding, integrating traffic violation detection, driver behavior analysis, and safety monitoring. Furthermore, a reinforcement learning-based approach for dynamic lane-change intention recognition using BiLSTM networks, attention mechanisms, and conditional random fields, achieves early prediction of potentially dangerous maneuvers in mixed-traffic environments [12]. Regarding proactive safety assessment, the importance of near-miss detection due to lane deviations, unseen regions, and trajectory overlaps is demonstrated, and YOLO-based models are shown to improve hazard detection performance across varying video quality conditions significantly [13].

Related work

The studies in the field of lane detection have progressed from manual methods in image processing to a combination of transformer-based methods and multimodal perception methods explicitly tailored to automated driving applications. The current trends in lane detection appear to be toward multi-granularity learning methods. The current methods in the field of lane detection must be robust across different conditions, such as shadows, high lighting, vehicle occlusion, poor road markings, and varying climatic and geographic conditions. A combined 2D-3D Multi-Granularity Lane Attention framework, coined MGA, focusing on point, line, and channel levels by Dai et al. [14] improved shadow robustness, missing lane robustness, and slope robustness. To overcome the shortcomings of camera-based solutions, the SRS involving magnetic sensors introduced by Sun et al. [15] targeted multilane data capture under varying lighting and weather conditions [16]. The significantly lower error rate achieved by this embedded, solution-based approach underscores the efficiency and applicability of sensor fusion, even in the face of the shortcomings of a vision-based approach.

Liu & Ling [17] optimized the efficiency of the model using the Sparse Lane Former, which is the fully sparse transformer pipeline for the detection of lanes and is the first fully sparse transformer pipeline for lane detection, using Lane-Aware Queries and sparse interactions that drastically reduced the computational time and simultaneously improved the continuity of detected lanes [18]. The lane detection was then further applied using the Virtual Witness system, which is a multi-camera deep learning system for lane detection, driver state estimation, and external event prediction for total safety [19]. The geometric view of lanes was then improved using the Vision-Based Geometric Model (VBGM), which removed spurious edges by using rotational coordinate systems, a valuable technique for occluded and nighttime scenarios [20]. Recent advancements in deep learning include HGLFNet, proposed by Ding et al. [21], which leverages both global semantic feature extraction and local refinement to improve thin and occluded lane markings. The global semantic feature extraction module adopts the large kernel convolution method to address long-range dependencies, and the fusion module bridges gaps in semantic feature values, integrating deep and shallow methods to improve accuracy. In this context, in addition to lane markers, danger-aware perception methods are also explored.

A Hybrid Deep Learning model combining a CNN and a ConvLSTM to anticipate driver danger measures, using spatial and temporal features such as deviation and an untoward following distance, has been proposed by Sakthivel et al. [22] for hazard awareness using available lane features. When vehicles are moving at high speed on the highway, object detection is needed to avoid potholes [23] in images and videos [24] using computer vision [25]. A framework has been designed for disabled persons using mining techniques [26]. Whenever the driver feels stressed due to lack of sleep or is not feeling well, there is a chance of an accident, so to avoid that, detection is needed [27], [28], [29]. For that, facial indicators are also required for road safety [30] while travelling on public transport [31]. Along with runtime deployment, there has been work on real-time deployment as well.

Mirdanies et al. [32] deployed Ultra Fast Lane Detection with Jetson Nano on an autonomous mobile robot, achieving speedups of up to 22x with TensorRT. The significance of rapid breakthroughs in lane detection has been noted in the existing literature. Bi et al. [33] have provided a comprehensive discussion of 2D and 3D lane detection methods, along with prominent issues and challenges, such as irregular lane markings, poor visibility, and the need for more general data and evaluation metrics. Whenever data is transformed from one system to another, it requires a novel clustering technique [34] and an ML framework for vehicle security [35]. For legal opinion, the data should be summarized using DL models [36], objects should be categorized from images [37], and encrypted features should be used for CBIR [38]. Shettar et al. [39] have noted that classical methods using image processing techniques with Gaussian and Canny edge detectors are effective on well-structured roads but are not sufficiently robust for realistic conditions. Zaidi et al. [40] have compared methods using gradient-based, thresholding, transformation, and CNN approaches, which are significant due to their greater adaptability and precision, particularly in low-visibility conditions. The combination of these works suggests that the community is increasingly interested in multimodal sensing, global-to-local fusion, sparse transformers, 3D geometric reasoning, and real-time operation on embedded hardware for lane detection. Each of these areas of research also contributes, in its own way, to the development of innovative, safety-oriented transport systems by addressing the challenges posed by contemporary road conditions and transport patterns.

Methodology

Objectives

1. To analyze the effectiveness of recent YOLO architectures (YOLOv8, YOLOv9, YOLOv10, and YOLOv11) for automatic road marking detection under diverse real-world conditions.
2. To identify the most effective YOLO variant for detecting thin, faded, and partially occluded road markings in intelligent transportation and autonomous driving applications.

Dataset

The Road Marking Detection Dataset is a collection of annotated road scene images designed to help detect and locate various road markings, including lane boundaries, dashed and solid lines, arrows, pedestrian crossings, stop lines, and directional symbols. The dataset captures real-world driving conditions using cameras mounted on forward-facing vehicles, ensuring practical relevance for intelligent transportation systems, ADAS, and autonomous driving applications. Illumination, weather, and road-surface conditions are highly variable: bright daylight, low-light conditions, nighttime, shadows, glare, roads affected by rain, and partially occluded or worn-out markings. This variability makes the dataset particularly challenging and well-suited for evaluating the robustness of the detectors under real constraints. Scenes range from urban roads to highways, intersections, and residential areas, while accounting for camera viewpoints, road curvature, and traffic flow conditions. Ground-truth labels are provided for each image as bounding boxes or segmentation masks, depending on the task formulation. These annotations specify the spatial location and class of each road marking, enabling supervised learning for object detection or segmentation-based approaches. The dataset is usually divided into training, validation, and test subsets to ensure fair performance evaluation and prevent overfitting.

Models Used

Specifically, the innovation of YOLO (You Only Look Once) emerged as a solution to the inherent weakness of traditional approaches to object detection, which had broken the tasks of proposal, extraction, and classification into several steps. Joseph Redmon, along with other researchers, developed this approach in 2016, suggesting a new object detection method that treated object detection as a regression task from images to bounding boxes and class probabilities, implemented within a one-pass deep learning architecture. This new approach was born from the idea of real-time perception, where not only accuracy but also speed matters considerably, especially for real-time tasks such as self-driving automobiles, robots, or surveillance cameras.

YOLOv8

YOLOv8 introduces a brand-new, fully anchor-free detector that does not rely on anchor boxes. It also features a decoupled head design, in which the classification and regression tasks are optimized separately, leading to faster convergence and better localization. Furthermore, YOLOv8 comes with the capability to handle a range of vision tasks, including object detection, instance segmentation, key point recognition, and image classification, within the same model, and thus YOLOv8 is highly versatile.

YOLOv9

YOLOv9 primarily aims to enhance the learning speed and gradient information flow of deep models through the concept of Programmable Gradient Information (PGI). Using PGI enables the retention of critical information from features during backpropagation. Consequently, YOLOv9 has shown better training stability and performance in complex scenes with highly overlapping objects or ambiguous boundaries.

YOLOv10

YOLOv10 offers a significant conceptual improvement over earlier versions by enabling complete end-to-end object detection without the need for Non-Maximum Suppression. This is achieved through the continuous dual assignment method used by YOLOv10, which eliminates redundancy in predictions during training. This leads to lower latency and more accurate results.

YOLOv11

YOLOv11 focuses on efficiency and edge-deployment readiness, proposing lightweight architectural improvements and new methods for feature interactions. It has been optimized to achieve highly optimal trade-offs between accuracy and speed when processing intensive tasks on platforms such as GPUs for embedded devices or automotive chips.

Although YOLOv8 provides a strong, flexible anchor-free architecture that supports multitasking, YOLOv9 improves the learning method by retaining gradient information during training. YOLOv10 breaks from the established object detection paradigm by removing NMS and enabling end-to-end inference. YOLOv11 continues to build on previous breakthroughs to enhance efficiency and push the model towards suitability for deployment on edge devices and for real-time applications. These models, taken together, reveal the development of YOLO through the following stages: architecture optimization (YOLOv8), learning method optimization (YOLOv9), inference optimization (YOLOv10), and deployment optimization (YOLOv11).

ALGORITHM-1

Step 1:	Given an input RGB image I, the image is resized to a fixed resolution, and pixel values are normalized $$I_{norm} = \frac{I}{255}\ i\ \in R^{H\ x\ w\ x\ 3}$$
Step 2:	A convolutional backbone network processes the normalized image to extract hierarchical feature (F) representations $$F = Backbone\ (I_{norm})$$
Step 3:	Feature maps obtained from different backbone stages are fused using a neck network to enhance scale aware representations $$F_{fused} = Neck\ (F)$$
Step 4:	The fused feature maps are forwarded to the detection head to generate dense predictions $$\hat{y} = (x, y, w, h, c, P_1,\ P_2, \dots, P_k)$$ where k is number of object classes, ŷ is an prediction vector, (x,y) is an bounding box centre coordinates, (w,h) is the width and height, c is the objectness confidence, P_x is the class probability for class k.
Step 5:	Bounding box coordinates are decoded from network outputs as $$x = \sigma\ (t_x) +\ C_x\ , y =\ \sigma\left(t_y\right) + C_y$$ $$\mathrm{w} = \exp(\mathrm{t_w})\ , \mathrm{h} = \exp(\mathrm{t_h})$$ where $(\mathrm{C_x}\ , \mathrm{C_y})$ denote grid-cell offsets, (t_x, t_y, t_w, t_h) is the raw network outputs, $\sigma(,)$ is the sigmoid activation function. This formulation follows an anchor-free design.
Step 6:	An objectness confidence score (C) is predicted to represent the likelihood of object presence $$C = P(object)x\ IoU_{pred}^{gt}$$ where IoU_{pred}^{gt} is the intersection over Union with ground truth.
Step 7:	Final class-wise confidence scores are computed as $$Score_k = C\ x\ P_k, K = 1,2, \dots., k$$
Step 8:	During training, the network parameters are optimized using a composite loss function: $$L_{total} = \lambda_{box}L_{box} +\ \lambda_{obj}L_{obj} +\ \lambda_{cls}L_{cls}$$ Where L_{box} is the bounding box loss, L_{obj} is the objectness Loss, L_{cls} is the Classification loss and (λ_{box}, λ_{obj}, λ_{cls}) is the Loss weights.
Step 9:	Overlapping detections are filtered using Non-Maximum Suppression (NMS) $$IoU = \frac{\mid B_{pred} \cap\ B_{gt} \mid}{\mid B_{pred} \cup\ B_{gt} \mid}$$ Where B_{pred} is the predicted bounding box and B_{gt} is the ground thruth box.
Step 10:	The final detection output is represented as $$D = \{\ (\ x, y, w, h, class, confidence)\}\pi r^2$$

While the overall YOLO detection pipeline remains unchanged, the evolution from YOLOv8 to YOLOv11 introduces targeted modifications at specific algorithmic steps. YOLOv8 primarily refines Steps 5 (Bounding Box Decoding) and 8 (Loss Optimization) by adopting a fully anchor-free design with decoupled detection heads, resulting in improved localization accuracy and more stable training. YOLOv9 introduces its key change at Step 2 (Feature Extraction), where the backbone architecture is redesigned to preserve gradient flow and information richness in deeper layers, while leaving the detection head and post-processing stages largely intact. YOLOv10 significantly alters Step 9 (Post-Processing) by eliminating Non-Maximum Suppression and reformulating detection as an actual end-to-end optimization problem, thereby reducing inference latency and simplifying deployment. YOLOv11 further enhances Steps 3 (Feature Fusion) and 8 (Loss Optimization) to improve cross-scale interactions and generalization across diverse datasets, optionally retaining or optimizing NMS based on application requirements. Thus, the progression from YOLOv8 to YOLOv11 reflects a systematic shift from architectural simplification to end-to-end efficiency and robustness, rather than a complete redesign of the YOLO algorithm.

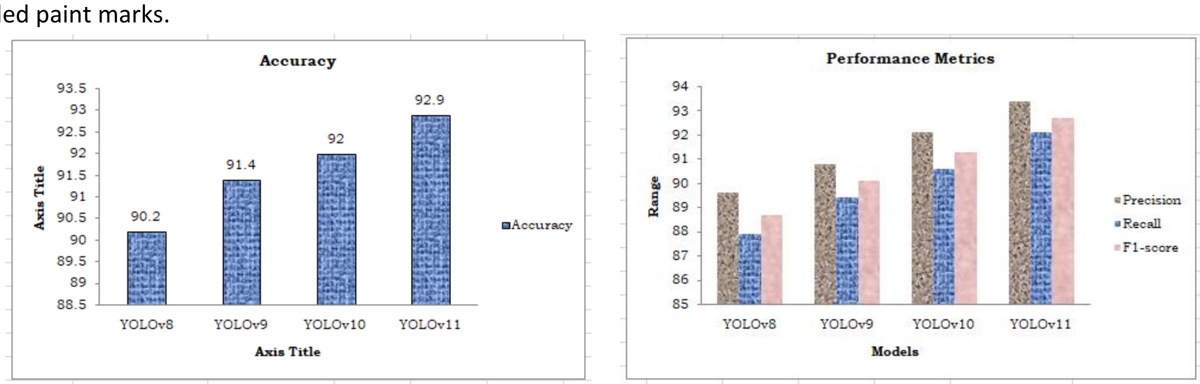
Result Analysis

A comparison study was also conducted to analyse the efficiency of the proposed method by applying it to four recently introduced versions of YOLO: YOLOv8, YOLOv9, YOLOv10, and YOLOv11, and then evaluating it on the Road Marking Detection Dataset. The comparison was conducted to assess the effect of architectural improvements in YOLO versions on the efficiency of accurate identification of road markings across varying surroundings and illumination conditions. The parameters used to measure the efficiency of the mentioned YOLO versions are Precision, Recall, F1-score, Average Precision at 0.5 IoU (mAP@0.5), and Detection Accuracy.

Table 1. Results Comparison

Model	Precision (%)	Recall (%)	F1-score (%)	mAP@0.5 (%)	Accuracy (%)
YOLOv8	89.6	87.9	88.7	90.8	90.2
YOLOv9	90.8	89.4	90.1	91.9	91.4
YOLOv10	92.1	90.6	91.3	92.6	92.0
YOLOv11	**93.4**	**92.1**	**92.7**	**93.8**	**92.9**

As shown in Table 1, detection accuracy increases from YOLOv8 to YOLOv11. YOLOv8 provides a competitive baseline for detecting prominent road markings; however, it slightly degrades at identifying thin and faded paint marks.



(a) (b)

Figure 1. Graph for the performance of the (a) Accuracy (b) Various Metrics

The accuracy and recall of YOLOv9 are enhanced, indicating optimized and sound model training and the effective use of feature representations learned during training. The accuracy of marking detections is also improved in YOLOv10 by avoiding reliance on Non-Maximum Suppression methods that could lead to missed detections of multiple overlapping road markings. Among these deep models tested, YOLOv11 achieves the highest detection accuracy of approximately 93% due to its optimized feature interaction techniques and a highly lightweight model structure.

Conclusion

Road marking identification is an essential part of intelligent transportation systems and autonomous vehicles, as it directly influences route guidance and road safety. However, due to varying light sources, weather conditions, faded paint, and complex road geometry, their identification is a challenging task for computers and machines to perform precise analysis and deduction. This paper conducts a comparative analysis of some new

YOLO-based techniques for tracking and identifying objects, YOLOv8, YOLOv9, YOLOv10, and YOLOv11, on a road marking identification dataset containing varied real-time situations on roads. The experiment on all techniques is conducted under similar settings for consistent analysis and comparison. The performance evaluation criteria for assessing their efficiency include precision, recall, F1-score, mAP value with a 0.5 IoU requirement, and accuracy. The accuracy for road marking identification reaches 93% with YOLOv11, which has notably superseded its predecessors by noticeable margins, thanks to improvements in architecture, the use of anchor-free techniques, new learning techniques, and end-to-end testing and analysis for enhanced accuracy and precision. This analysis clearly predicts that YOLO-based techniques, especially YOLOv11, are exceptionally efficient and well-suited for real-time, precise road marking identification in advanced driver assistance systems, automated vehicles, and other road vehicles, thereby enhancing road safety and efficiency.

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