UnLanedet: A Unified Lane Detection Toolbox

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Abstract

Lane detection is an important topic in autonomous driving and computer vision. However, the community currently lacks a unified and comprehensive benchmark specifically tailored for lane detection models. To address this issue, we develop a unified, highly modular, and lightweight codebase named **UnLanedet**, supporting a majority of the mainstream lane detection methods and datasets. We benchmark the lane detection methods under UnLanedet and provide fair comparison results. Besides, we optimize the training loop to enhance the model performance. We hope that UnLanedet can benefit the lane detection community and offer a unified platform to compare different lane detection models. Our code is available at https://github.com/zkyntu/UnLanedet.

1 Introduction

Lane detection is a fundamental problem in the autonomous driving and computer vision. In the past decade, the significant advancements have been achieved in this field. Exisitng lane detection methods can be divided into four categories: segmentation-based [11, 24], anchor-based [25, 6, 28], keypoint-based [19, 13], and parameter-based [7, 4] methods.

With the rapid development of lane detection algorithms, we have observed that existing algorithms are implemented independently. There is still a lack of a unified and comprehensive benchmark to ensure the effectiveness of newly developed lane detection methods and fair comparisons among them. The existing frameworks like Lanedet and PPLanedet [26] face challenges in evaluating lane detection algorithms comprehensively. Specifically, Lanedet and PPLanedet only contain the segmentation-based and anchor-based methods, ignoring the parameter-based and keypoint-based methods. Besides, PPLanedet and lanedet reproduce the Tusimple [24] and CULane [11] datasets, but other datasets such as VIL100 [22] and CurveLane [10] datasets are not provided. To address the above issues and facilitate the research community and industry in developing more efficient and high-performance lane detection methods, we develop a unified lane detection toolbox with highly modular and lightweight advantages, named **UnLanedet**.

Within UnLanedet, we implement a unified and modular design for the lane detection models and incorporate a lightweight training engine along with a concise and effective configuration system. Based on the above design, researchers can develop lane detection methods more effectively. UnLanedet allows researchers to adjust configurations and modify model structures more flexibly during training and evaluation. Furthermore, UnLanedet contains all types of lane detection methods and supports VIL100 dataset. As a result, the UnLanedet framework provides a comprehensive toolbox for training, validation, and benchmarking of lane detection methods.

With a well-structured and unified codebase, we have conducted extensive experiments, supporting and reproducing over 10 mainstream lane detection methods. We then conducted fair comparisons to benchmark the lane detection methods, with respect to various aspects such as the model performance, inference speed, the impact of different backbones on performance, and the influence of different modules within the algorithm on the final performance. We summarize our main contributions as follows:

A Comprehensive Toolbox for Lane Detection Algorithms. We provide a unified open-source toolbox called **UnLanedet** with a highly modular and extensible design for lane detection. We provide a rich set of model reproductions, including SCNN [11], RESA [24], UFLD [12], CLRNet [25], CLRerNet [6], LaneATT [17], BezierNet [16], GANet [19], etc. In addition, we offer comprehensive documentation and tutorials to facilitate easy modification of our codebase, which is open for ongoing development.

Comprehensive Lane Detection Benchmark. We conducted a comprehensive benchmarking analysis primarily focused on lane detection models. Firstly, we validate the model performance on Tusimple, CULane, and VIL100 datasets. Subsequently, we evaluated the effectiveness of the latest backbones based on the CLRNet detector.

Strong Baselines for Lane Detection. In addition to reproducing the model results based on our codebase, we also conducted extensive experiments on the hyper-parameters of each model, resulting in a performance improvement in the reproduced results. Besides, we provide a strong baseline, named UnCLRNet, which is based on CLRNet by combining existing tricks in the backbone, neck, and loss function. UnCLRNet gets **80.21%** F1 score on CULane with ConvNeXt-tiny [9] backbone.

2 Related Work

2.1 Lane Detection

According to the representation of the lane, existing lane detection methods can be categorized into four classes: segmentation-based, anchor-based, keypoint-based, and parameter-based methods.

Segmentation-based methods view lane detection as a segmentation task. SCNN [11] proposes a novel message-passing module to capture the spatial dependency. RESA [24] develops a feature aggregation module to learn global features while keeping real-time detection.

Anchor-based methods regress the accurate lanes by redefining lane anchors. UFLD [12] predicts lanes by a novel row-wise lane anchor. Line-CNN [8] adopts the dense lane anchors and RCNN-like architecture to detect lanes. CLRNet [25] uses the learnable lane anchors and the progressive lane anchor refinement to perform lane detection. CLRerNet [6] proposes a new Lane-IoU loss to improve the prediction confidence. ADNet [21] analyses the influence of lane anchors and proposes a novel lane anchor decomposition.

Keypoint-based methods treat the lane detection task as a keypoint detection task. PINet [7] combines keypoint detection and instance segmentation to realize lane detection. GANet [19] fuses the global features into the keypoint detection model and achieves real-time detection.

Parameter-based methods view lane detection as a parameter modeling task. PolyLaneNet [18] casts a lane as a polynomial function and predicts the parameter of the polynomial function. Bezier-LaneNet [4] utilizes the Bézier curve to model a lane for its ease of computation.

Besides, several studies have proposed a unified architecture for lane detection. Lane2Seq [27] proposes a sequence generation framework for lane detection and a novel reinforcement learning-based model tuning method to improve the model performance. LaneLM [23] proposes a prompt-based framework for lane detection and supports multi-turn conversations.

2.2 Lane Detection Toolboxes

Over the years, the field of object detection and semantic segmentation has witnessed significant progress with the development of various detection toolboxes, such as Detectron2 [20], MMDetection [2], and MMSegmentation [3]. These toolboxes have played a crucial role in advancing object detection and semantic segmentation research and facilitating practical applications. In the field of lane detection, several developers provide the toolbox for lane detection, such as Lanedet and PPLanedet [26]. They provide a comprehensive set of pre-defined models, training pipelines, and evaluation metrics, making it easier for researchers and practitioners to develop and deploy lane detection systems.

However, existing lane detection toolboxes focus on the segmentation-based and anchor-based methods, ignoring the parameter-based and keypoint-based methods. The UnLanedet, on the other

hand, contains all types of lane detection methods, providing more concise and well-structured support for lane detection models.

3 Highlights of UnLanedet

In this section, we focus on the modular design of lane detection methods and the system design within UnLanedet.
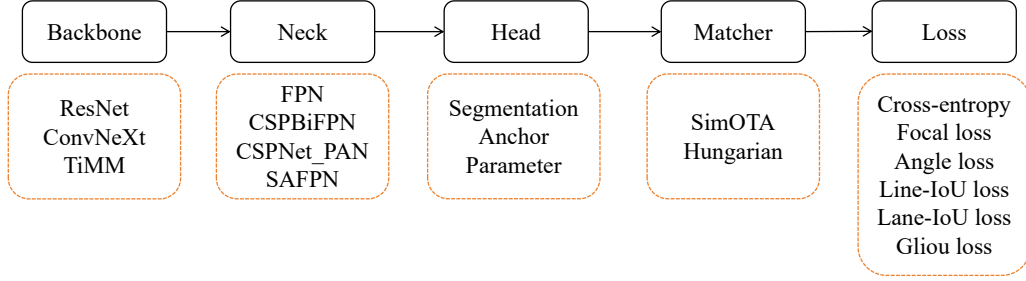

Figure 1: The modular design for lane detection methods under UnLanedet.

3.1 Modular and Extensible Design for Lane Detection Methods

Under the UnLanedet framework, we develop a unified modular design for the lane detection methods, which is a highly extensible system. Lane detection is modularized into five components, i.e., Backbone, Neck, Head, Matcher, and loss. The modular design is illustrated in Fig. 1. We have already incorporated multiple state-of-the-art methods as off-the-shelf options for developers. The modular design allows the smooth incorporation of user-defined modules into any system component.
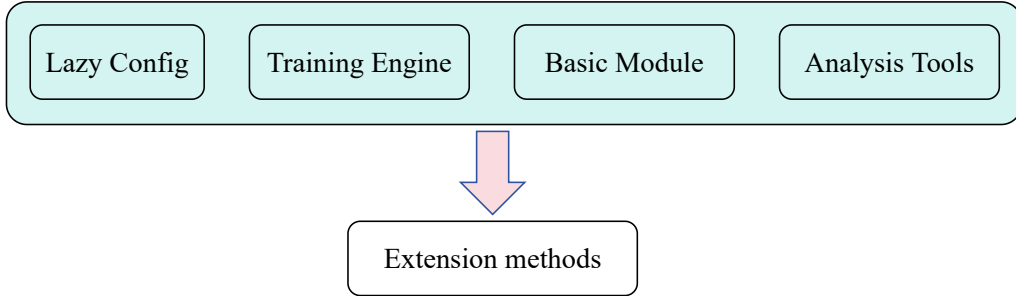

Figure 2: The architecture of UnLanedet.

3.2 Design Principle

The overall architecture of UnLanedet is illustrated in Fig.2, and our design principles for UnLanedet can be summarized as follows:

Highly flexible configuration system. Within the UnLanedet framework, we adopted the **LazyConfig** configuration system, developed in the latest version of Detectron2. In contrast to the traditional approach of utilizing registry mechanisms and string-based configuration in PPLanedet and LaneDet. LazyConfig employs a non-intrusive design and enables users to define its configuration, even complex data types or objects, entirely using Python syntax. Moreover, The entirety of the configuration content is notably **concise**, **clean**, and **lightweight**. This affords users great convenience in customizing the configurations to their specific needs.

Advanced training techniques. Currently, UnLanedet supports the Mixed Precision Training, Activation Checkpointing, and Distributed Data-Parallel Training, which does not be provided in

PPLanedet and LaneDet. Exponential Moving Average will be supported in the future. These techniques can help users effectively train their models under resource-constrained environments.

Effective project management practices. UnLanedet utilizes a project-based management approach, where each algorithm is treated as an independent project, maintained separately from the core code. This decoupling of projects and core code ensures that algorithms are self-contained and unaffected by changes in the core code.

Rich and practical analysis tools. UnLanedet supports a rich set of practical tools for users to analyze the existing algorithms or their models, including counting FLOPs, testing inference speed, during training times, or visualizing the inference results.

Support for a range of datasets. UnLanedet contains three lane detection benchmarks, including Tusimple, CULane, and VIL100. Besides, we provide the basic class of the dataset, which develops can inherit it to achieve various datasets.

3.3 Comparison between UnLanedet and Previous Frameworks

Table 1: Comparison between UnLanedet and other related frameworks.

Benchmark	Supported methods	Suppoerted datasets	DDP
LaneDet	5	2	✗
PPLanedet [26]	7	2	✗
UnLanedet	12	3	✓

We compare UnLanedet and previous codebases in Table 1, where UnLanedet offers distinct advantages for the development of lane detection algorithms: UnLanedet suppoers all kinds of lane detection methods, offering a fair evaluation platform for lane detection. UnLanedet supports Distributed Data-Parallel Training (DDP), which can speed up the training but PPLanedet and LaneDet does not. Besides, UnLanedet contains more datasets than other toolboxes.

4 Benchmarking Lane Detection Models

In this section, we first conducted a comprehensive benchmark of lane detection models using the standard ImageNet-1K pre-trained ResNet [5] backbone. Then, we benchmark the newly proposed CNN-based model, i.e., ConvNext [9].

Dataset and implementation details. All experiments are conducted on Tusimple, CULane, and VIL100 datasets. The architectures of all models were aligned with their original implementations, including the number of layers in the backbone, neck, and head. We employ the same data augmentation as the original paper. All models are trained and tested on a single 3090 GPU with 24 GB memory. Models on CULane datset are trained 15 and 20 epochs and trained over 70 epochs on Tusimple dataset.

Main results on Tusimple. We present the reproduced performance on Tusimple dataset in Table 2. It can be observed that the reproduced results are similar to those in the original paper. ADNet in UnLanedet achieves the better performance than the official implementation.

Main results on CULane. Results on CULane dataset are shown in Table 3. CondLaneNet with ResNet34 achieves 79.69% F1 score, better than the official implementation. CLRNet with ConvNext-tiny backbone gets 80.21% F1 score, demonstrating that the strong backbone is beneficial to model performance.

Main results on VIL100 . For the VIL100 dataset, we only support ADNet. We reproduce ADNet dataset with 89.43% F1 score. It should be noted that we select the result of the last epoch as the final result.s

Table 2: Model performance on Tusimple dataset

Model	Venue	Backbone	Accuracy
SCNN [11]	AAAI	ResNet18	96.02
RESA [24]	AAAI	ResNet18	96.27
UFLD [12]	ECCV	ResNet18	95.17
CLRNet [25]	CVPR	ResNet34	96.64
LaneATT [17]	CVPR	ResNet34	94.65
ADNet [21]	ICCV	ResNet34	96.65
SRLane [1]	AAAI	ResNet34	96.21
BezierNet [16]	CVPR	ResNet18	94.55
GANet [19]	CVPR	ResNet18	96.18
GSENet [15]	AAAI	ResNet18	96.16

Table 3: Model performance on CULane dataset. * denotes the model training without segmentation loss. All models are trained without EMA.

Model	Venue	Backbone	F1
UFLD [12]*	ECCV	ResNet18	63.41
CLRNet [25]	CVPR	ResNet34	78.99
CLRNet [25]	CVPR	ResNet50	79.30
CLRNet [25]	CVPR	ConvNext-tiny	80.21
CondLaneNet	ICCV	ResNet34	79.69
CLRerNet [6]	WACV	ResNet34	79.20
CLRerNet [6]	WACV	ConvNexT-Tiny	79.89
ADNet [21]	ICCV	ResNet34	77.88

5 Conclusion

In this report, we present UnLanedet, a benchmarking platform specifically designed for lane detection models, addressing the lack of a unified and comprehensive benchmark in the field. By offering a highly modular and lightweight framework, UnLanedet supports a wide range of tasks and enables effective evaluation and comparison of lane detection algorithms. We hope that UnLanedet will serve as a standardized and consistent platform for the research community, fostering a deeper understanding and driving advancements in lane detection models.

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References

[1] Chao Chen, Jie Liu, Chang Zhou, Jie Tang, and Gangshan Wu. Sketch and refine: Towards fast and accurate lane detection. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pages 1001–1009, 2024. 5

[2] Kai Chen, Jiaqi Wang, Jiangmiao Pang, Yuhang Cao, Yu Xiong, Xiaoxiao Li, Shuyang Sun, Wansen Feng, Ziwei Liu, Jiarui Xu, et al. MMDetection: Open MMLab Detection Toolbox and Benchmark. *arXiv preprint arXiv:1906.07155*, 2019. 2

[3] MMSegmentation Contributors. MMSegmentation: Openmmlab semantic segmentation toolbox and benchmark. https://github.com/open-mmlab/mmsegmentation, 2020. 2

[4] Zhengyang Feng, Shaohua Guo, Xin Tan, Ke Xu, Min Wang, and Lizhuang Ma. Rethinking efficient lane detection via curve modeling. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 17062–17070, 2022. 1, 2

[5] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep Residual Learning for Image Recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, 2016. 4

[6] Hiroto Honda and Yusuke Uchida. Clrernet: improving confidence of lane detection with laneiou. In *Proceedings of the IEEE/CVF winter conference on applications of computer vision*, pages 1176–1185, 2024. 1, 2, 5

[7] Yeongmin Ko, Younkwan Lee, Shoaib Azam, Farzeen Munir, Moongu Jeon, and Witold Pedrycz. Key points estimation and point instance segmentation approach for lane detection. *IEEE Transactions on Intelligent Transportation Systems*, 23(7):8949–8958, 2021. 1, 2

[8] Xiang Li, Jun Li, Xiaolin Hu, and Jian Yang. Line-cnn: End-to-end traffic line detection with line proposal unit. *IEEE Transactions on Intelligent Transportation Systems*, 21(1):248–258, 2019. 2

[9] Zhuang Liu, Hanzi Mao, Chao-Yuan Wu, Christoph Feichtenhofer, Trevor Darrell, and Saining Xie. A ConvNet for the 2020s. *CVPR*, 2022. 2, 4

[10] Depu Meng, Xiaokang Chen, Zejia Fan, Gang Zeng, Houqiang Li, Yuhui Yuan, Lei Sun, and Jingdong Wang. Conditional DETR for Fast Training Convergence. *arXiv preprint arXiv:2108.06152*, 2021. 1

[11] Xingang Pan, Jianping Shi, Ping Luo, Xiaogang Wang, and Xiaoou Tang. Spatial as deep: Spatial cnn for traffic scene understanding. In *Proceedings of the AAAI conference on artificial intelligence*, volume 32, 2018. 1, 2, 5

[12] Zequn Qin, Huanyu Wang, and Xi Li. Ultra fast structure-aware deep lane detection. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XXIV 16*, pages 276–291. Springer, 2020. 2, 5

[13] Zhan Qu, Huan Jin, Yang Zhou, Zhen Yang, and Wei Zhang. Focus on local: Detecting lane marker from bottom up via key point. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 14122–14130, 2021. 1

[14] Tianhe Ren, Shilong Liu, Feng Li, Hao Zhang, Ailing Zeng, Jie Yang, Xingyu Liao, Ding Jia, Hongyang Li, He Cao, Jianan Wang, Zhaoyang Zeng, Xianbiao Qi, Yuhui Yuan, Jianwei Yang, and Lei Zhang. detrex: Benchmarking detection transformers, 2023. 5

[15] Junhao Su, Zhenghan Chen, Chenghao He, Dongzhi Guan, Changpeng Cai, Tongxi Zhou, Jiashen Wei, Wenhua Tian, and Zhihuai Xie. Gsenet: global semantic enhancement network for lane detection. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pages 15108–15116, 2024. 5

[16] Zhiqing Sun, Shengcao Cao, Yiming Yang, and Kris Kitani. Rethinking transformer-based set prediction for object detection. *arXiv preprint arXiv:2011.10881*, 2020. 2, 5

[17] Lucas Tabelini, Rodrigo Berriel, Thiago M Paixao, Claudine Badue, Alberto F De Souza, and Thiago Oliveira-Santos. Keep your eyes on the lane: Real-time attention-guided lane detection. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 294–302, 2021. 2, 5

[18] Lucas Tabelini, Rodrigo Berriel, Thiago M Paixao, Claudine Badue, Alberto F De Souza, and Thiago Oliveira-Santos. Polylanenet: Lane estimation via deep polynomial regression. In *2020 25th international conference on pattern recognition (ICPR)*, pages 6150–6156. IEEE, 2021. 2

[19] Jinsheng Wang, Yinchao Ma, Shaofei Huang, Tianrui Hui, Fei Wang, Chen Qian, and Tianzhu Zhang. A keypoint-based global association network for lane detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1392–1401, 2022. 1, 2, 5

[20] Yuxin Wu, Alexander Kirillov, Francisco Massa, Wan-Yen Lo, and Ross Girshick. Detectron2. https://github.com/facebookresearch/detectron2, 2019. 2

[21] Lingyu Xiao, Xiang Li, Sen Yang, and Wankou Yang. Adnet: Lane shape prediction via anchor decomposition. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 6404–6413, 2023. 2, 5

[22] Yujun Zhang, Lei Zhu, Wei Feng, Huazhu Fu, Mingqian Wang, Qingxia Li, Cheng Li, and Song Wang. Vil-100: A new dataset and a baseline model for video instance lane detection. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 15681–15690, 2021. 1

[23] Yunzhi Zhang and Xiuxiu Bai. Lanelm: Lane detection as language modeling. *Preprints*, April 2025. 2

[24] Tu Zheng, Hao Fang, Yi Zhang, Wenjian Tang, Zheng Yang, Haifeng Liu, and Deng Cai. Resa: Recurrent feature-shift aggregator for lane detection. In *Proceedings of the AAAI conference on artificial intelligence*, volume 35, pages 3547–3554, 2021. 1, 2, 5

[25] Tu Zheng, Yifei Huang, Yang Liu, Wenjian Tang, Zheng Yang, Deng Cai, and Xiaofei He. Clrnet: Cross layer refinement network for lane detection. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 898–907, 2022. 1, 2, 5

[26] Kunyang Zhou. Pplanedet, a toolkit for lane detection based on paddlepaddle. https://github.com/zkyseu/PPlanedet, 2022. 1, 2, 4

[27] Kunyang Zhou. Lane2seq: towards unified lane detection via sequence generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 16944–16953, 2024. 2

[28] Kunyang Zhou and Rui Zhou. End-to-end lane detection with one-to-several transformer. *arXiv preprint arXiv:2305.00675*, 2023. 1