Rethinking Efficient Lane Detection via Curve Modeling
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Zhengyang Feng1∗ , Shaohua Guo1*, Xin Tan2,1 , Ke Xu3 , Min Wang4 , Lizhuang Ma1,2,5†
1Shanghai Jiao Tong University 2East China Normal University 3City University of Hong Kong
4SenseTime Research 5MoE Key Lab of Artificial Intelligence, Shanghai Jiao Tong University

Speaker: Po-Jui Su
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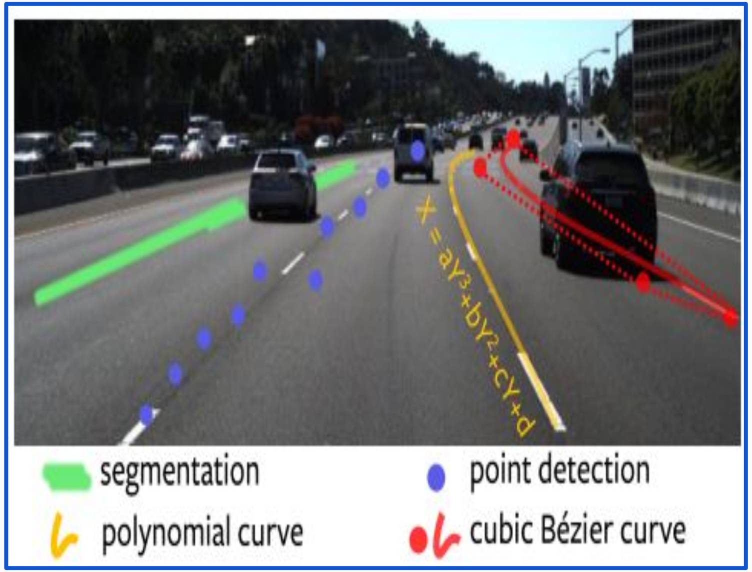
01 Introduction

Lane detection tasks

Lane detection tasks involves identifying lane markings on roadways using image processing techniques, and it is currently widely used in autonomous driving technology.



Introduction: Current Approaches

Current Approaches:

- **Segmentation-based Lane Detection:**

  Segments lanes by classifying each pixel in the image and uses post-processing to aggregate these pixels into lane instances.

- **Point Detection-based Lane Detection**:

  Detects lanes as a sequence of discrete points along the vertical axis, usually **employing object detection frameworks (eg: DETR).**

- **Curve-based Lane Detection:**

  Represents lanes as holistic curves, **typically using polynomial equations** to model lane geometry and optimizing coefficients for precise curve fitting.

Introduction: Problem Definition

Challenges and Limitations in Existing Methods:

- **Segmentation-based Lane Detection:**

  Relies on per-pixel segmentation and heavy post-processing, **struggling with occlusions and challenging lighting conditions.**

- **Point Detection-based Lane Detection**:

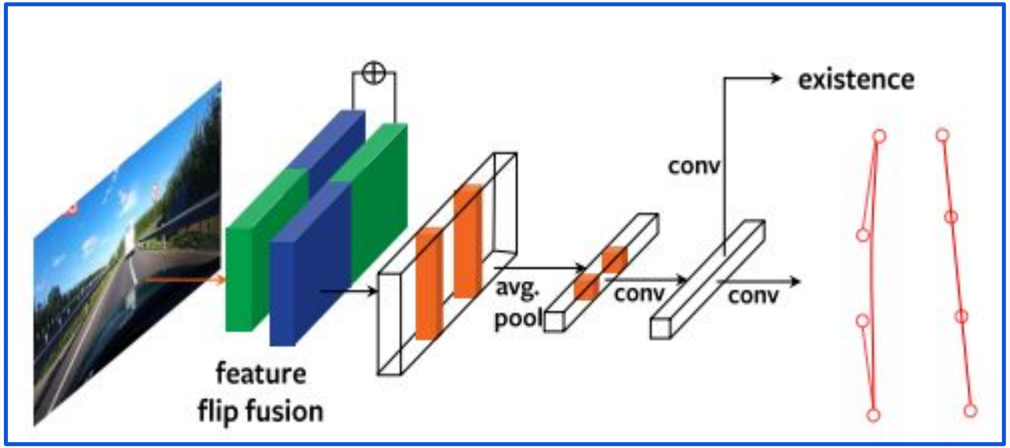
  Requiring Non-Maximum Suppression, the use of anchors and heuristics in point detection-based methods is **highly dataset-dependent, limiting their generalization.**

- **Curve-based Lane Detection:**

  Optimization is challenging due to slow convergence and computational overhead, leading to **lagging performance on complex datasets.**

Introduction: Purpose and Contribution

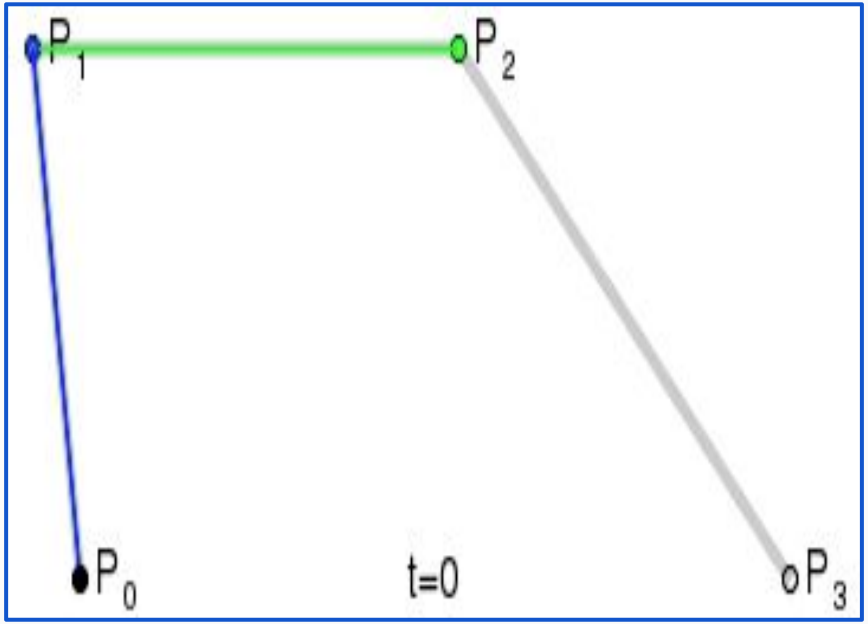
To overcome the limitations of existing methods, such as **high post-processing requirements**, **insufficient generalization and lagging performance**, this study proposes a **Bézier curve-based deep learning model (BézierLaneNet)** and introduces a **deformable convolution-based feature flip fusion module** to enhance the performance of existing approaches.



BézierLaneNet Architecture

02 Method

Bézier Curve and Considerations for the Value of n



Bézier Curve

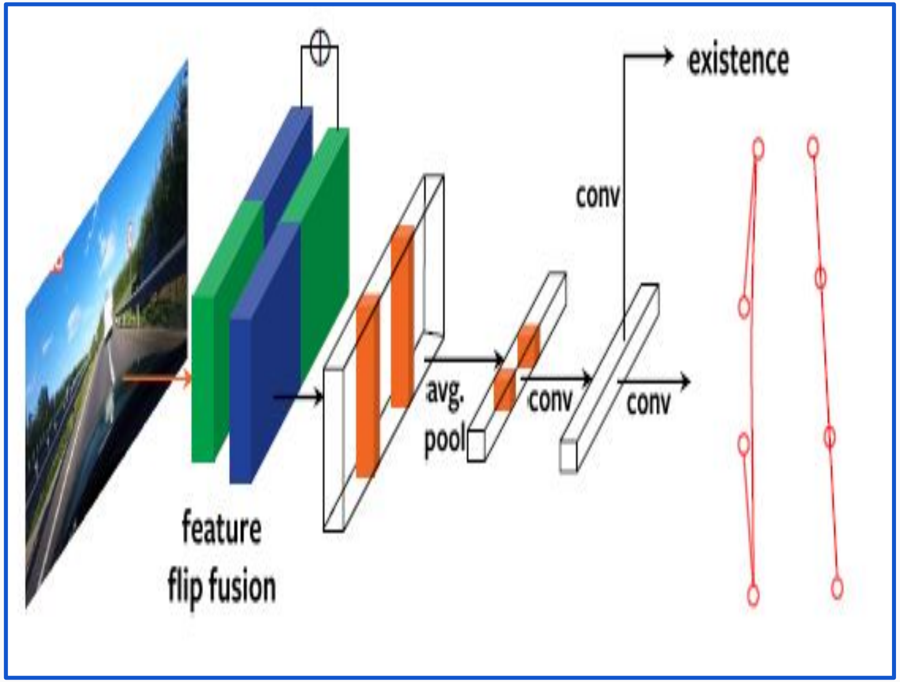
- Fitting Capability

- Degree of Freedom

- Efficiency and Real-Time Requirements

- Considering the above factors, the authors ultimately **set the value of n to 3.**

Architecture



- **Image and Feature Extraction:**

The image inputs into an encoder (ResNet) which **extracts high-level features** from the image.

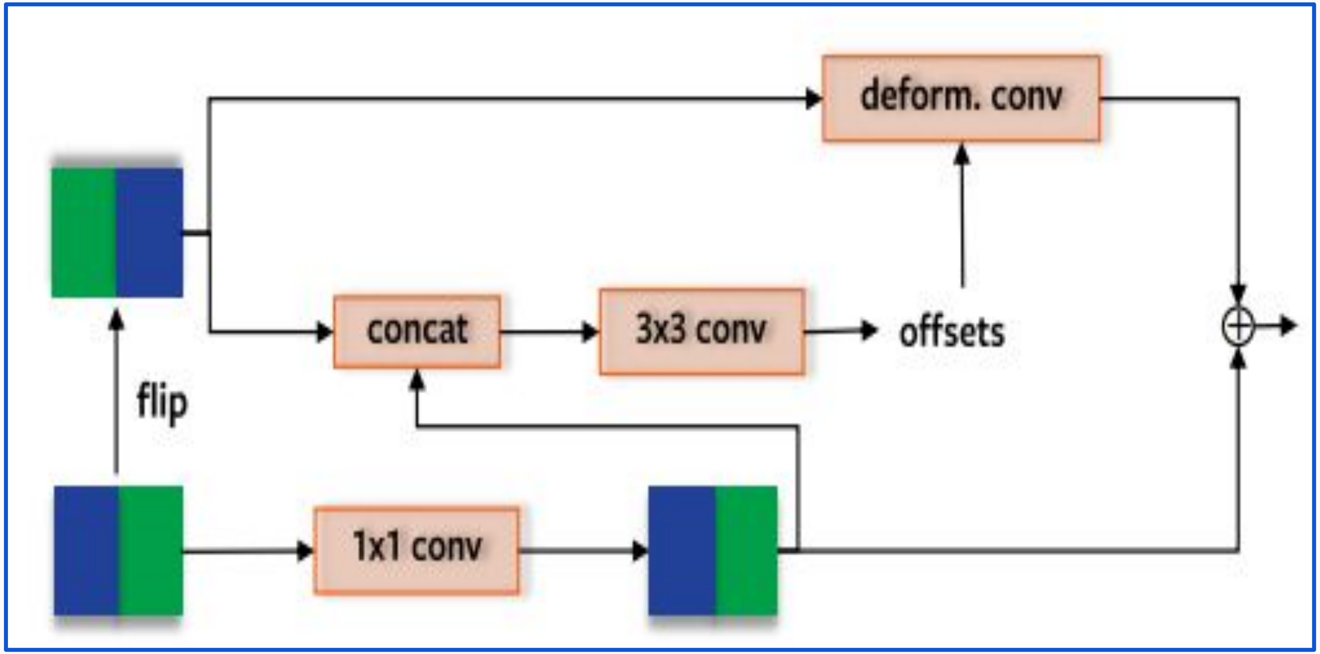
- **Feature Flip Fusion:**

Features are horizontally flipped and merged with original features to **enhance lane line symmetry** in the detection process.

- **Output Prediction:**

The processed features are used to predict lane presence through **classification** and **regression branches**, each containing a **1x1 convolutional layer.**

Feature Flip Fusion



Ground Truth Generation

$$\begin{bmatrix} b_{0,n}(t_0) & \cdots & b_{n,n}(t_0) \\ b_{0,n}(t_1) & \cdots & b_{n,n}(t_1) \\ \vdots & \ddots & \vdots \\ b_{0,n}(t_m) & \cdots & b_{n,n}(t_m) \end{bmatrix} \boxed{\begin{bmatrix} \mathcal{P}_0 \\ \mathcal{P}_1 \\ \vdots \\ \mathcal{P}_n \end{bmatrix}} = \boxed{\begin{bmatrix} k_{x_0} & k_{y_0} \\ k_{x_1} & k_{y_1} \\ \vdots & \vdots \\ k_{x_m} & k_{y_m} \end{bmatrix}}$$

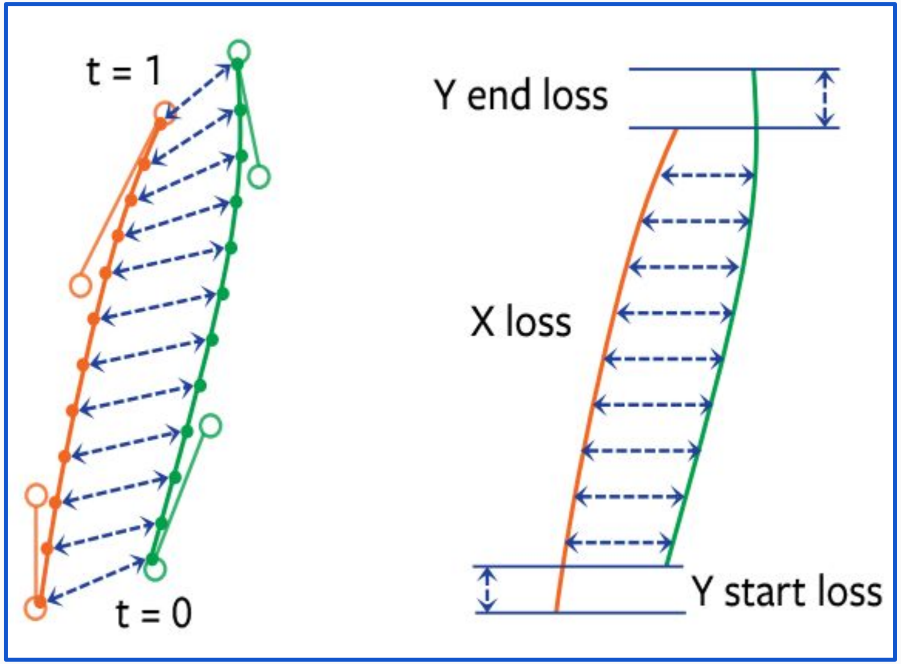
$$\boxed{\mathcal{B}(t) = \sum_{i=0}^{n} b_{i,n}(t)\mathcal{P}_i,\ 0 \le t \le 1,}$$

map groundtruth to Bézier curve(n=3)

P: corresponding control points, k: ground truth points

Distances Between Bézier Curves

$$\mathcal{L}_{reg} = \frac{1}{n}\sum_{t\in T}||\mathcal{B}(f(t)) - \hat{\mathcal{B}}(f(t))||_1,$$



Label and Prediction Matching

$$\hat{\pi} = \underset{\pi \in \Pi_G^N}{\arg\max} \sum_{i}^{G} Q_{i,\pi(i)},$$

$$Q_{i,\pi(i)} = \left(\hat{p}_{\pi(i)}\right)^{1-\alpha} \cdot \left(1 - L_1\left(b_i, \hat{b}_{\pi(i)}\right)\right)^{\alpha},$$

Equation Explanation:

- Match prediction curve and groundtruth
- Find G most possible curves from N predictions
- p: probability given by classifier
- L1: lane distance, alpha: weight coefficient(0.8 in this paper)

Training Loss

1. **Overall Loss:**

$$\mathcal{L} = \lambda_1 \mathcal{L}_{reg} + \lambda_2 \mathcal{L}_{cls} + \lambda_3 \mathcal{L}_{seg}$$

2. **Loss Function:**

- **L_{reg}: Quantifing curve differences by uniformly sampling across t values.** #1
- **L_{cls} : Classifying the existence of lane lines.** #2
- **L_{seg}: Classifying each pixel as lane region or non-lane region.** #3

3. **Weights for Loss: $\lambda_1 = 1$; $\lambda_2 = 0.1$; $\lambda_3 = 0.75$**

$$\mathcal{L}_{reg} = \frac{1}{n} \sum_{t \in T} ||\mathcal{B}(f(t)) - \hat{\mathcal{B}}(f(t))||_1,$$

$$\mathcal{L}_{cls} = -(y \log(p) + w(1 - y) \log(1 - p))$$

#1 Mentioned in the previous slide.
#2、3 Using Weighted Binary Cross Entropy

03 Experiments

Experiment Details

Dataset:

- TuSimple、CULane、LLAMAS

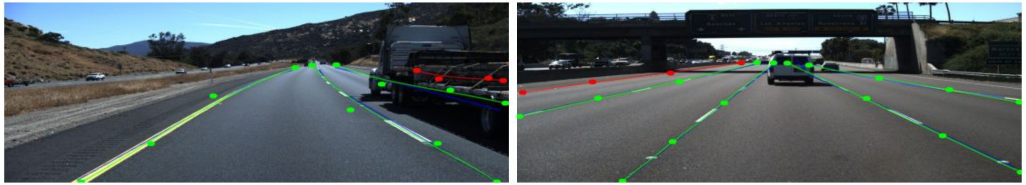
Evaluation Metrics:

- **F1 Score↑、Accuracy↑、FPR↓、FNR↓**

Training Configuration:

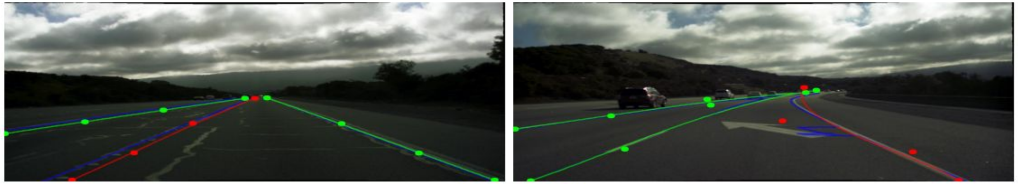
- **GPU:** 1× RTX 2080 Ti
- **Optimization:** Adam
- **Scheduler:** Cosine Annealing
- **Learning rate:** 6E-4
- **Weight Decay:** 1E-4
- **Batch size:** 20

Dataset	Train	Val	Test	Resolution	#Lines
TuSimple [1]	3268	358	2782	720×1280	≤ 5
CULane [22]	88880	9675	34680	590×1640	≤ 4
LLAMAS [3]	58269	20844	20929	717×1276	$\leq 4^*$



(a) TuSimple [1].

(b) CULane [22].



(c) LLAMAS [3].

Results on CULane and TuSimple Dataset

Method	CULane [22]											TuSimple [1]				
	Ep.	Total	Normal	Crowd	Night	No line	Shadow	Arrow	Dazzle light	Curve	Cross ↓	train+val	Ep.	Acc.	FPR ↓	FNR ↓
Segmentation-based																
Baseline (ResNet-18)*	12	65.30	85.45	62.63	61.04	33.88	51.72	78.15	53.05	59.70	1915		50	94.25	0.088	0.089
Baseline (ResNet-34)*	12	69.92	89.46	66.66	65.38	40.43	62.17	83.18	58.51	63.00	1713		50	95.31	0.064	0.062
Baseline (ResNet-101)*	12	71.37	90.11	67.89	67.01	43.10	70.56	85.09	61.77	65.47	1883		50	95.19	0.062	0.062
SCNN (ResNet-18) [22]*	12	72.19	90.98	70.17	66.54	43.12	66.31	85.62	62.20	65.58	1808		50	94.77	0.075	0.074
SCNN (ResNet-34) [22]*	12	72.70	91.06	70.41	67.75	44.64	68.98	86.50	61.57	65.75	2017		50	95.25	0.063	0.063
SCNN (ResNet-101) [22]*	12	73.58	91.10	71.43	68.53	46.39	72.61	86.87	61.95	67.01	1720		50	**95.69**	0.052	0.050
UFLD (ResNet-18) [26]**	50	68.4	87.7	66.0	62.1	40.2	62.8	81.0	58.4	57.9	1743	-	–	–	–	–
UFLD (ResNet-34) [26]**	50	72.3	90.7	70.2	66.7	44.4	69.3	85.7	59.5	69.5	2037	-	–	–	–	–
RESA (ResNet-18) [41]*	12	72.90	91.23	70.57	67.16	45.24	68.01	86.56	64.32	66.19	1679		50	95.24	0.069	0.057
RESA (ResNet-34) [41]*	12	73.66	91.31	71.80	67.54	46.57	72.74	86.94	64.46	67.31	1701		50	95.15	0.069	0.059
RESA (ResNet-101) [41]*	12	**74.04**	91.45	71.51	69.01	46.54	75.83	87.75	63.90	68.24	1522		50	95.56	0.058	0.051
Point detection-based																
FastDraw (ResNet-18) [25]	–	–	–	–	–	–	–	–	–	–	–	✓	7	94.9	0.061	0.047
CurveLanes-NAS-S [39]	12	71.4	88.3	68.6	66.2	47.9	68.0	82.5	63.2	66.0	2817	-	–	–	–	–
CurveLanes-NAS-M [39]	12	73.5	90.2	70.5	68.2	48.8	69.3	85.7	65.9	67.5	2359	-	–	–	–	–
CurveLanes-NAS-L [39]	12	74.8	90.7	72.3	68.9	49.4	70.1	85.8	67.7	68.4	1746	-	–	–	–	–
LaneATT (ResNet-18) [33]**	15	74.88	90.98	72.78	68.61	48.23	69.68	85.44	65.43	63.18	1163	✓	100	95.57	0.036	0.030
LaneATT (ResNet-34) [33]**	15	76.42	91.94	74.76	70.32	49.17	77.68	88.14	65.92	68.07	1323	✓	100	95.63	0.035	0.029
LaneATT (ResNet-122) [33]**	15	**76.79**	91.50	76.04	70.43	50.29	75.96	86.16	68.99	63.99	1265	✓	100	**96.10**	0.056	0.022
Curve-based																
PolyLaneNet (EfficientNet-B0) [32]**	–	–	–	–	–	–	–	–	–	–	–	✓	2695	93.36	0.094	0.093
LSTR (ResNet-18, 1×) [19]*	–	–	–	–	–	–	–	–	–	–	–		2000	95.06	0.049	0.042
LSTR (ResNet-18, 2×) [19]*	150	68.72	86.78	67.34	59.92	40.10	59.82	78.66	56.63	56.64	1166	-	–	–	–	–
BézierLaneNet (ResNet-18)	36	73.67	90.22	71.55	68.70	45.30	70.91	84.09	62.49	58.98	996		400	95.41	0.053	0.046
BézierLaneNet (ResNet-34)	36	**75.57**	91.59	73.20	69.90	48.05	76.74	87.16	69.20	62.45	888		400	**95.65**	0.051	0.039

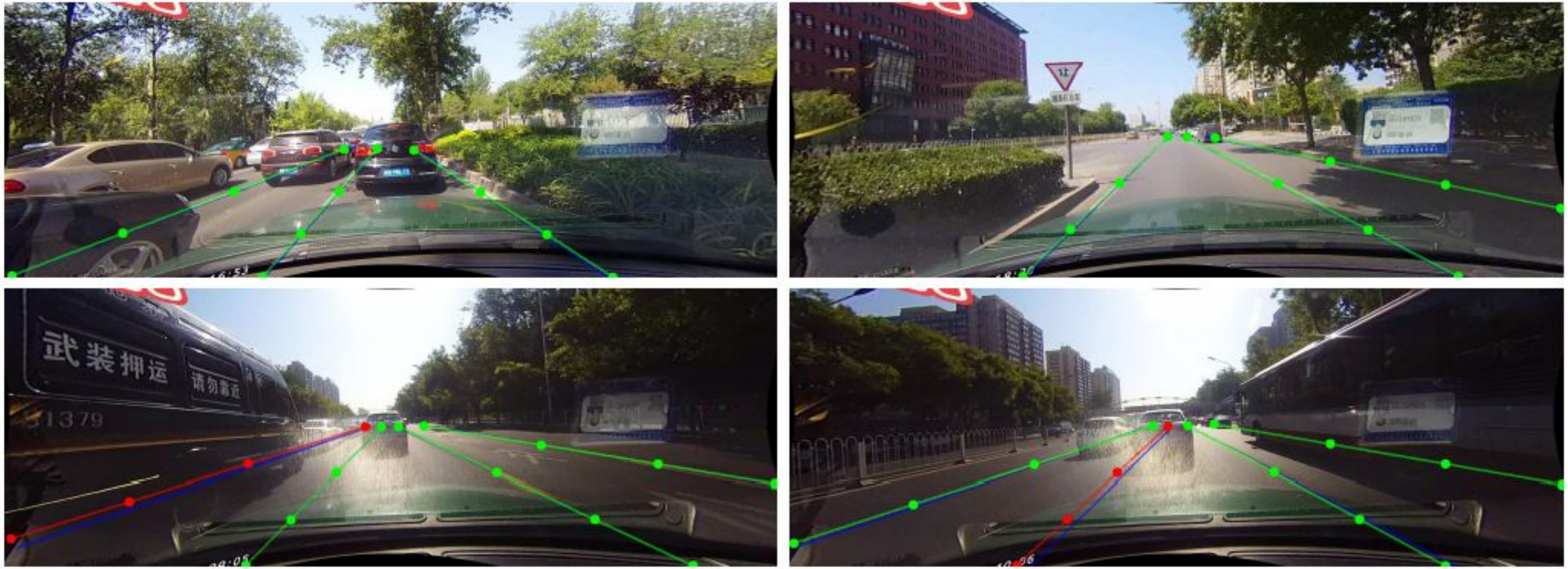
Results on LLAMAS Dataset

	LLAMAS [3]			
Method	**Ep.**	**F1**	**Precision**	**Recall**
Segmentation-based				
Baseline (ResNet-34)*	18	93.43	92.61	94.27
SCNN (ResNet-34) [22]*	18	94.25	94.11	94.39
Point detection-based				
LaneATT (ResNet-18) [33]**	15	93.46	96.92	90.24
LaneATT (ResNet-34) [33]**	15	93.74	96.79	90.88
LaneATT (ResNet-122) [33]**	15	93.54	96.82	90.47
Curve-based				
PolyLaneNet (EfficientNet-B0) [32]**	75	88.40	88.87	87.93
BézierLaneNet (ResNet-18)	20	94.91	95.71	94.13
BézierLaneNet (ResNet-34)	20	**95.17**	95.89	94.46

FPS and model size

Method	FPS ↑	Params (M) ↓
Segmentation-based (ignored post-processing time)		
Baseline (ResNet-101)	27	43.56
SCNN (ResNet-18) [22]	21	12.63
SCNN (ResNet-34) [22]	21	22.74
SCNN (ResNet-101) [22]	14	44.15
UFLD (ResNet-34) [26]	144	71.58
RESA (ResNet-18) [41]	68	6.61
RESA (ResNet-34) [41]	54	11.99
RESA (ResNet-101) [41]	25	31.46
Point detection-based (ignored NMS time in real images)		
LaneATT (ResNet-18) [33]	165	12.02
LaneATT (ResNet-34) [33]	117	22.13
LaneATT (ResNet-122) [33]	26	~~8.55~~ 85.5
Curve-based (entirely end-to-end)		
BézierLaneNet (ResNet-18)	**213**	**4.10**
BézierLaneNet (ResNet-34)	150	9.49

Experiment Results - Visualization



(b) CULane [22].

Ablation Study

CP	SP	Flip	Deform	Seg	F1
✓					63.74
	✓				68.89
	✓			✓	65.82
	✓	✓			70.28
	✓	✓	✓		72.96
	✓	✓		✓	73.97
	✓	✓	✓	✓	**75.41**

Table 7. Ablations. **CP**: Control point loss [20]. **SP**: The proposed sampling loss. **Flip**: The feature flip fusion module. **Deform**: Employ the deformable convolution in feature flip fusion. **Seg**: Auxiliary segmentation loss.

04 Conclusion

Comparison with Existing Methods

- **Curve-based Methods**

(1) BézierLaneNet runs over 2× faster than LSTR due to its fully convolutional, end-to-end design.

(2) It converges **4-5× faster** than LSTR, significantly reducing training time.

- **Segmentation-based Methods**

(1) BézierLaneNet outperforms segmentation-based methods in both **speed** and **accuracy**.

- **Point Detection-based Methods**

(1) Although Point Detection-based methods outperform BézierLaneNet in certain scenarios, **BézierLaneNet performs better in Dazzle Light scenarios, demonstrating greater stability.**

(2) It is approximately **30% faster** and requires **2.5× fewer parameters** compared to LaneATT.

Conclusion

- Introduced a novel lane detection framework leveraging **Bézier curves**, combined with a **feature flip fusion module** to utilize the symmetric property of road lanes, enhancing accuracy and robustness.

- Achieved SOTA performance across datasets with a **lightweight design (<10 million parameters)** and **real-time speed (>150 FPS)**, ensuring efficiency and practicality for real-world applications.