

Robust Lane Detection through Self Pre-training with Masked Sequential Autoencoders and Fine-tuning with Customized PolyLoss

Dong, Y.; Li, Ruohan; Farah, H.

Publication date

2023

Document Version

Final published version

Citation (APA)

Dong, Y., Li, R., & Farah, H. (2023). *Robust Lane Detection through Self Pre-training with Masked Sequential Autoencoders and Fine-tuning with Customized PolyLoss*. 1. Poster session presented at 102nd Annual Meeting of the Transportation Research Board (TRB), Washington, District of Columbia, United States.

Important note

To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

Robust Lane Detection through Self Pre-training with Masked Sequential Autoencoders and Fine-tuning with Customized PolyLoss

Authors: Yongqi Dong | Ruohan Li | Haneen Farah

Y.Dong-4@tudelft.nl



Background & Aim

- ❖ Lane detection is crucial for Automated Vehicles and ADAS
- ❖ Available vision based methods usually use one image to do lane detection
- ❖ Traditional methods usually adopted cumbersome hand-crafted features
- ❖ Deep learning based methods in literature still can not make full use of spatial-temporal information and correlation
- ❖ Available methods can not handle challenging driving scenes well

The main aim of this study is:

- To develop robust detection model handling challenging driving scenes
- To make full use of valuable features and aggregate contextual information
- To develop pre-training method for sequential vision based lane detection



Figure 1. Examples of challenging driving scenes.

The framework of the proposed pipeline

- End-to-end Encoder-decoder Structure
- Self Pre-training to Reconstruct Images
 - Masked sequential autoencoders
- Fine-tuning Segmentation
 - Transfer pre-trained model weights to the segmentation model
- Customized PolyLoss
- Post-processing with clustering & curve fitting
- Tested and verified on two data sets
 - tvtLANE normal (TuSimple lane)
 - tvtLANE challenging (12 cases)

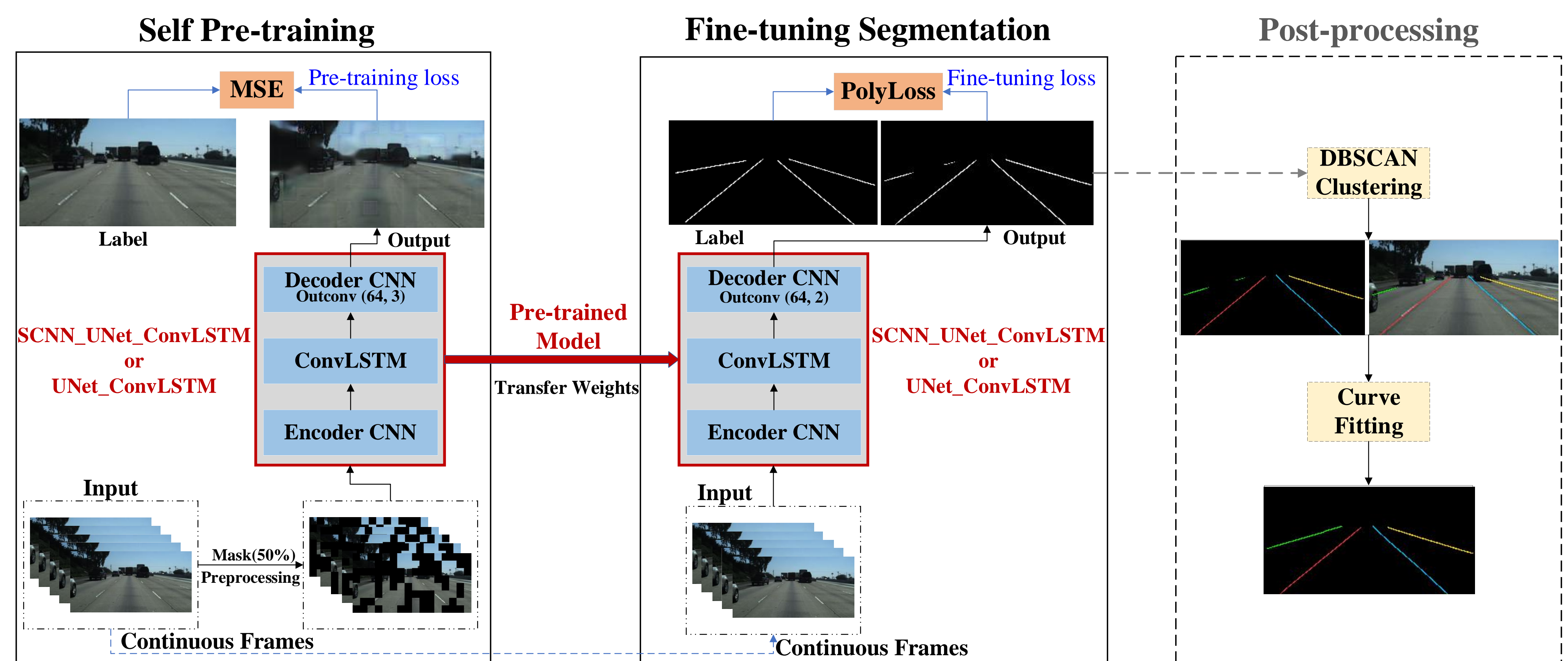


Figure 2. The framework of the proposed pipeline

Evaluation Metrics

- Accuracy
- Precision
- Parameter Size
- F1-Measure
- Recall
- MACs (Multiply-accumulate operations)

Results

	Models	Test_Acc (%)	Precision	Recall	F1-Measure	MACs (G)	Params (M)
Using single image	Baseline Models						
	SegNet	96.93	0.796	0.962	0.871	50.2	29.4
	UNet	96.54	0.790	0.985	0.877	15.5	13.4
	SCNN*	96.79	0.654	0.808	0.722	77.7	19.2
	LaneNet*	97.94	0.875	0.927	0.901	44.5	19.7
	SegNet_ConvLSTM	97.92	0.874	0.931	0.901	217.0	67.2
Using multi-continuous images	UNet_ConvLSTM	98.00	0.857	0.958	0.904	69.0	51.1
	Pre-trained Models						
	UNet_ConvLSTM_CE**	98.19	0.882	0.940	0.910	69.0	51.1
	UNet_ConvLSTM_PL**	98.34	0.921	0.909	0.915	69.0	51.1
	Baseline Models						
	SCNN_SegNet	98.07	0.893	0.928	0.910	223.0	67.3
	SCNN_UNet_ConvLSTM	98.19	0.889	0.950	0.918	93.0	51.3
	Pre-trained Models						
	SCNN_UNet_ConvLSTM_CE**	98.20	0.891	0.952	0.921	93.0	51.3
	SCNN_UNet_ConvLSTM_PL**	98.38	0.929	0.915	0.922	93.0	51.3
Inputs							
Masked images							
Reconstruct images							

Figure 3. Visualization of the reconstructing results in the pre-training phase.

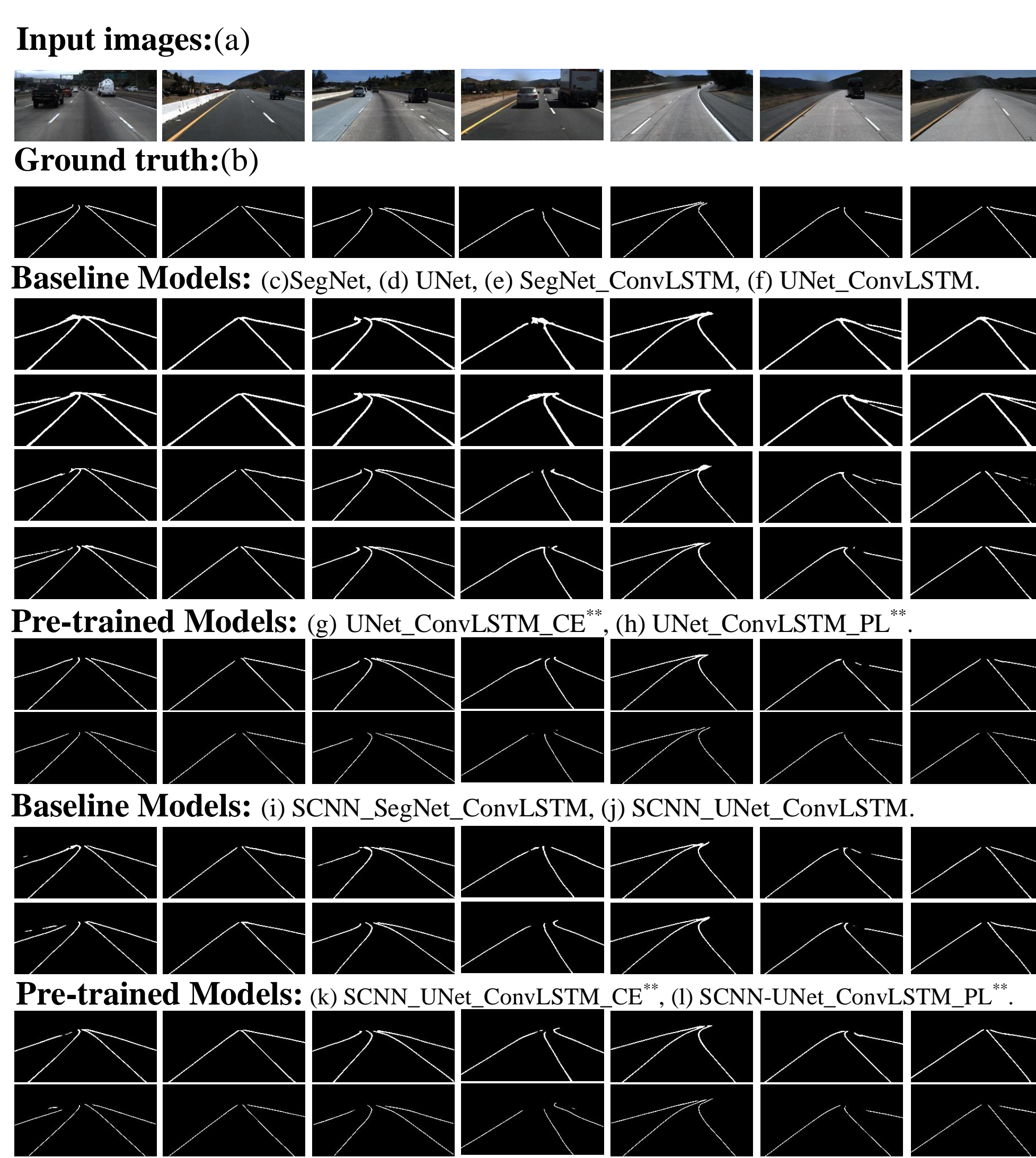


Figure 4. Visualization of lane-detection results on normal cases.

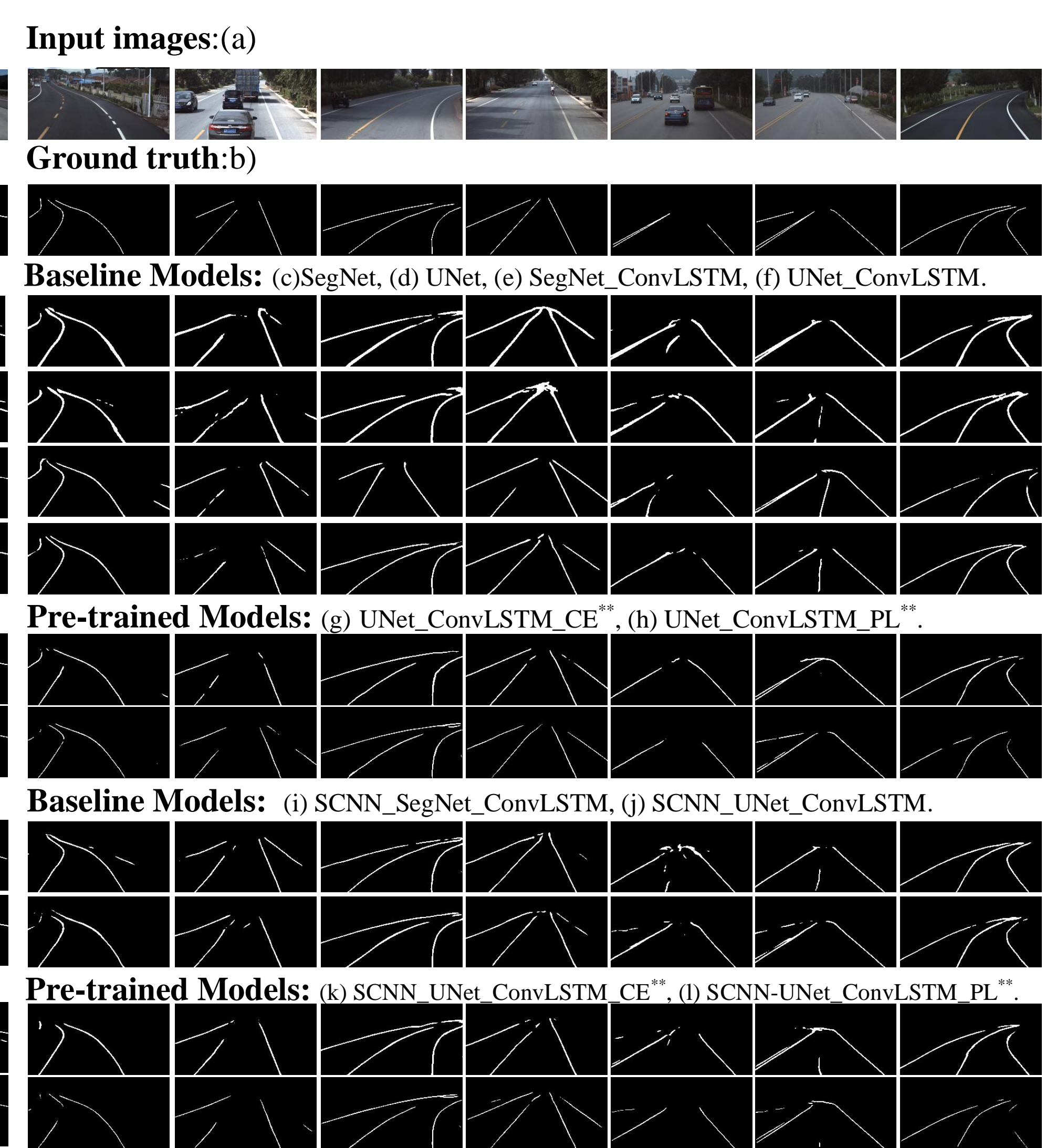


Figure 5. Visualization of lane-detection results on 7 challenging driving scenes.

Ablation Study

Testing Datasets	Testing Models	Testset #1 (Normal Situations)				Testset #2 (Challenging Situations)			
		Loss Function	Test_Acc (%)	Precision	F1-Measure	Loss Function	Test_Acc (%)	Precision	F1-Measure
Testing different loss functions and models	UNet_ConvLSTM	CE	98.19	0.882	0.910	CE	98.13	0.7932	0.6537
		PL	98.34	0.921	0.915	PL	98.38	0.8331	0.6284
	SCNN_UNet_ConvLSTM	CE	98.20	0.891	0.921	CE	98.03	0.8001	0.7327
		PL	98.38	0.929	0.922	PL	98.36	0.8444	0.6711

Conclusions

- The proposed masked sequential autoencoder based pre-training and customized PolyLoss are useful
- The proposed pipeline is effective and robust which can improve the performances of SOTA models in both normal and challenging cases