

# Making Lane Detection Efficient for Autonomous Model Cars

Anthony B Song\*, Riley Francis\*, Kanishk Tihaiya\*, Jiangwei Wang<sup>^</sup>, Shanglin Zhou<sup>^</sup>, Fei Miao<sup>^</sup>, Caiwen Ding<sup>^</sup>

\* *Edwin O Smith High School*, <sup>^</sup> *University of Connecticut*

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## Background and Motivation

- Lane detection is prerequisite and important for autonomous driving
- Deep Learning models have explosive model sizes for embedded systems
  - DL models are time consuming and power consuming
  - Embedded devices are light in storage and memory

## Major Contributions

- Created model cars with real-time Lane Detection
- Tested ADMM-based model compression to compress Ultra-Fast-Lane-Detection (a fast lane detection algorithm from ECCV2020)

## Weight Pruning

TABLE II: ADMM results and its Power Consumption on Lane-Detection-Model under different compression rates

(%) Baseline Accuracy	Compression Rate	(%) After Training	(%) After Hardpruning	(%) After Retraining	(ms/img) Baseline On TX2	(ms/img) On TX2	(ms/img) On CPU	(W) Quadro RTX 6000	(W) Jetson TX2
95.8	1.82×	92.87	92.76	94.46	67.34	29.46	150.24	114	4.494
	2.54×	93.59	93.50	94.38		25.05	149.47	93	3.848
	4.21×	93.83	90.66	94.20		22.71	135.77	87	3.423

- Performance test: TuSimple lane detection benchmark
- Method: Alternating Direction Method of Multipliers (ADMM)-based pruning

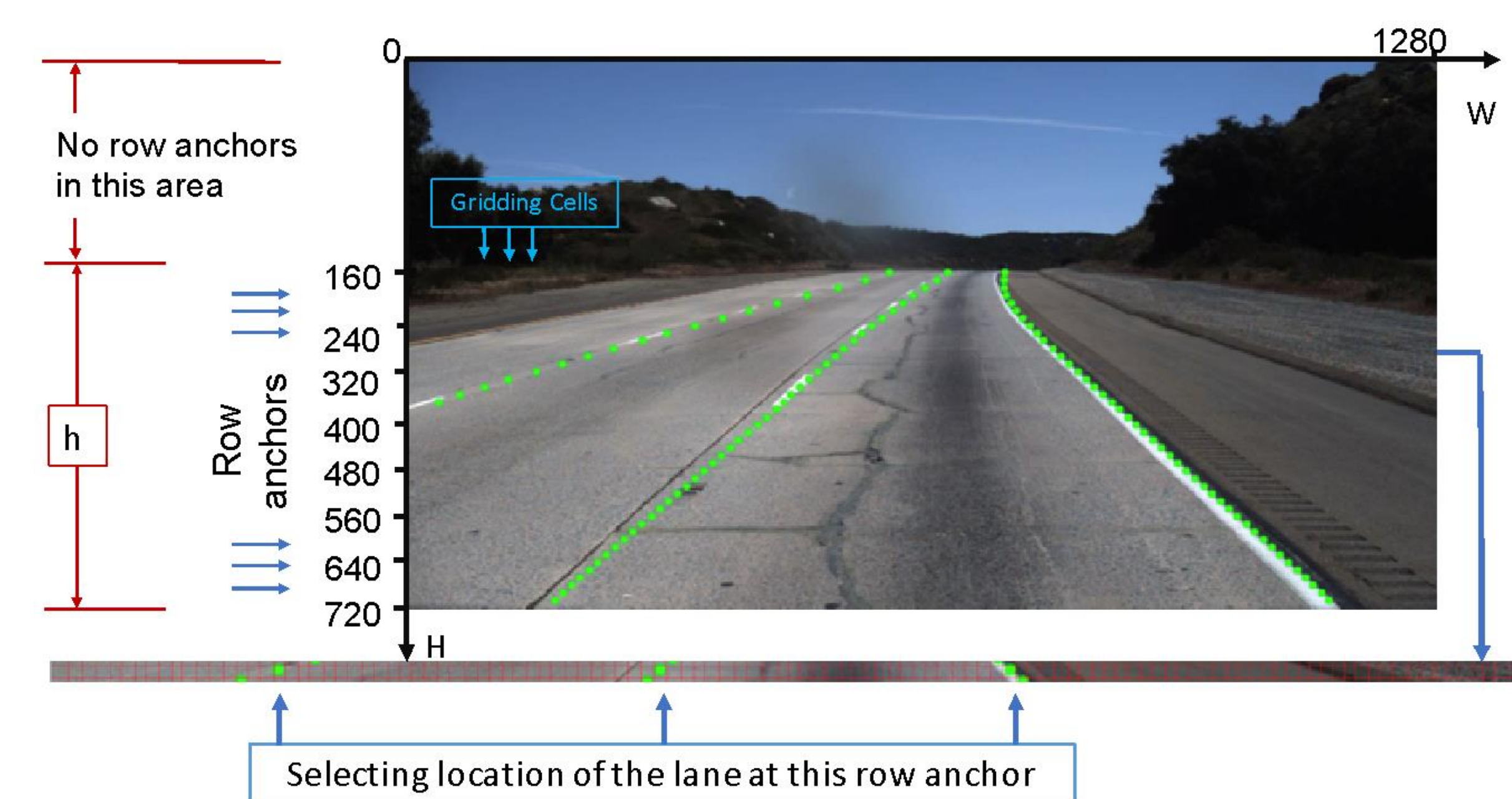
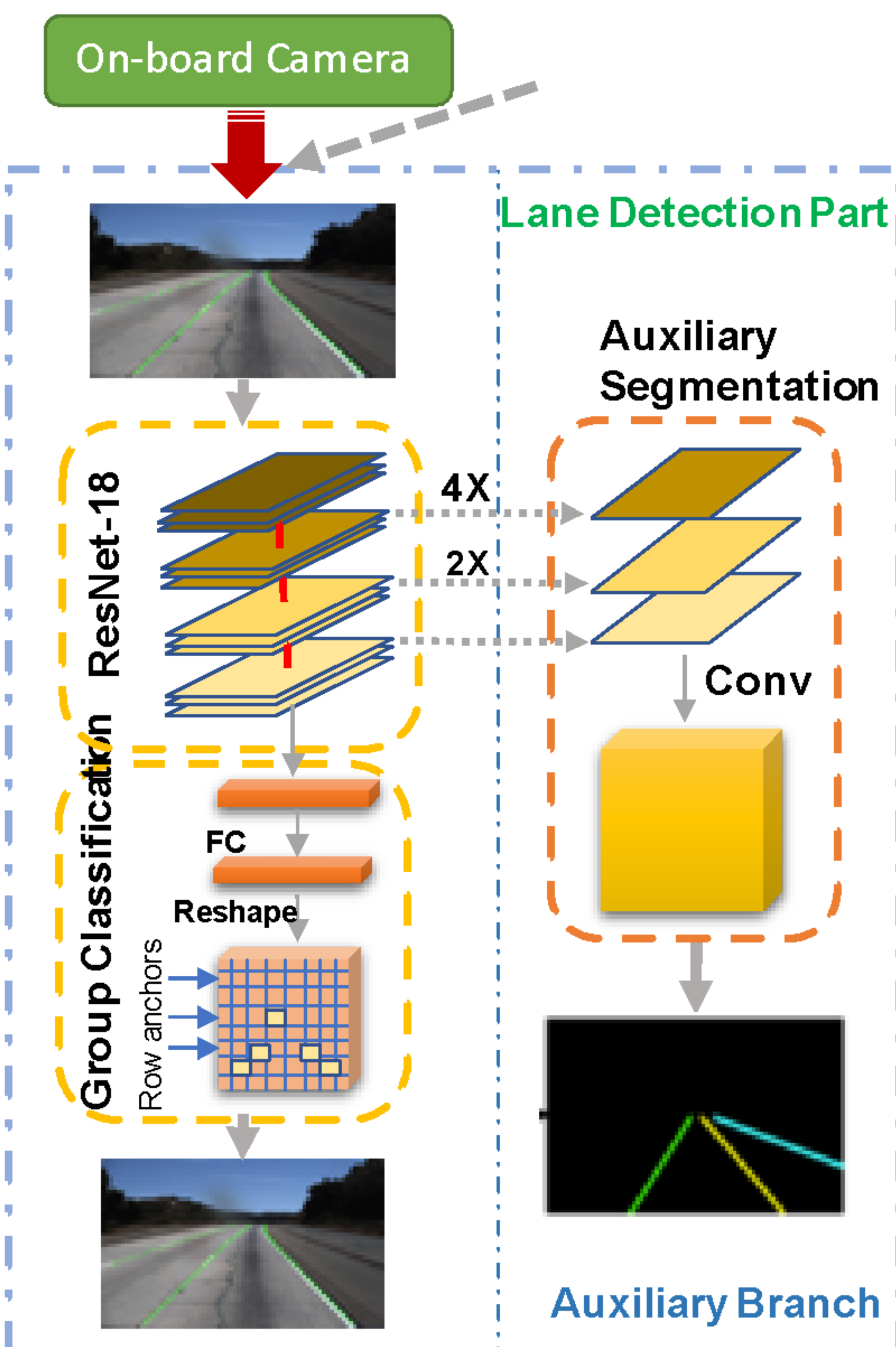
• Loss Function:

$$\begin{aligned} & \underset{\{\Theta_i\}}{\text{minimize}} && f(\{\Theta_i\}_{i=1}^N) + \sum_{i=1}^N g_i(\mathbf{P}_i) \\ & \text{subject to} && \Theta_i = \mathbf{P}_i, i = 1, \dots, N \end{aligned} \quad g_i(\mathbf{P}_i) = \begin{cases} 0 & \text{if } \text{card}(\mathbf{P}_i) \leq t_i \\ +\infty & \text{otherwise} \end{cases}$$

## Model Detail

- Input: Camera RGB Images
- Output: Coordinate of lane markings
- Model: Ultra-Fast-Lane-Detection
  - Different Image Processing Method
    - a) Decompose images to collection of rows (row anchors)
    - b) Divide row anchors into grids
    - c) Localize cells that contain lane mark over row anchors
  - Use ResNet-18 as backbone for global context detect
  - Use auxiliary branch to extract middle step feature maps
  - Address no-visual-clue problem in lane detection area

Convert traditional  $H \times W$  classification problems to classification problems on  $h$  rows, while each row is  $W$ -dimensional

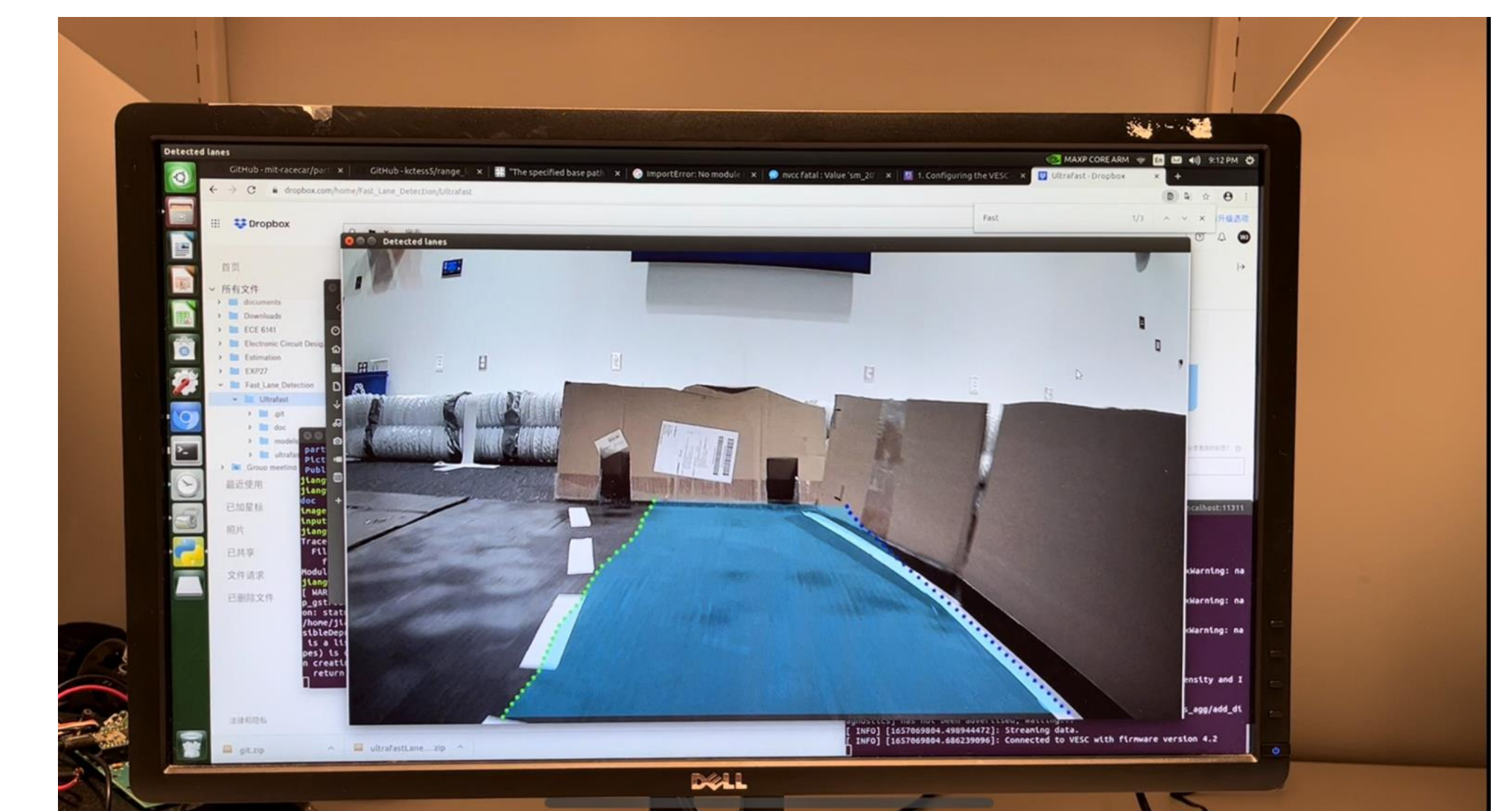


- Subproblem 1: Use Stochastic Gradient Descent to solve “Loss Function” of DNN
- Subproblem 2: Solve “Cardinality” through Pruning by using Projections onto Discrete Subspace



Fully constructed autonomous car running on the testbed track

## Demo



Ultrafast Lane Detection tracking the lane - represented in blue - in demonstration.