

TinyLidarNet: 2D LiDAR-based End-to-End Deep Learning Model for F1TENTH Autonomous Racing

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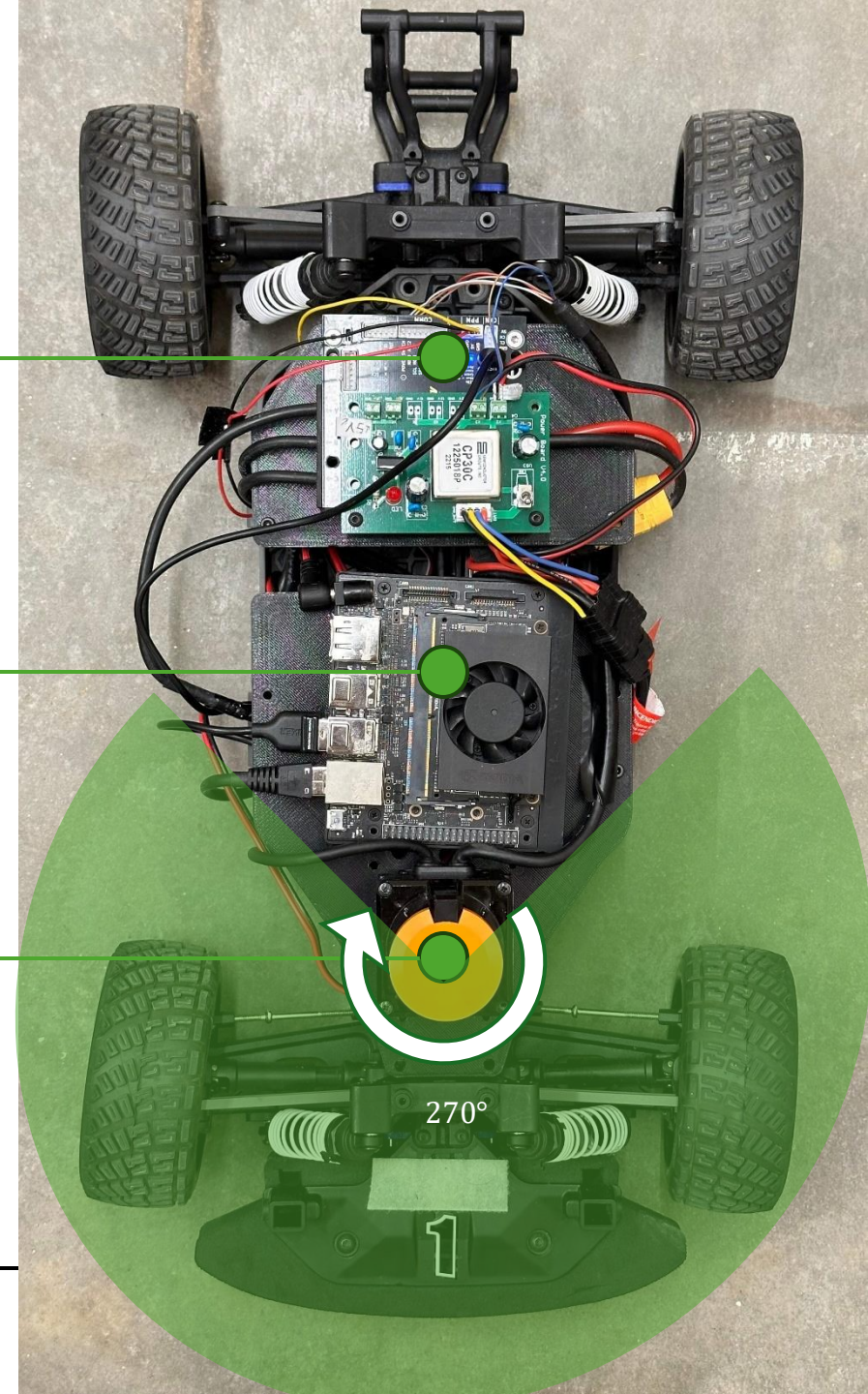
F1Tenth Autonomous Racing

- F1TENTH autonomous racing¹ presents unique challenges due to constraints in size, weight, and power.
- Developing a computationally efficient, intelligent control algorithm is critical for fast, collision-free navigation.

VESC IV

NVIDIA Jetson
Xavier NX

Hokuyo UST-10LX
2D Planner LiDAR

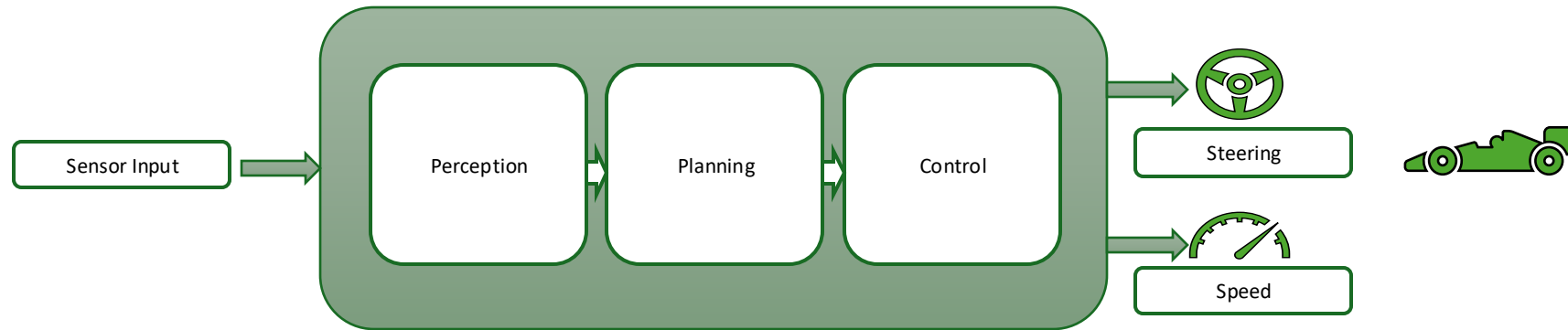


270°

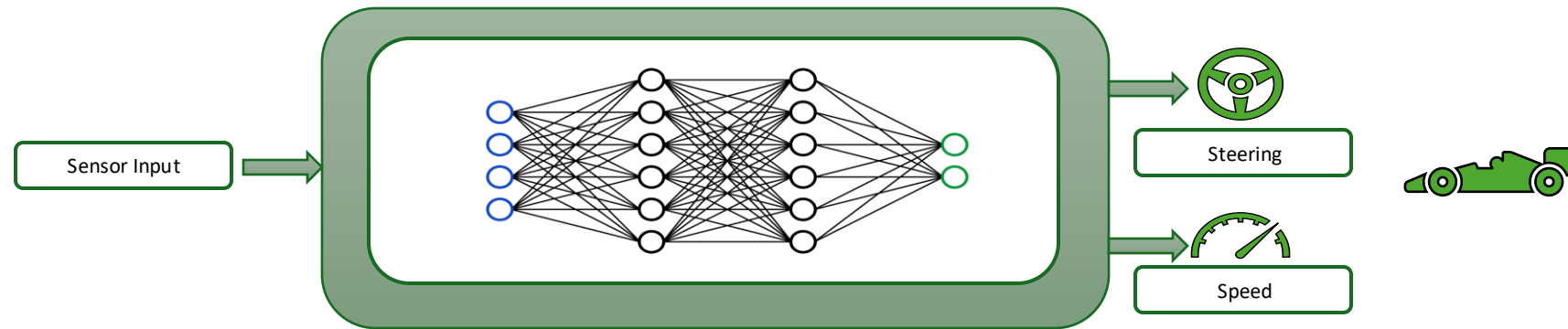
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1. 1. F1Tenth, "F1/10 autonomous racing competition." <http://f1tenth.org>.

End-to-End Deep Learning



(a) Standard robotics control pipeline



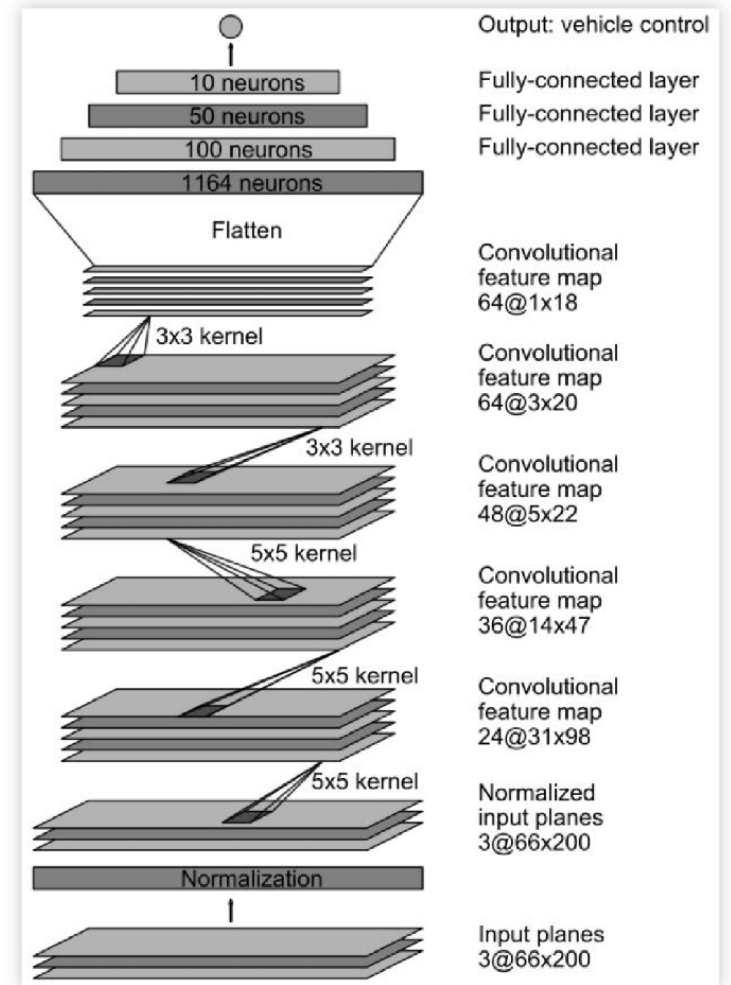
(b) End-to-end deep learning control

PilotNet

- NVIDIA's **vision**-based end-to-end deep learning model for autonomous driving.
- Successfully drove a real car on public roads.



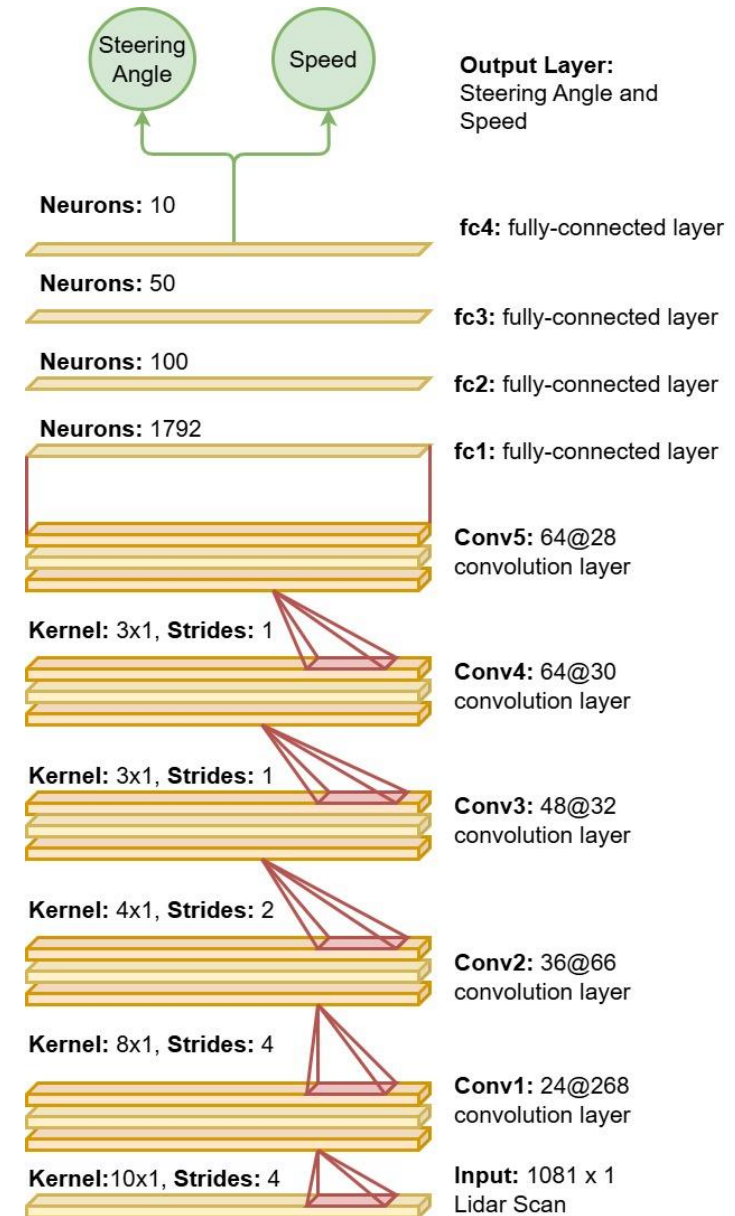
Source: <https://devblogs.nvidia.com/deep-learning-self-driving-cars/>



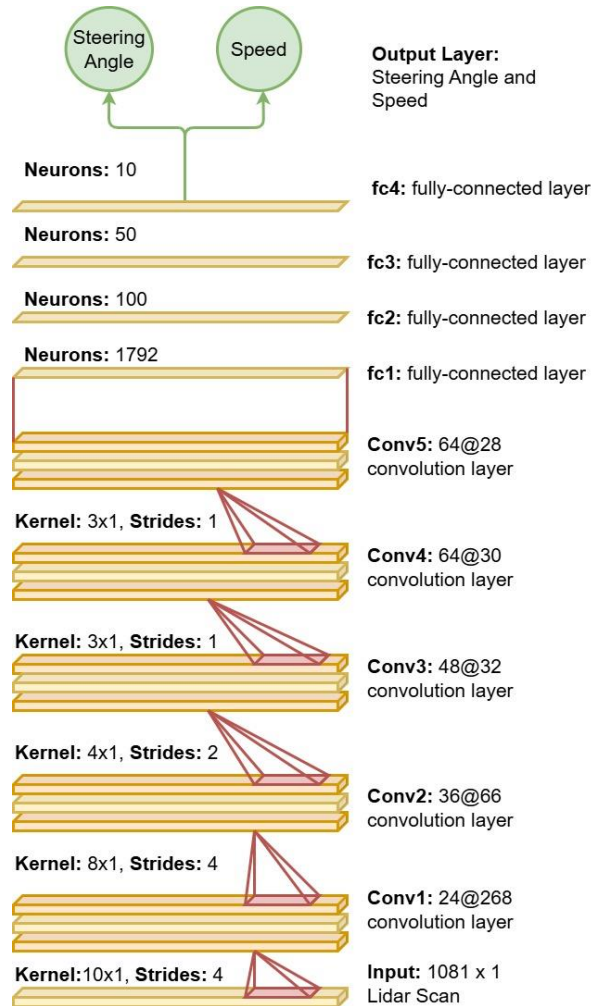
9 layers (5 conv, 4 fc), ~250K weights

TinyLidarNet

- 2D LiDAR-based end-to-end CNN model for F1TENTH racing
- Inspired by PilotNet, but
- Takes **2D LiDAR scan** as input instead of camera image
- Uses **1D convolutional filters** for feature extraction
- Low computational cost (**1/18 of the PilotNet**)

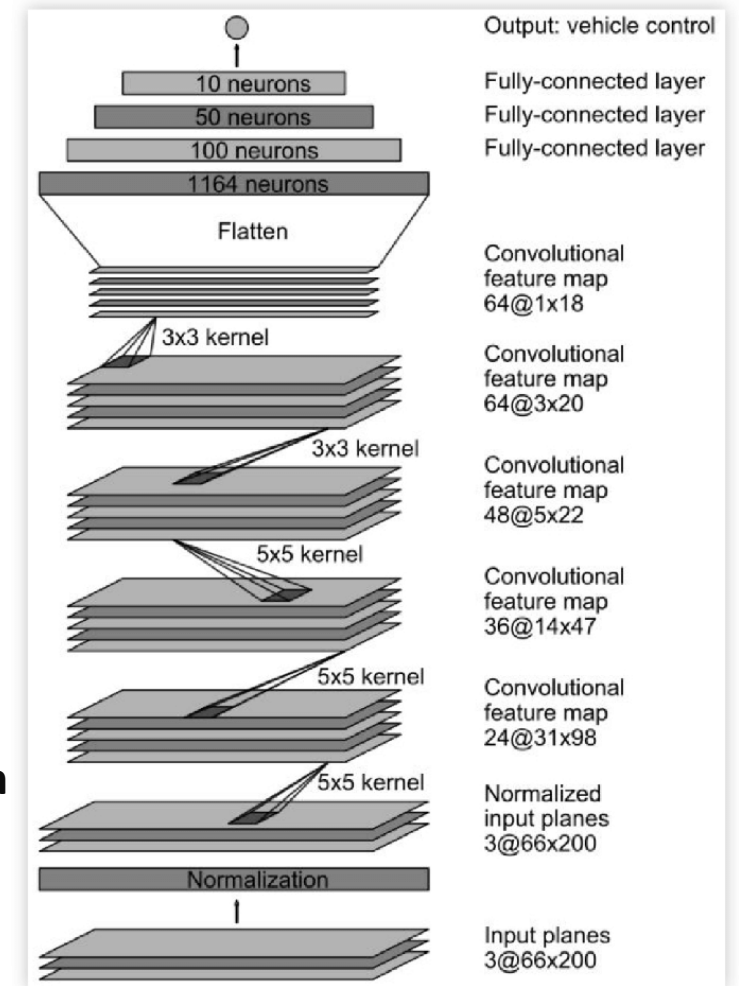


TinyLidarNet



Parameters: 220,686
MACs: 1.5 million

PilotNet



Parameters: 252,219
MACs: 26.9 million

12th F1TENTH Grand Prix: Results and Insights

- Competitive performance
 - **3rd Place** out of 13 teams
- Overtaking capability
 - Can overtake other vehicles
 - Without having seen such scenarios in training
- Generalizability
 - Robust under frequent alterations of tracks due to collisions



Experimental Setup



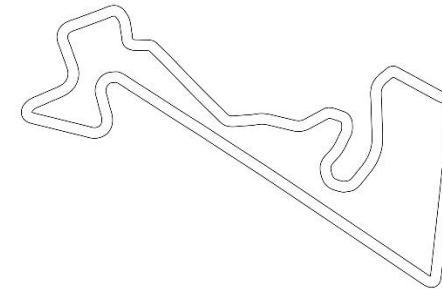
12th F1tenth Racetrack

Training

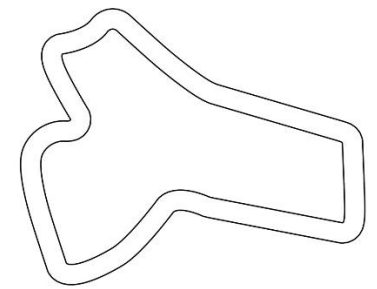
Testing



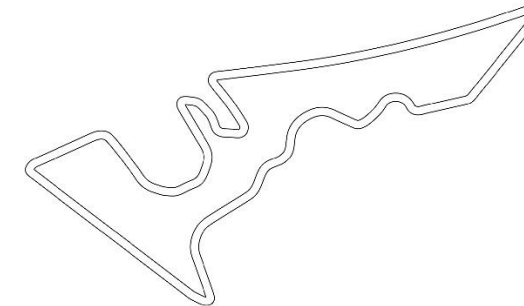
Real World Racetrack



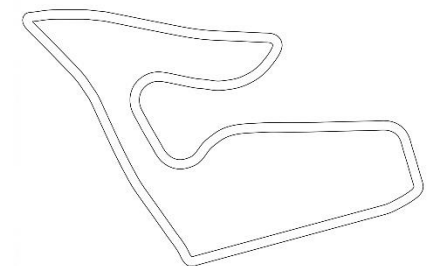
Moscow Raceway Track (MOS)



F1tenth GYM Track (GYM)



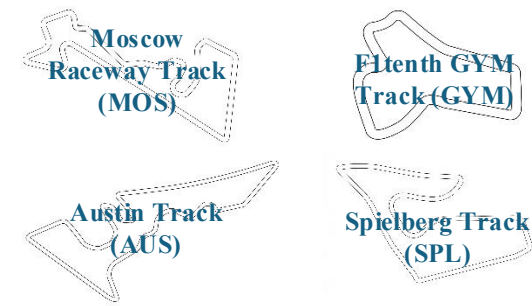
Austin Track (AUS)



Spielberg Track (SPL)

1. M. O'Kelly et al. "F1tenth: An open-source evaluation environment for continuous control and reinforcement learning," in NeurIPS 2019
2. J. Betz et al. "Autonomous vehicles on the edge: A survey on autonomous vehicle racing," IEEE Open J. Intell. Transp. Syst, 2022

Simulated Track Performance



	Average Lap Time (s)				Average Progress (%)			
Model	GYM	AUS	MOS	SPL	GYM	AUS	MOS	SPL
TinyLidarNet ^L	25.8	85.7	63.3	65.3	100	100	100	100
TinyLidarNet ^M	25.3	80	59.5	61.5	100	100	100	100
TinyLidarNet ^S	26.9	83.4	61.8	64.1	100	100	100	100
MLP256 ^L [1]	N/A	N/A	58.8	58.3	31	16	42	61
MLP256 ^M	28.4	N/A	64.3	65.7	100	17	58	78
MLP256 ^S	27.6	N/A	N/A	62.2	77	48	29	37

1. X. Sun et al., "A benchmark comparison of imitation learning-based control policies for autonomous racing" (2023 IEEE Intelligent Vehicles Symposium)
2. B. D. Evans, et al. "Unifying f1tenth autonomous racing: Survey, methods and benchmarks," (arXIV 2024).

Inference Latency

Platform	CPU	Memory	Storage
Xavier NX	NVIDIA Carmel 6C @ 1.9 GHz	8GB LPDDR4x	16GB eMMC
ESP32-S3	Xtensa LX7 2C @ 240 MHz	8MB PSRAM	8MB Flash
RPi Pico	ARM Cortex-M0+ 2C @ 133 MHz	264KB SRAM	2MB Flash

Model	Xavier NX (ms)	ESP32-S3 (ms)	RPi Pico (ms)
TinyLidarNet ^L (fp32)	<1	838	2642
TinyLidarNet ^L (int8)	<1	16	196
TinyLidarNet ^M (int8)	<1	8	91
TinyLidarNet ^S (int8)	<1	4	36

Inference latency (ms) comparison on different computing platforms

Conclusion

- **TinyLidarNet:** Lightweight 2D LiDAR-based end-to-end model for F1TENTH racing.
- **1D CNN Filters:** Effectively processes 2D LiDAR scans, outperforming state-of-the-art MLP models.
- **Generalizability:** Good performance on *unseen* simulated and real-world tracks.
- **Low computing cost:** Can run on low-cost microcontrollers (MCUs) and achieve real-time performance
- **Future Research:** Improvements in training data and model architecture.

Thank You!

