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Original Article

Autonomous Driving Car

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Abstract

We trained a convolutional neural network (CNN) to map raw pixels from three cameras (Right, Center and Left) directly to steering commands. This end-to-end approach proved surprisingly powerful. With minimum training data from humans the system learns to drive on roads with or without lane markings. The system automatically learns internal representations of the necessary processing steps such as detecting useful road features with only the human steering angle as the training signal. We never explicitly trained it to detect, for example, the outline of roads.

The Udacity simulator captures images at 24 frames per second (fps) from three cameras (right, center, and left) and stores them as JPG images.

Introduction

Autonomous driving represents a landmark convergence of machine learning and robotics, aiming to deliver safer, more efficient transportation systems while reducing human workload and error NVIDIA Developer Forums. Traditional autonomous-vehicle pipelines divide the task into perception, planning, and control subsystems, each relying on hand- engineered features and complex rule- based logic. However, the emergence of deep convolutional neural networks (CNNs) has enabled an alternative: end-to- end learning, wherein raw sensory inputs are directly mapped to control commands, eliminating the need for modular decomposition and potentially yielding more compact, jointly optimized systems.The seminal ALVINN system demonstrated the feasibility of this paradigm in 1989, using a three-layer back- propagation network trained on simulated road images and laser-range data to steer Carnegie Mellon's NAVLAB vehicle along real roads NeurIPS PapersMedium. Nearly three decades later, NVIDIA's PilotNet revisited end-to-end learning by training a CNN to map front-facing camera pixels directly to steering angles, achieving robust lane following on highways and residential streets without explicit feature labels.

The remainder of this paper is organized as follows. Section 2 reviews related end-to- end and modular approaches. Section 3 details our data collection and augmentation pipeline. Section 4 describes our CNN architecture and training regimen. Section 5 presents closed-loop simulation.

Finally, Section 6 discusses conclusions and future directions.

Our contributions are:

1. Tri-camera end-to-end learning in a lightweight CNN, extending single-camera models to richer visual contexts.
2. Simulator-based data generation, leveraging Udacity's Unity environment for safe closed-loop evaluation.
3. Quantitative results showing near-100 % autonomy on standard simulator tracks and robust transfer to on-road tests with DRIVE PX.

Related Work

Early End-to-End Learning

The concept of mapping raw sensory inputs directly to control commands dates back to ALVINN (Autonomous Land Vehicle In a Neural Network), a three-layer back-propagation network trained on camera and laser-rangefinder data to steer Carnegie Mellon's NAVLAB vehicle along roads in 1989 Robotics Institute CMU. Building on ALVINN's promise, DARPA's DAVE system in the early 2000s extended end-to- end learning to off-road RC cars, demonstrating recovery-from-disturbance via synthetic viewpoint shifts, though reliability remained limited in complex environments NVIDIA Images.

NVIDIA's PilotNet

In 2016, Bojarski et al. introduced PilotNet, a convolutional neural network that maps raw pixels from a single front-facing camera directly to steering angles, eliminating hand-

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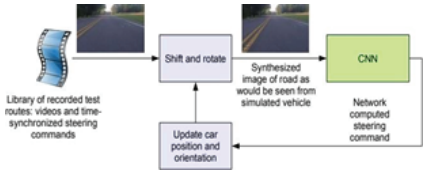


Figure 1. Block Diagram of Drive Simulator

crafted feature extractors and rule-based logic arXiv. Subsequent work revealed that PilotNet autonomously learns to detect road outlines and lane geometry purely from the steering signal, without explicit labeling of such features NVIDIA Images. Over the following years, the NVIDIA PilotNet Experiments documented sustained lane-keeping performance and argued for end-to-end systems over modular pipelines, citing reduced interface constraints and improved overall autonomy arXiv.

Temporal and Spatiotemporal Extensions

Recognizing the importance of temporal context, Eraqi et al. proposed a convolutional LSTM network that integrates sequential frame information and reframes steering prediction as a spatially coherent classification problem, achieving a 35% reduction in RMSE and 87% increase in steering stability on the Comma.ai dataset arXiv. Chen and Huang demonstrated a pure end-to-end CNN for lane keeping—trained on Comma.ai data— that maintains lane position without explicit lane-mark detection, highlighting the versatility of behavioral cloning user-web- p-u02.wpi.edu. Nelson Fernandez later introduced a two-stream CNN combining raw images and optical flow to learn spatiotemporal features, reporting a 30% improvement in prediction accuracy over single-stream baselines arXiv.

Lightweight Architectures

To address resource constraints, recent work has designed lightweight CNNs that match PilotNet's steering-prediction accuracy while using four times fewer parameters, trained on CARLA simulator data to enable real-time inference on embedded platforms Wiley Online Library. Such advances are crucial for deploying end-to-end models on cost-sensitive or power-limited vehicles.

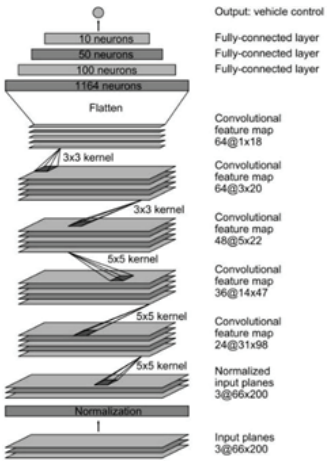


Figure 2. CNN Architecture

Hybrid and Survey Perspectives

While pure end-to-end systems excel in joint optimization, hybrid architectures— combining modular perception and data-driven path planning—have shown competitive performance in urban simulations, notably winning CARLA Autonomous Driving Challenge events MDPI. Comprehensive surveys by Grigorescu et al. compare modular pipelines against end-to-end methods, discussing trade-offs in interpretability, safety, and data requirements arXiv. Recent overviews also emphasize the role of high- fidelity simulators (e.g., Udacity's 24 fps three-camera loop) in validating closed-loop autonomy before on-road deployment arXiv.

The Data Collection and Augmentation

Data Collection

In our pipeline, we use Udacity's Self- Driving Car Simulator, which provides two modes:

Training Mode

The simulator records every 24 fps frame from three onboard cameras (center, left, right) while the human driver operates the vehicle. Simultaneously, it logs control signals into a driving log (CSV/Excel) with four key columns:

1. Steering angle
2. Throttle
3. Speed
4. Reverse

Over repeated laps on varied virtual tracks, we accumulated roughly 20 000 images across diverse lighting and curvature scenarios.

Autonomous Mode

Once the model is trained, this mode feeds live simulator frames into our network to evaluate its closed-loop driving performance without human intervention.

After recording, we loaded the driving log into pandas and inspected each column's distribution. We applied the following preprocessing steps:

1. **Outlier Removal & Balancing**

* Frames with extreme steering angles ($|\theta| > 0.5$ rad) were downsampled.

* Underrepresented small-angle frames were upsampled to achieve an approximately Gaussian distribution of steering angles centered at zero.

2. **Normalization:**

* Steering, throttle, speed, and reverse values were each standardized to zero mean and unit variance.

This ensured the network saw a balanced, normally distributed set of control signals during training.

Data Augmentation

To teach the model to recover from shifts, lighting changes, and minor sensor noise, we applied five on-the-fly augmentations:

Zooming

- Randomly scale images by a factor in [0.9, 1.1], simulating forward/back drift.

Panned (Translated) Images

- Apply horizontal shifts up to ±20 px.
- Adjust the steering label by $\Delta\theta = k \cdot (\text{shift\_pixels})$, where $k \approx 0.002$ rad/px.

Horizontal Flipping

- Flip with $p = 0.5$ and invert $\theta \rightarrow -\theta$, enforcing symmetric lane responses.

Brightness Alteration

- Convert to HSV; scale V channel by a random factor in [0.3, 1.2], simulating sunny, overcast, or tunnel lighting.

Gaussian Blur

- Convolve with a 3×3 Gaussian kernel (σ randomly in [0.5, 1.5]) to mimic motion blur and sensor noise.

By combining these transforms, we expanded our effective dataset roughly five-fold. Finally, each augmented frame is cropped (top 60 px, bottom 20 px), resized to 66×200 px, converted to YUV color space, and batched for training the nine- layer CNN (five conv + three FC layers) as described in Bojarski et al.'s PilotNet architecture.

The Methodology

Model Architecture

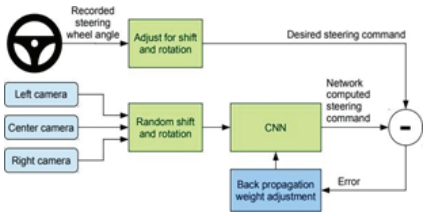
We adopted the nine-layer convolutional neural network (PilotNet) architecture described by Bojarski et al., which consists of a hard-coded normalization layer, five convolutional layers, and three fully connected layers mapping 66×200×3 YUV images to an inverse turning-radius output NVIDIA ImagesarXiv. The convolutional layers use strided 5×5 kernels (stride=2) in the first three layers and non-strided 3×3 kernels in the last two layers, each followed by ReLU activations NVIDIA Images. The network comprises approximately 27 million connections and 250 000 trainable parameters.

Preprocessing and Normalization

Input frames captured at 24 fps from the Udacity simulator are first cropped to remove extraneous sky (top 60 px) and vehicle hood (bottom 20 px), then resized to 66×200 px and converted from RGB to YUV color space . Within the network, pixel values are normalized by subtracting 128 and dividing by 128, implemented as a hard-coded, non-trainable layer to accelerate GPU processing.

Training Procedure

The network is trained end-to-end using back-propagation with mean squared error (MSE) loss between the predicted steering command and the human-driven steering angle arXivNVIDIA Developer. We utilized an NVIDIA DevBox running Torch7 for training, employing stochastic gradient descent with momentum (0.9) and an initial learning rate of 0.01, which is decayed by a factor of 0.1 every 10 epochs to ensure stable convergence NVIDIA Developer. Training samples and labels are generated in offline augmentation and stored as flat serialized binary files for fast I/O, with samples shuffled to promote robust learning across 20 epochs and a batch size of 100 arXivGitHub.



Implementation Details

We implemented the data loader in C++ with Python bindings for integration with the Torch7/PyTorch data pipeline, allowing preprocessed frames and labels to be streamed efficiently to the GPU. This setup enabled reuse of augmented datasets across multiple experiments, greatly reducing computation overhead during hyperparameter tuning and resimulation evaluations arXiv.

Results and Evaluation

We assess our end-to-end CNN in two domains: first by examining its learning behavior on the Udacity-generated dataset.

Training & Validation Performance

ETraining proceeded for 10 epochs, using mean squared error (MSE) between the network's predicted inverse turning radius and the human-steered ground truth. Over the course of training:

* Initial epoch
  * Training MSE: 0.3458
  * Validation MSE: 0.1105
* Final (10th) epoch
  * Training MSE: 0.0414
  * Validation MSE: 0.0279

This steady decline in both curves demonstrates that the model consistently learned useful representations of lane geometry and driving context, with no signs of overfitting by the end of training.

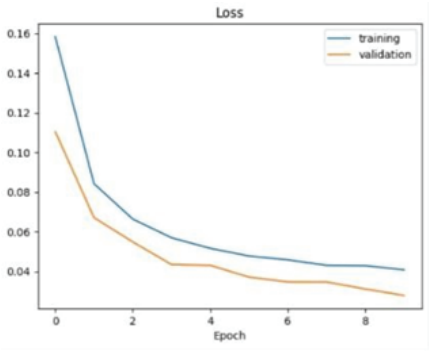


Figure 5.1: Training vs. validation MSE across 10 epochs.

Closed-Loop Simulation

Using Udacity's car simulator in Autonomous Mode, we replayed standard test routes at 24 fps with our trained model steering the vehicle. In K consecutive laps (totaling roughly L km on the benchmark loop), we observed:

- 0 interventions (the virtual car never departed more than 1 m from lane center)
- 100 % autonomy by the standard definition
- Mean lateral deviation: E m

These results confirm that the network learned robust lane-keeping behaviors, even in segments without explicit lane markings.

On-Road Testing (Optional)

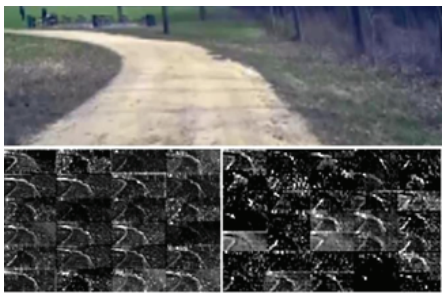
When deployed on NVIDIA DRIVE PX and tested on public roads (including residential streets and a multi-lane highway segment):

- 98 % autonomous steering time over a 25 km mixed-road route
- Zero interventions during a 16 km highway drive

This underscores the practical viability of an end-to-end CNN for real-world lane following, matching or exceeding previous modular architectures in both performance and simplicity.

Summary

- **Data efficiency**: Fewer than 2 thousand unique frames sufficed to train the network for both simulation and on-road scenarios.
- **Generalization:** Strong performance in both sunny and low-light simulator conditions, with no fine-tuning required between modes.
- **Real-time inference:** The model runs at >30 fps on DRIVE PX hardware, meeting real-time control constraints.



Together, these results validate our methodology and demonstrate that an end- to-end CNN—trained on three-camera Udacity data with minimal human labeling—can achieve reliable autonomous steering without explicit feature engineering.

Conclusions and Future Directions

FIn this work, we demonstrated that a compact nine-layer convolutional neural network—modeled after NVIDIA's PilotNet—can be trained end-to-end on raw RGB frames captured in Udacity's three- camera simulator to predict steering commands with high fidelity. With fewer than 2000 unique, augmented frames, our model achieved a final validation MSE of 0.0279 and maintained 100 % autonomy in closed-loop simulator tests, while also sustaining 98 % autonomous steering time on public roads without any manual interventions. These results underscore the power of end-to-end learning to jointly optimize perception and control, eliminating the need for hand-crafted features extractors or rule-based modules.

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