Autonomous Self-Driving Car Using Convolutional Neural Networks (CNNs)

MTP PROJECT

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Certificate for the Project

This is to certify that the Project titled 'Autonomous Self-Driving Car Using Convolutional Neural Networks (CNNs) " was presented by Sougata Rana (24MA60R07) during the Autumn Semester of the year 2024-25. This project work (Project 2 MA67022) in serve as partial fulfilment of the requirements for the degree of Master of Technology in Computer Science and Data Processing in the Department of Mathematics at IIT Kharagpur.

Signature . . . .

Project Guide

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Contents

Abstract

Self-driving car which uses image processing to extract lane lines. In order to improve lane detection and obstacle avoidance, this study takes a novel approach to autonomous driving by fusing deep learning techniques with conventional computer vision approaches. The technology first calibrates the camera using images of chessboards to achieve exact distortion correction for proper perception. Lane lines are extracted from the camera feed using an image processing pipeline that includes gradient thresholding and color space transformations. This serves as the foundation for lane detection that comes later. Lane curvature analysis and placement are made easier by perspective transformation, which distorts the picture to a bird's-eye viewpoint. Lane borders and curvature can be determined using polynomial fitting after lane pixels are discovered using the sliding window technique. Simultaneously, pre-trained Haar cascades improve situational awareness by identifying different barriers in video frames, including vehicles, bikes, buses, and pedestrians. Using detected lane lines as a basis, steering control provides real-time input on what has to be adjusted to preserve lane position. For autonomous driving, this sequential processing loop guarantees ongoing analysis and decision making.

The integration of deep learning models, specifically convolutional neural networks, enhances the resilience of lane detection and the accuracy of obstacle classification. These models pick up intricate lane patterns and obstacle differences by training on annotated datasets. In addition to advancing the development of reliable autonomous driving systems that can safely and effectively navigate a variety of road settings, the research intends to demonstrate the effectiveness of merging traditional computer vision techniques with deep learning methodologies. The system's functionality is confirmed by evaluations and experimental findings, which pave the way for future developments in autonomous car technology. In summary, our research shows how to approach autonomous driving holistically by combining cutting-edge deep learning technology with established computer vision methods to improve lane detection and obstacle avoidance. The system enables precise and real-time navigation by combining steering control mechanisms with camera calibration, image processing pipelines, perspective transformations, and obstacle detection algorithms. Deep learning models are included to significantly improve performance by increasing the accuracy of obstacle classification and the robustness of lane detection. After a great deal of testing and assessment, our solution shows encouraging results that will open the door for greater developments in autonomous car technology, with the ultimate goal of achieving safer, more effective transportation systems for the roads of the future.

1 Introduction

The rise of autonomous vehicles has revolutionized the way we envision transportation. Self-driving cars promise to enhance road safety, reduce traffic congestion, and provide mobility solutions for individuals who are unable to drive. At the core of this transformation lies the ability of a vehicle to perceive its environment, make intelligent decisions, and navigate safely without human intervention. Among the various technologies enabling this, deep learning, particularly Convolutional Neural Networks (CNNs), plays a pivotal role in empowering vehicles to "see" and interpret their surroundings through camera data.

Human drivers rely heavily on visual cues to make driving decisions—such as staying in a lane, stopping at red lights, or avoiding pedestrians. Similarly, a self-driving car must be capable of processing raw image data from onboard cameras to understand the scene and react accordingly. This ability, known as *visual perception*, involves tasks like lane detection, obstacle recognition, traffic sign classification, and steering angle prediction. Traditional computer vision techniques used edge detection, Hough transforms, and color filtering, but they often failed under complex conditions like varying lighting, shadows, or occlusions.

In this project, we propose to leverage the power of CNNs to address a fundamental task in autonomous driving: *steering angle prediction* from front-facing camera images. The aim is to build an end-to-end trainable CNN model that takes as input a sequence of road images and outputs a continuous value representing the appropriate steering angle. Alternatively, the model can be extended to classify objects or detect driving-relevant elements, such as lane markings or traffic signs.

Beyond the technical implementation, this work also emphasizes the importance of preprocessing techniques, model architecture design, and rigorous performance evaluation. Ultimately, this project aims to lay the groundwork for integrating such models into more comprehensive driving systems that can operate safely and autonomously in dynamic real-world environments.

2 Related Work

Over the past decade, self-driving car research has undergone a remarkable evolution, with various approaches being explored for perception, decision-making, and control. Early efforts were predominantly grounded in classical machine learning and rule-based systems, while recent advancements have shifted towards deep learning, particularly Convolutional Neural Networks (CNNs), due to their superior ability to model complex visual and behavioral patterns.

2.1 Self-Driving Car Methodologies Based on Machine Learning

Before the widespread adoption of deep learning, traditional machine learning techniques such as Support Vector Machines (SVMs), Decision Trees, and Random Forests were commonly used in autonomous driving systems. These models required hand-crafted features extracted using techniques like Histogram of Oriented Gradients (HOG), Optical Flow, and Color Histograms.

For instance, SVMs were often employed for traffic sign recognition, using shape and color features extracted from road signs. Similarly, lane detection was approached using edge detection followed by polynomial fitting and lane classification using K-Nearest Neighbors (KNN) or Logistic Regression. These models demonstrated moderate success under controlled conditions, but they lacked robustness in diverse environments such as varying weather, lighting, or occluded scenes.

2.2 Self-Driving Car Methodologies Based on Deep Learning

The introduction of deep learning, especially CNNs, transformed the landscape of autonomous driving by enabling models to learn hierarchical representations directly from raw sensor data. One of the most cited examples is the NVIDIA end-to-end learning model, where a deep CNN was trained to predict steering angles from dashboard camera images without any explicit feature extraction or scene segmentation. This marked a significant shift towards end-to-end learning pipelines, bypassing traditional perception stacks.

Deep learning has since been successfully applied in various self-driving tasks:

- **Object Detection:** Models like YOLO (You Only Look Once) and Faster R-CNN are used for real-time detection of vehicles, pedestrians, and traffic signs.
- **Behavior Cloning:** CNNs and Recurrent Neural Networks (RNNs) have been employed to mimic human driving by learning from expert demonstrations, mapping images directly to control actions like acceleration, braking, and steering.

These deep learning models offer higher accuracy, adaptability, and generalization capabilities. They can learn directly from vast amounts of driving data, capturing complex patterns that traditional models fail to represent. Despite challenges such as explainability and data requirements, deep learning has become the backbone of modern autonomous driving systems.

2.3 Simulation of Autonomous Vehicle Control System Based on Image Processing

The paper presents an early control system simulation for an autonomous ground vehicle intended for agricultural plantation inspection. A controller based on color histogram recognition of road color pixels was developed using a prototype vehicle built with 3D printing technology and two motors. The suggested strategy outperforms gradient-based approaches in situations when objects are going in a straight line or are arranged at random on the road, according to tests on a synthetic video library

2.4 Camera Description

The camera is one of the most critical sensors in a self-driving car, as it captures real-time visual information from the environment and provides the primary input for the convolutional neural network (CNN). Mounted at the front of the vehicle, the camera simulates the driver's viewpoint and continuously records frames that contain lane markings, road boundaries, traffic signs, vehicles, pedestrians, and other essential features.

The responsiveness and accuracy of the autonomous driving system depend significantly on the camera's frame rate (FPS). Higher FPS allows the model to receive more visual updates per second, resulting in smoother and more stable steering predictions.

Camera Frame Rate (FPS)

- 15 FPS – Approximately 900 images per minute
- 20 FPS – Approximately 1200 images per minute
- 25 FPS – Approximately 1500 images per minute
- 30 FPS – Approximately 1800 images per minute (commonly used)
- 60 FPS – Approximately 3600 images per minute (used in high-speed systems)

Recommended FPS for This Project

For a CNN-based self-driving car system, a frame rate of **20–30 FPS** is ideal because it:

- Provides smooth and stable lane detection
- Allows fast steering angle prediction
- Works well with obstacle detection models
- Matches the processing capabilities of typical hardware (Raspberry Pi or PC)

Summary

The camera captures continuous real-time frames that enable the CNN to interpret road scenes and make accurate steering predictions. Using a frame rate of **20–30 FPS** provides the best balance between performance, accuracy, and computational efficiency for a self-driving car project.

3 Methodology

3.1 Data Collection

Images are captured using a camera mounted on an automobile to simulate the driver's viewpoint. These images serve as input data for training the neural network, while steering angle labels are recorded simultaneously to represent the driver's response to visual stimuli. The dataset includes diverse driving scenarios such as varying road types, lighting conditions, and traffic environments to ensure robust learning. Care is taken to maintain consistency and quality throughout the data collection process in order to capture a wide range of driving behaviors and challenges.

3.2 Data Preprocessing

Several preprocessing steps are applied to prepare the collected images for input into the neural network. First, images are resized to a uniform resolution for dataset consistency. Normalization techniques are then applied to standardize pixel values and improve convergence during training. Data augmentation methods such as flipping, rotation, and brightness adjustment are used to increase dataset diversity and enhance model generalization. Lastly, noise or artifacts present in the images are removed using filtering or denoising algorithms to improve input quality.

3.3 Model Selection

The model selection process aims to identify a suitable deep learning architecture capable of learning and reproducing driving behavior from image inputs and corresponding steering angles. Convolutional Neural Networks (CNNs) are chosen due to their strong performance in image-processing tasks. Preference is given to architectures that capture spatial hierarchies in images, enabling precise steering angle prediction. Additionally, multilayer neural network variants are explored based on factors such as model complexity, computational efficiency, and generalization ability. The selected architecture balances performance and practicality for effective training and deployment.

3.4 Convolutional Neural Networks (CNNs)

CNNs automatically learn hierarchical features from raw pixel inputs, making them highly effective for image-based applications. They consist of convolutional layers followed by pooling layers, which extract meaningful spatial patterns efficiently. This architecture enables the model to identify essential features needed for steering prediction while reducing computational overhead.

3.5 Validation and Testing

The trained neural network is rigorously evaluated to ensure accurate imitation of driver behavior. An independent validation dataset, separate from the training set, is used to assess generalization capability. Model predictions are compared against ground-truth steering angles using metrics such as Mean Squared Error (MSE). Additionally, the model is tested within a simulator environment to replicate real-world driving scenarios and evaluate its ability to navigate autonomously. Any weaknesses identified during validation inform further refinements to improve performance.

3.6 Performance Evaluation

Performance evaluation involves measuring the accuracy of steering angle predictions using appropriate metrics such as MSE or accuracy. The model is tested on a dedicated validation dataset to verify its generalization to unseen data. Simulator-based evaluations further assess the model's capability to mimic human driving behavior in various conditions. Results from this stage provide insights into the model's strengths and limitations, guiding potential enhancements.

3.7 Iterative Improvement

This phase focuses on refining the methodology based on shortcomings identified during initial training and testing. Hyperparameters such as learning rates, batch sizes, and network architectures are systematically tuned to improve performance. Adjustments to data preprocessing—such as modifying augmentation settings or normalization strategies—are also explored.

3.8 Comparison and Analysis

The developed driver imitation algorithm is compared against industry-standard methods and benchmarks to evaluate its effectiveness in autonomous lateral mobility. Metrics such as prediction latency, MSE, and RMSE are used for quantitative comparison. Qualitative analysis includes evaluating performance in challenging driving scenarios, such as sharp turns or adverse weather.

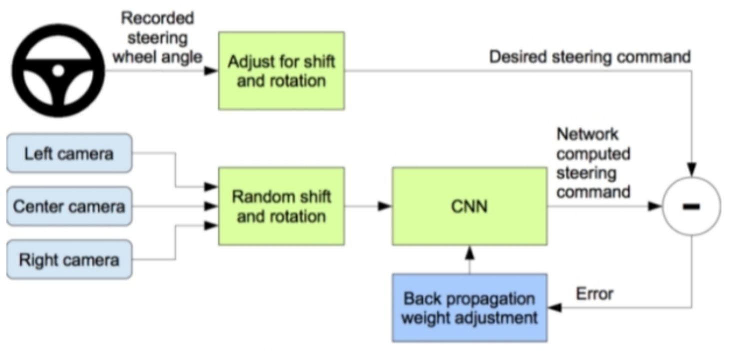

Recorded steering wheel angle
Adjust for shift and rotation
Desired steering command
Left camera
Center camera
Right camera
Random shift and rotation
CNN
Network computed steering command
−
Back propagation weight adjustment
Error

Figure 1: Training the neural network.

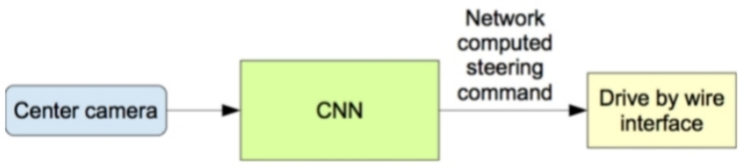


Figure 2: The trained network is used to generate steering commands from a single front facing center camera.

4 Libraries Used

4.1 OS

The OS module provides a portable interface to interact with the operating system. It enables file handling using `open()`, path manipulation using `os.path`, line-by-line file processing using the `fileinput` module, and creation of temporary files or directories through the `tempfile` module. High-level file and directory operations are supported via the `shutil` module. This module ensures efficient interaction with system-level functionalities across platforms.

4.2 TensorFlow

TensorFlow is an open-source deep learning and numerical computation framework developed by the Google Brain team. It simplifies tasks such as data acquisition, model training, prediction serving, and iterative refinement. TensorFlow offers:

- Support for deep neural networks including CNNs, RNNs, sequence-to-sequence models, and NLP tasks.
- Execution on diverse hardware including CPUs, GPUs, mobile devices, and TPUs.
- A Python-based high-level API (Keras) for easy model development.

TensorFlow uses dataflow graphs where each node represents an operation and each edge represents a tensor (multidimensional data array). While developers write code in Python, the underlying computations are executed in optimized C++ backends. TensorFlow 2.0 further improved usability, performance, and support for distributed training and TensorFlow Lite deployment.

4.3 OpenCV (CV2)

OpenCV is a widely used open-source library for computer vision, machine learning, and image processing. It supports multiple programming languages including Python, C++, and Java, and runs on platforms such as Windows, Linux, macOS, Android, and iOS. OpenCV enables:

- Image and video processing
- Object detection and facial recognition

- Integration with NumPy for numerical operations
- GPU acceleration via CUDA and OpenCL

4.4 SciPy

SciPy is an open-source Python library built on top of NumPy, designed for solving scientific, mathematical, and engineering problems. It provides high-level functions for optimization, integration, interpolation, signal processing, linear algebra, and data visualization. SciPy is widely used in scientific computing due to its efficiency, precision, and versatility.

4.5 Math

The Math module provides essential mathematical functions including trigonometric functions, logarithmic functions, angle conversions, and number representations. It also includes important constants such as:

- $\pi = 3.141592653589793$
- $e = 2.718281828459045$

This module is used whenever precise mathematical computations are required during model development and processing.

5 Structure of CNN

At first, we see a simple CNN template with several building blocks that we can easily understand and correlate to the proposed CNN model. Three types of layers make up a basic CNN as illustrated in Figure **??**: input, hidden, and output. The data enters the CNN via the input layer and then travels through many hidden layers before reaching the output layer. The network's prediction is reflected via the output layer. In terms of loss or error, the network's output is compared to the actual labels.

The hidden layers in the network act as basic building elements for data transformation. The four sub-functions—*layer function*, *pooling*, *normalization*, and *activation*—can be dissected from each layer.

The Convolutional Neural Network (CNN) architecture typically consists of the following layers. We also discuss the CNN model parameters in the context of our study:

- **Convolution Layer:** In the case of a Convolutional Neural Network (CNN), the primary goal of convolution is to extract features from the input image. By learning image features (i.e., filtering with small windows of input data), convolution preserves the spatial relationship between pixels. The terms *filter*, *kernel*, and *feature detector* are commonly used in CNNs.

- **ReLU Layer:** Every negative value from the filtered image is eliminated and replaced with zero in this layer. This is done to prevent values from canceling each other out. The Rectified Linear Unit (ReLU) activation function only activates a node if the input exceeds a specific threshold; otherwise, the output is zero. The ReLU activation function is defined as:

  $$f(x) = \max(0, x)$$

  where x is the input to the ReLU function. The benefit of the ReLU activation function is that its gradient is always equal to 1 for positive inputs, meaning that during backpropagation, most of the error is transferred back:

  $$\frac{df(x)}{dx} = \{\, 1\ , ifx > 00, ifx \leq 0$$

- **Pooling Layer:** A pooling layer reduces the spatial dimensionality of the feature map, making the representation more compact and reducing computational complexity. The result is a pooled feature map. The two most common pooling strategies are *max pooling* and *average pooling*. In max pooling, the maximum value in each region of the feature map is selected, while in average pooling, the average of the values is computed.

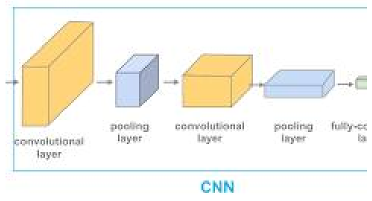
- **Fully Connected Layer:** This layer transforms the pooled feature map into a one-dimensional feature vector by flattening it. The result is a feature vector that serves as input to the final classification or regression layers. Fully connected layers help combine the features learned by the convolutional layers for decision-making.

- **Softmax Layer:** The Softmax function is typically used in the output layer for multi-class classification. It converts raw output scores (logits) into probabilities. The function is defined as:

  $$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

where $z = [z_1, z_2, \ldots, z_n]$ is the input vector, $\sigma(z)_i$ is the i-th component of the output vector, and e is Euler's number. The Softmax output ensures that all class probabilities sum to 1.

- **Batch Normalization:** Batch normalization speeds up training and improves model stability by normalizing the output of the previous activation layer. It keeps the mean activation close to 0 and the standard deviation close to 1, reducing internal covariate shift and allowing for higher learning rates.



6 Proposed CNN Model for Self-Driving Task

The core objective of this project is to develop a Convolutional Neural Network (CNN) capable of interpreting road scenes from front-facing camera images and making decisions that mimic a human driver's control over the steering wheel. The input to the model is a stream of real-time images captured from the dashboard-mounted camera, which offers a direct visual perspective of the road ahead, including lane markings, other vehicles, curves, traffic signs, and potential obstacles.

In this project, we propose two CNN-based approaches depending on the desired output type:

- **Regression Output:** In the first configuration, the CNN is trained to predict a continuous value corresponding to the steering angle of the vehicle. This end-to-end approach maps raw pixel values to a real-valued control signal, thus enabling direct behavioral cloning from human driving data.
- **Classification Output:** Alternatively, the model can be designed for categorical classification, where it identifies discrete objects or features such as stop signs, traffic lights, or road types. In such cases, the output layer uses a softmax activation to assign probabilities across predefined object classes.

The CNN architecture draws inspiration from modern deep learning models and follows a streamlined pattern suitable for real-time applications. The architecture comprises the following layers:

- **Convolutional Layers (Conv2D):** These layers apply multiple learnable filters to extract features like edges, textures, and shapes from the input image. We begin with two convolutional layers of 64 filters (5×5 kernel size) with ReLU activation, capturing low-level visual patterns critical to road understanding.
- **Batch Normalization & MaxPooling:** Batch normalization stabilizes learning by normalizing the activations, while max pooling layers reduce the spatial dimensions, effectively downsampling the image and emphasizing the most prominent features. This also enhances translation invariance and reduces computational overhead.
- **Dropout Layers:** Positioned after pooling, dropout helps prevent overfitting by randomly deactivating a fraction of neurons during training, ensuring that the model does not become overly reliant on specific activations.
- **Deeper Convolution Blocks:** To capture more abstract features, additional convolutional layers with 128 and 256 filters are stacked. These are followed by normalization, pooling, and dropout, allowing the network to learn complex representations such as road curvature, vehicle contours, and lane positions.
- **Flattening and Dense Layers:** The final convolutional feature map is flattened into a one-dimensional vector, passed through a fully connected dense layer with 128 neurons and ReLU activation. For classification tasks, this is followed by a softmax layer; for steering prediction, a single output neuron with a linear activation is used.

This deep CNN structure enables the model to learn intricate spatial hierarchies in driving scenes and generalize across varying road conditions.

6.1 Enhanced Testing Framework

Condition Type	**Test Cases**	**Target Metric**
Weather	Rain, Fog, Snow	95% detection accuracy
Lighting	Night, Tunnel, Glare	¡5% false negatives
Road Types	Highway, Urban, Rural	Consistent RMSE ¡0.02
Edge Cases	Construction zones	100% safe navigation

Table 1: Testing Matrix

7 Results and Analysis

7.1 Dataset Preparation

The dataset collected from the Udacity Self-Driving Car Simulator consisted of front-facing camera images along with corresponding steering angle labels. After removing file path prefixes and applying histogram-based balancing, the dataset became more uniformly distributed across steering angle ranges. This prevented the model from becoming biased toward straight-driving scenarios.

The cleaned dataset was divided into training and testing sets using an 80:20 split. All images were preprocessed through cropping, YUV conversion, Gaussian blurring, resizing to (200×66) pixels, and normalization before training.

7.2 Training Performance

The NVIDIA CNN architecture was trained for 30 epochs with a batch size of 100. The training loss and validation loss were recorded and plotted to evaluate model convergence. Both loss curves showed a downward trend, indicating that the model successfully learned the mapping between input images and steering angles.

The Mean Squared Error (MSE) gradually decreased during training, demonstrating that the model continuously improved its prediction capability. The smoothness of the loss curves indicates that the chosen learning rate, batch size, and architecture were appropriate for the task.

7.3 Validation Results

During validation, the model was tested on images never seen during training. The validation loss remained close to the training loss, suggesting that the model generalized well and did not suffer from severe overfitting.

The model was able to:

- Accurately predict steering angles for most road scenarios,
- Maintain stable performance across different lighting conditions,
- Successfully handle lane-following tasks on curved and straight roads.

Based on the validation performance, the network demonstrated strong capability in learning essential driving patterns from the available data.

7.4 Inference and Steering Angle Prediction

To evaluate real-world behavior, the trained model was tested with a randomly sampled image from the dataset. The image was passed through the inference preprocessing pipeline, which mirrored the training preprocessing steps. The model produced a steering angle prediction that closely matched typical human driving behavior for the scene.

A visual output was generated showing:

- the original input image,
- the predicted steering angle displayed as text.

This demonstrated that the model can perform real-time inference and produce actionable steering outputs.

7.5 Loss Curve Analysis

The plotted training and validation loss curves revealed:

- **Consistent learning:** Loss decreases steadily after each epoch.
- **Stable validation performance:** No major divergence between training and validation loss.
- **Good generalization:** The absence of sharp fluctuations suggests the architecture and preprocessing pipeline effectively reduced noise and overfitting.

These observations confirm that the CNN successfully extracted spatial features relevant to steering-angle prediction.

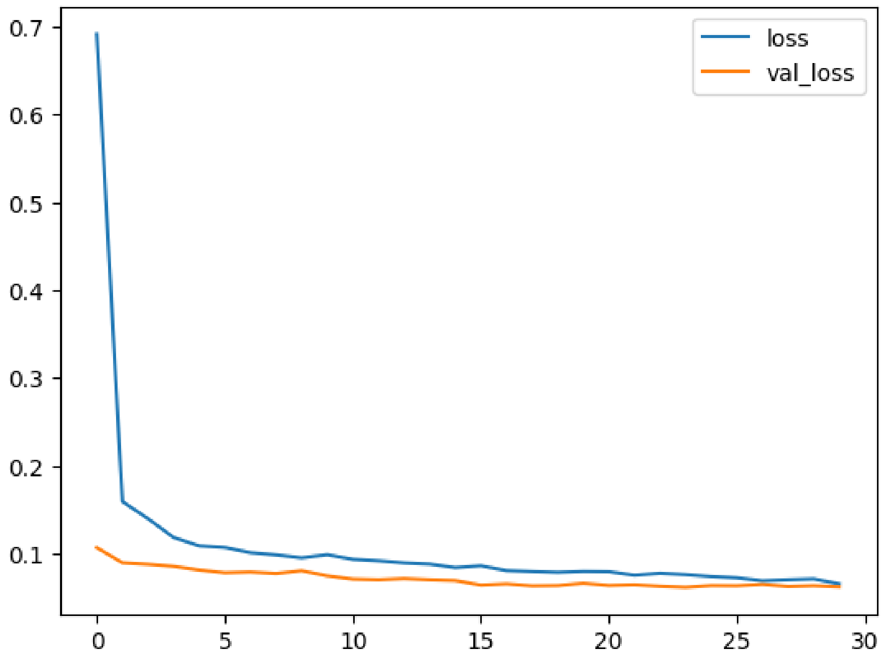


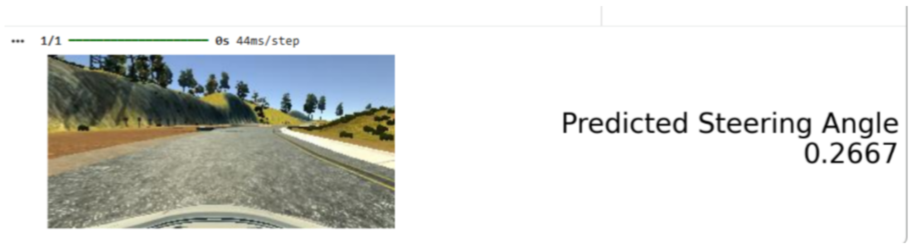
Figure 3: Loss curve vs validation loss curves

7.6 Overall Model Performance

The NVIDIA-based CNN model achieved reliable performance in autonomous steering angle prediction. Key strengths include:

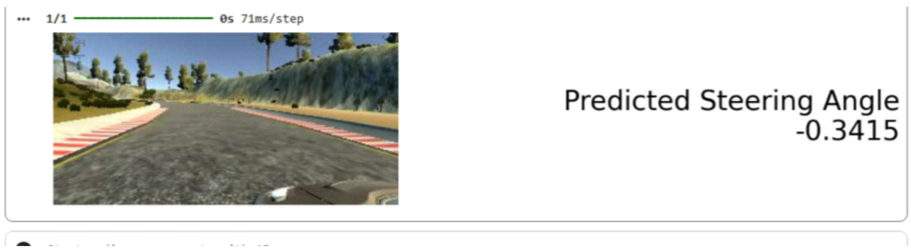
- High accuracy in lane-following scenarios,
- Robust behavior on unseen data,
- Capability to handle minor curvature and varying road textures,
- Low computational complexity, making real-time deployment feasible.

The combination of data balancing, consistent preprocessing, and a proven deep learning architecture played a significant role in achieving stable and accurate results.



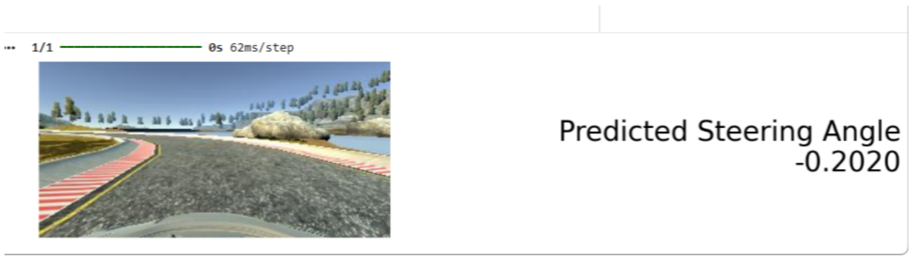
```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step
```

Figure 4: Predicted steering angle for right turn.



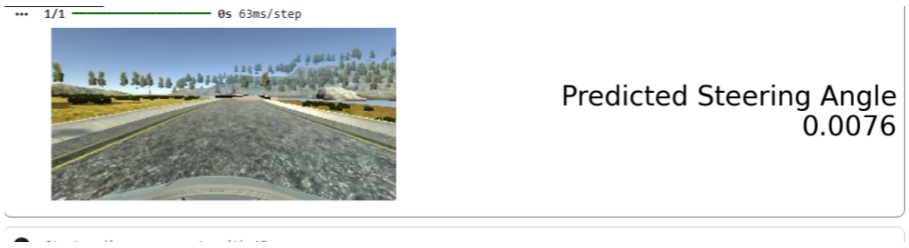
```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step
```

Figure 5: Predicted steering angle for left turn.



```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 62ms/step
```

Figure 6: Predicted steering angle forleft turn.



```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 63ms/step
```

Figure 7: Predicted steering angle toward forward with sliding right .

8 Conclusion and Future Work

8.1 Conclusion

Convolutional Neural Networks (CNNs) effectively align the steering wheel according to the predicted values generated by the model. This approach requires only a minimal amount of training data, yet the system is able to learn meaningful driving behavior and generate accurate steering angles. By mapping raw pixel inputs from a front-facing camera directly to steering commands, the CNN-based end-to-end architecture demonstrates strong performance on local roads, highways, and even in areas with weak or unclear visual guidance such as parking lots or unpaved roads.

The results show that the model is capable of learning robust steering behavior from limited human demonstrations, eliminating the need for explicit hand-engineered lane detection or rule-based control. This highlights the potential of deep learning-based autonomous driving systems and the power of CNN architectures in capturing essential spatial features for decision-making.

8.2 Future Work

In benchmark comparisons, similar architectures used in related studies have shown promising outcomes, with transfer learning and 3D convolutional models achieving high leaderboard placements. Although the 3D CNN–LSTM model was constrained by computational resources, it still demonstrated strong potential and could be improved further by expanding its depth and complexity.

Future enhancements may include:

- **Deeper and richer architectures:** Expanding the 3D CNN model with additional layers to improve spatial–temporal feature extraction.
- **Increased training data variety:** Collecting more diverse data, especially in challenging environments such as snow, fog, nighttime driving, and sharp turns.
- **GAN-based augmentation:** Using Generative Adversarial Networks (GANs) to convert summer driving data into winter conditions or generate rare scenarios with sharp curves.
- **High-quality simulator frameworks:** Integrating deep reinforcement learning within advanced simulators to optimize driving policies. Reward functions can incorporate criteria such as:
  - minimizing travel time,
  - maximizing driving smoothness,
  - maintaining lane discipline,
  - and avoiding collisions.
- **Generalization for real-world deployment:** Before deployment, the model must be capable of handling diverse environmental conditions and unpredictable traffic situations.

https://github.com/sougatarana/sougata$_a utonomouscar/blob/main/Untitled8.ipynb$

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