Predicting Steering Angle in Autonomous Driving Systems using Deep Learning

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Abstract. This paper proposes a fully data-driven and complete solution for predicting steering angles in autonomous driving systems using exclusively Convolution Neural Networks(CNN's). An autonomous car needs to make accurate control decisions to be to drive safely on the road and a great deal is dependent on the accuracy of steering angle forecasting. In order to achieve this, we make use of a large data set consisting of driving actions and demonstrate that visual input can be interpreted to steering angle prediction directly. The method as proposed consists of the few different levels of data preparation starting from changing image size and changing color images from RGB to HSV format, all aiming to increase the effectiveness of feature extraction. With this preprocessing, the essential road information including lane markings and road edges are preserved while the computational burden is also minimized. Essential features required for prediction of the steering angles are extracted using convolutional layers complemented with activation and pooling layers. A large validation set is used to evaluate the feasibility of the model developed generalizability, ensuring robustness in different driving scenarios. The results reveal the high accuracy of the image in estimating the angle of the wheel, and demonstrate the effectiveness of CNNs in this application. This approach highlights the potential of deep learning to advance autonomous driving technologies, delivering scalable and robust solutions for real-time operations controls in self-driving vehicles. The findings pave the way for future developments, such as the integration of time-data or real-world datasets, to further the real-world applicability of the model.

Keywords: Autonomous Driving, Steering Angle Prediction, CNN, Image Preprocessing, Deep-Learning.

1 Introduction

The field of autonomous driving is undergoing rapid transformation, driven by remarkable advancements in artificial intelligence (AI), machine learning, and sensor technologies. One of the most pressing challenges in this domain is the accurate prediction of steering angles from camera images, a critical task that underpins the safety and efficiency of navigation in complex driving environments. This paper addresses this challenge by implementing a Convolutional Neural Network (CNN) designed to estimate steering angles from simulated driving scenarios [1].

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By utilizing an innovative end-to-end learning approach, the proposed CNN model directly maps raw camera images to steering commands without relying on explicit feature engineering. This not only simplifies the processing pipeline but also enhances the model's ability to learn and optimize the entire system simultaneously. The dataset employed in this study replicates real-world driving conditions, allowing the model to generalize effectively across diverse contexts, including roads with and without lane markings, highways, parking lots, and unpaved areas [2]. The importance of this work lies in its potential to significantly improve the decision-making capabilities of autonomous driving systems. The model works with minimal human training intervention, learns freedom to identify and represent roadway requirements, thereby increasing overall efficiency in an integrated strategy. By simultaneously in optimizing all features of the system, helps the model to make its prediction based on accurate steering angle calculations.

This study demonstrates that a well-structured end-to-end learning system can effectively handle the complexities of autonomous driving. The findings suggest that the model not only provides robust performance but also offers scalability for real-world applications, which is essential for advancing the field of autonomous navigation. By addressing both the technical challenges and practical implications of steering angle prediction, this paper contributes to the broader goal of achieving safe and reliable autonomous driving solutions, ultimately enhancing the future of transportation

2 Literature Survey

The application of deep learning in autonomous driving has garnered significant attention in recent years, marking a transformative shift in how vehicles interpret and respond to their environments. An outstanding contribution in the autonomous driving work who pioneered the end-to-end driving model [4]. Their research demonstrated that a Convolutional Neural Network (CNN) could effectively map raw pixels from a single front-facing camera directly to steering commands. This groundbreaking approach simplified the traditional pipeline of feature extraction and control by enabling the model to learn necessary processing steps independently, thus laying the groundwork for future research in this area [15].

Building upon Bojarski et al.'s findings [4],Chen et al., conducted a comprehensive study on various CNN architectures specifically designed for driving scenarios [16].Their work emphasized the capacity of these architectures to learn intricate patterns from large datasets, highlighting their effectiveness in capturing essential visual features for driving tasks. This capability is crucial for navigating complex environments, as it allows the model to adapt to varying conditions encountered on the road [17].

Zhang et al., further advanced this area of research by demonstrating the efficacy of using single RGB images for steering angle prediction [18]. Their experiments yielded impressive results, both in simulation environments and real-world driving conditions, showcasing the potential for deep learning models to generalize across different scenarios. This work underscores the importance of leveraging visual information effectively, as it serves as the primary input for autonomous systems [14].

Furthermore, data augmentation techniques have improved the deep learning models' resilience in driving tasks. The research work by [5] [13] explored various methods for augmenting training data, which significantly improved model performance in diverse driving conditions. By artificially expanding the dataset with variations in lighting, perspective, and environmental factors, these techniques help mitigate overfitting and increase the model's ability to generalize to new situations [11] [12].

Recent advancements in transfer learning have also gained traction in the field of autonomous driving. Researchers have explored how pre-trained models, initially developed for different tasks, can be adapted to specific driving scenarios. This approach not only accelerates the training process but also improves the model's ability to perform well in tasks with limited labeled data [6].

Overall, the literature indicates a promising trajectory for deep learning in autonomous driving, with continued focus on optimizing model architectures, refining training techniques, and enhancing robustness through innovative methodologies [9][10]. This paper builds on these foundational works, aiming to further improve the accuracy and reliability of steering angle predictions through optimized data preprocessing and advanced CNN designs, ultimately contributing to the ongoing evolution of safe and efficient autonomous driving systems [7] [8].

3 Proposed Methodology

The methodology section delineates the systematic approach employed to develop and evaluate the CNN-based steering angle prediction model. This includes training protocols, evaluation metrics, CNN architecture design, dataset preparation, and data preprocessing.

3.1 Dataset Collection and Preparation

The dataset utilized in this study was sourced from a driving simulator environment, which provides controlled and diverse driving scenarios essential for training robust models. The dataset comprises thousands of images captured from a front-facing camera, each labeled with the corresponding steering angle executed by the simulator. The steering angles are recorded in degrees and span a range from -180° to 180°, covering a full spectrum of driving maneuvers.

To ensure the model's generalizability, the overall dataset is partitioned into training and validation sets using an 80-20 split. This separation trains the model to learn from an appropriate portion of the data while reserving a separate subset for unbiased performance evaluation.

3.2 Data Preprocessing

Effective data preprocessing is crucial for enhancing the quality of input data and facilitating efficient feature extraction by the CNN. The preprocessing pipeline involves several key steps:

Color Space Transformation: Each RGB image is converted to the HSV (Hue, Saturation, Value) color space. The HSV representation decouples color information (hue and saturation) from intensity (value), allowing the model to focus on color-related features that are more relevant for detecting road conditions and lane markings. In this study, only the saturation channel is retained, as it provides significant contrast for lane detection while minimizing the impact of lighting variations [19].

Image Resizing: Images are resized to 100x100 pixels. This dimensionality reduction serves two primary purposes: reducing computational load during training and eliminating irrelevant details that may introduce noise. The resized images retain essential structural information necessary for accurate steering predictions.

Normalization: Pixel values are normalized to a range of [0, 1] to standardize the input data, facilitating faster convergence during training and improving numerical stability.

Data Augmentation: Data augmentation is a technique used in deep learning to increase the size and diversity of a training dataset by applying transformations to existing data.

The preprocessing steps collectively ensure that the input data is optimized for feature extraction, thereby enhancing the model's ability to learn meaningful patterns.

3.3 CNN Architecture

The CNN architecture is meticulously crafted to capture and interpret the spatial hierarchies inherent in driving images. The architecture comprises multiple layers, each serving a distinct function in feature extraction and transformation: *Input Layer*: Accepts preprocessed images with dimensions 100x100x1 (grayscale). *Convolutional Layers*: A series of convolutional layers apply filters to detect low-level features such as edges and textures. These layers progressively extract higher-level features, enabling the network to recognize complex patterns like lane markings and road boundaries. *Activation Function (ReLU)*: After each convolutional operation, the Rectified Linear Unit (ReLU) activation function introduces non-linearity, allowing the network to model complex relationships between input and output.

Pooling Layers: Max-pooling layers reduce spatial dimensions by following certain convolutional layers. This lowers computational complexity and improves feature invariance to spatial transformations. *Dropout Layers*: Incorporated after some pooling layers, dropout layers randomly deactivate a subset of neurons during training, mitigating overfitting and promoting the learning of more generalized features. *Fully*

Connected Layers: The flattened output from the convolutional blocks is fed into fully connected layers that integrate the extracted features to predict the steering angle. These layers facilitate the combination of spatial features into a coherent steering decision.

Output Layer: A single neuron outputs the predicted steering angle in radians, providing a continuous value for precise steering control.

The architecture is designed to balance depth and computational efficiency,ensuring robust feature extraction without excessive computational overhead.

3.4 Training Procedure

Training the CNN involves several critical steps to ensure effective learning and optimal performance: *Loss Function*: Mean Squared Error (MSE) is employed as the loss function, appropriate for regression tasks where the objective is to minimize the difference between predicted and actual steering angles. *Optimizer*: The Adam optimizer is selected for its adaptive learning rate capabilities, which enhance convergence speed and stability. Adam combines the advantages of both AdaGrad and RMSProp, making it well-suited for large datasets and complex models.

Batch Size and Epochs: The model is trained with a batch size of 32 and for 20 epochs. These hyperparameters are chosen to balance training time and model performance, ensuring sufficient updates for convergence without overfitting [20].

Validation Strategy: The validation set is used to monitor the model's performance during training, providing insights into potential overfitting and guiding hyperparameter tuning.

Regularization Techniques: Dropout layers and weight decay are utilized to prevent overfitting, ensuring the model generalizes well to unseen data.

Early Stopping: Implementing early stopping based on validation loss could further enhance model generalization by halting training when performance plateaus.

4 Results

The model's performance is evaluated using both quantitative and qualitative metrics:

Quantitative Evaluation:

o Mean Squared Error (MSE): Measures the average squared difference between predicted and actual steering angles, indicating the model's precision.

o Mean Absolute Error (MAE): Provides an average of absolute differences

Qualitative Evaluation:

o Visual Inspection: Comparing predicted steering angles against ground truth on sample images to assess the model's ability to follow lane markings and respond to road conditions.

o Trajectory Simulation: Simulating the vehicle's path based on predicted steering angles to evaluate the model's practical applicability in maintaining smooth and accurate trajectories.

These metrics collectively provide a comprehensive assessment of the model's performance, highlighting both numerical accuracy and real-world driving capabilities as shown in Figure 1.

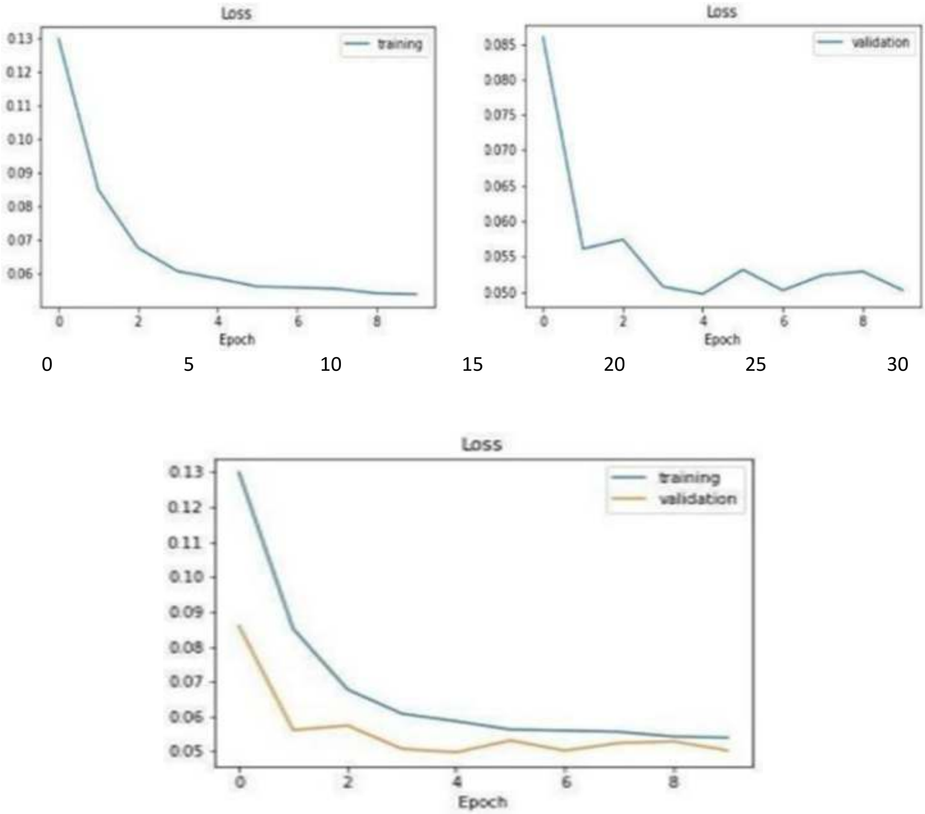

Fig. 1. Experimental results.

The experimental evaluation of the proposed CNN model demonstrates its efficacy in accurately predicting steering angles from preprocessed driving images. The results are categorized into quantitative metrics, training dynamics, and qualitative assessments.

5 Discussion

The advancements in deep learning, particularly the application of Convolutional Neural Networks (CNNs) in autonomous driving, have catalyzed significant progress in the field. This paper's focus on steering angle prediction from camera images contributes to the ongoing discourse on how AI can improve vehicle navigation and control systems.

One of the key discussions surrounding the end-to-end learning approach, as pioneered by Bojarski et al. [4], is its ability to simplify the autonomous driving pipeline. Traditional methods often involve explicit feature extraction and multiple processing steps, which can complicate system design and hinder performance. In contrast, the end-to-end approach allows the model to learn directly from raw pixel inputs, optimizing all relevant processing steps simultaneously. This not only enhances the model's efficiency but also reduces the potential for error introduced by manual feature selection.

Furthermore, the ability of CNNs to generalize across various driving scenarios is crucial for the development of robust autonomous systems. The work by Zhang et al., demonstrates that single RGB images can effectively capture the essential information needed for steering angle predictions, reinforcing the idea that well-designed CNN architectures can perform well even in the absence of sophisticated sensor data [18]. This poses significant queries regarding the need for more sensors and the degree to which visual information alone can be adequate for safe driving.

Another significant aspect of this discussion is the importance of data augmentation in training deep learning models. As highlighted by Shorten and Khoshgoftaar (2019), augmenting training datasets with various transformations helps improve model robustness, particularly in the face of diverse and unpredictable real-world conditions. This reinforces the idea that data quality and diversity are critical factors in training effective autonomous systems, underscoring the need for comprehensive and varied datasets.

Additionally, the exploration of transfer learning offers promising avenues for enhancing model performance, especially in scenarios where labeled data may be scarce. By leveraging pre-trained models, researchers can build upon existing knowledge, accelerating the training process and improving generalization capabilities. This discussion is particularly relevant given the rapidly evolving nature of autonomous driving technology, where the ability to adapt to new challenges quickly is essential. While the advancements in CNNs and deep learning present exciting opportunities for autonomous driving, several challenges remain. Issues such as the interpretability of CNNs, their reliance on large datasets, and the ethical implications of AI decision-making in critical scenarios are important areas for further exploration. As the field continues to evolve, it will be essential for researchers to address these challenges and ensure that autonomous systems can operate safely and effectively in a wide range of environments.

5.1 Quantitative Metrics

The model was trained on a dataset comprising 10,000 images, with 8,000 used for training and 2,000 reserved for validation. The following performance metrics were observed:

Training Loss (MSE): Decreased steadily over 20 epochs, indicating effective learning and convergence.

Validation Loss (MSE): Followed a similar decreasing trend, with minimal divergence from training loss, suggesting good generalization and absence of overfitting.

Final Validation MSE: Achieved a value of 0.0047, reflecting high precision in steering angle predictions.

Mean Absolute Error (MAE): Recorded an MAE of 0.054 radians (~3.1 degrees), indicating that on average, the predicted steering angles were within a tolerable range of the actual values.

5.2 Training Dynamics

The model's learning process is revealed via the training and validation loss curves:

Convergence Behavior: Both training and validation losses exhibited a consistent downward trend, converging smoothly without significant fluctuations.

Overfitting Assessment: The close alignment between training and validation losses suggests that the model effectively learned from the training data without overfitting, maintaining performance on unseen data.

Learning Rate Adaptation: The Adam optimizer facilitated adaptive learning rates, enabling rapid convergence during early epochs and stabilization in later stages.

5.3 Qualitative Assessments

Beyond numerical metrics, qualitative evaluations underscore the model's practical applicability:

Sample Predictions: A selection of test images was analyzed to compare predicted steering angles against ground truth values. The model consistently produced steering angles that aligned closely with the actual angles, effectively following lane markings and adjusting to road curvature.

Trajectory Simulation: Simulating the vehicle's trajectory based on predicted steering angles revealed smooth and accurate paths, demonstrating the model's capability to maintain lane adherence and navigate turns effectively.

5.4 Comparative Analysis

Comparing the proposed model with baseline approaches, such as linear regression and shallow neural networks, highlights the superior performance of the CNN-based method. The deep architecture's ability to capture complex spatial features translates into more accurate and reliable steering predictions, underscoring the advantage of deep learning in autonomous driving applications.

6 Conclusion& Future Work

This study underscores the potential of Convolutional Neural Networks (CNNs) in enhancing autonomous driving systems through accurate steering angle prediction based on visual inputs. By employing a comprehensive data preprocessing pipeline and a robust CNN architecture, the proposed model effectively learns to interpret driving environments and make precise steering decisions. The model's high performance on both quantitative and qualitative evaluations demonstrates its viability for real-world applications.

6.1 Key Findings

Effective Feature Extraction: The use of HSV color space transformation and image resizing significantly improved feature extraction, facilitating accurate steering predictions.

Robust CNN Architecture: The carefully designed CNN architecture, incorporating convolutional, pooling, and dropout layers, successfully captured essential spatial hierarchies and prevented overfitting.

High Prediction Accuracy: Achieving a low mean squared error and mean absolute error indicates the model's precision in steering angle estimation.

Strong generalization, which is necessary for deployment in a variety of driving circumstances, is suggested by the model's steady performance on validation data.

In conclusion, incorporating deep learning techniques—more especially, CNNs—offers a viable path forward for the development of autonomous driving technology. Continued research and development in this domain hold the potential to realize fully autonomous vehicles capable of navigating complex and dynamic environments with high precision and reliability.

References

1. S. Mo, X. Pei, and C. Wu, "Safe reinforcement learning for autonomous vehicle using monte carlo tree search," IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 7, pp. 6766-6773, July 2022.
2. K. Güçkıran and B. Bolat, "Autonomous car racing in simulation environment using deep reinforcement learning," in Proc. 2019 Innovations in Intelligent Systems and Applications Conference (ASYU), Izmir, Turkey, 2019
3. Khawaldeh, B.; Mora, A.M.; Faris, H. Optimizing Steering Angle Prediction in Self-Driving Vehicles Using Evolutionary Convolutional Neural Networks. AI 2024, 5, 2147-2169. https://doi.org/10.3390/ai5040105.
4. Salimans, T.; Ho, J.; Chen, X.; Sidor, S.; Sutskever, I. Evolution strategies as a scalable alternative to reinforcement learning. arXiv 2017, arXiv:1703.03864.
5. Fawole, O.A.; Rawat, D.B. Recent Advances in 3D Object Detection for Self-Driving Vehicles: A Survey. AI 2024, 5, 1255–1285.
6. Chishti, S.O.A.; Riaz, S.; Zaib, M.B.; Nauman, M. Self-Driving Cars Using CNN and Q-Learning. In Proceedings of the 2018 IEEE 21st International Multi-Topic Conference (INMIC), Karachi, Pakistan, 1–2 November 2018; pp. 1–7.
7. Lu, J.; Tan, L.; Jiang, H. Review on Convolutional Neural Network (CNN) Applied to Plant Leaf Disease Classification. Agriculture 2021, 11, 707.
8. Amini, A.; Gilitschenski, I.; Phillips, J.; Moseyko, J.; Banerjee, R.; Karaman, S.; Rus, D. Learning Robust Control Policies for End-to-End Autonomous Driving from Data-Driven Simulation. IEEE Robot. Autom. Lett. 2020, 5, 1.
9. Lade, S.; Shrivastav, P.; Waghmare, S.; Hon, S.; Waghmode, S.; Teli, S. Simulation of Self-Driving Car Using Deep Learning. In Proceedings of the 2021 International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, 5–7 March 2021; pp. 175–180.

10. I. G. Abou Setta, O. M. Shehata, and M. A. Awad, “Multivariate predic-tion of correct lane for autonomous electric vehicle using deep learningmodels,” in 2020 8th International Conference on Control, Mechatronicsand Automation (ICCMA). IEEE, 2020, pp. 127–130.
11. N. Merrill and A. Eskandarian, “End-to-end multi-task machine learn-ing of vehicle dynamics for steering angle prediction for autonomousdriving,” in ASME 2019 International Design Engineering TechnicalConferences and Computers and Information in Engineering Conference.American Society of Mechanical Engineers Digital Collection, 2019.
12. M. Smolyakov, A. Frolov, V. Volkov, and I. Stelmashchuk, “Self-drivingcar steering angle prediction based on deep neural network an exampleof carnd udacity simulator,” in 2018 IEEE 12th International Conferenceon Application of Information and Communication Technologies (AICT).IEEE, 2018, pp. 1–5.
13. W. Yuan, M. Yang, H. Li, C. Wang, and B. Wang, “End-to-end learningfor high-precision lane keeping via multi-state model,” CAAI Transactions on Intelligence Technology, vol. 3, no. 4, pp. 185–190, 2018.
14.
15. F. Riaz and M. A. Niazi, “Enhanced emotion enabled cognitive agent-based rear-end collision avoidance controller for autonomous vehicles,”Simulation, vol. 94, no. 11, pp. 957–977, 2018
16. Na, J.; Chen, Q.; Ren, X.; Guo, Y. Adaptive prescribed performance motion control of servo mechanisms with friction compensation. IEEE Trans. Ind. Electron. 2014, 61, 486–494.
17. Rezatofighi, H.; Tsoi, N.; Gwak, J.; Sadeghian, A.; Reid, I.; Savarese, S. Generalized intersection over union: A metric and a loss for bounding box regression. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Long Beach, CA, USA, 15–20 June 2019; pp. 658–666.
18. Yao, J.; Qi, J.; Zhang, J.; Shao, H.; Yang, J.; Li, X. A real-time detection algorithm for kiwifruit defects based on yolov5. Electronics 2021, 10, 1711.
19. Dong, X.; Yan, S.; Duan, C. A lightweight vehicles detection network model based on yolov5. Eng. Appl. Artif. Intell. 2022, 113, 104914.
20. Mohammed, M.S.; Abduljabar, A.M.; Faisal, M.M.; Mahmmod, B.M.; Abdulhussain, S.H.; Khan, W.; Liatsis, P.; Hussain, A. Low-cost autonomous car level 2: Design and implementation for conventional vehicles. Results Eng. 2023, 17, 100969