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AI End-to-End Autonomous Driving

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Abstract: ***This study aims to explore the performance and challenges of an end-to-end autonomous driving decision model based on a deep convolutional neural network (CNN) in practical applications. Firstly, this paper introduces the basic principles of deep convolutional neural networks and their application background in autonomous driving. Subsequently, it describes in detail the spatial feature extraction models based on deep convolutional networks, including the PilotNet baseline model and the spatial feature extraction model based on transfer learning. Based on this, an end-to-end decision model for longitudinal and lateral control of intelligent vehicles is constructed. The longitudinal and lateral control models are discussed separately, and more complex decision-making capabilities in autonomous driving scenarios are achieved through a combined model. Through experiments on the Udacity and Comma2k19 datasets, this paper demonstrates the performance of the end-to-end model. The experimental results show that the end-to-end model can effectively learn driving strategies from image data and exhibits good generalization ability and robustness under different environmental conditions. Feature visualization analysis further reveals the internal mechanism and decision basis of the model. Although the end-to-end model shows great potential in autonomous driving, this study also reveals some challenges in its practical application, including the interpretability of the model, the quality and diversity of the dataset, and the decision-making ability in complex environments. Future research should focus on addressing these issues to promote the further development and application of autonomous driving technology. Overall, this study provides a comprehensive research framework and practical foundation for end-to-end autonomous driving decision models based on deep learning.***

Keywords: AI; End-to-End; Autonomous Driving.

1. INTRODUCTION

With the rapid advancement of artificial intelligence and deep learning technologies, autonomous driving has gradually become a focal point of interest in both the automotive industry and academia. Autonomous vehicles, as an integral component of intelligent transportation systems (ITS), are a new type of vehicle that processes road information through technologies such as computer vision and neural networks to make corresponding judgments and achieve autonomous driving or assist drivers in completing specified tasks. Autonomous driving technology not only helps enhance road traffic safety and reduce the occurrence of traffic accidents but also improves traffic efficiency and reduces the driving stress on drivers (Litman, 2020). Currently, vision-based and speech recognition-based vehicle assistance driving technologies have gradually matured and are widely applied on actual roads. In the application of autonomous driving systems, the end-to-end decision model has garnered significant attention due to its simple structure and direct input-output relationship. Among them, adaptive modeling and reasoning methods based on machine vision are the most widely used and significant. This type of model learns driving strategies directly from sensor inputs (e.g., camera images) through deep neural networks, thus avoiding the complex intermediate steps and manual feature design in traditional modular methods (Bojarski et al., 2016) [1].

Early research on autonomous driving primarily focused on modular methods, where the perception, decision-making, and control subsystems were developed independently (Badue et al., 2021). With the continuous development of automotive technology, it has gradually been realized that traditional distributed modeling and simulation methods can no longer meet the future needs of intelligent vehicle systems, leading to the proposal of an end-to-end modeling and simulation technology. However, this approach often relies on a large number of manually designed rules and complex parameter optimization processes. Moreover, due to the lack of a thorough understanding of underlying physical systems and environmental information, these algorithms are difficult to meet the future need of real-time and efficient unmanned driving in smart transportation. In contrast, end-to-end autonomous driving models employ deep convolutional neural networks (CNNs) to directly learn the mapping relationship from perception to control, which makes them more flexible and capable of autonomous learning (Codevilla et al., 2018). Currently, end-to-end models have been widely applied in vehicle intelligent assistant systems. PilotNet, as a typical representative of end-to-end driving models, has demonstrated its outstanding driving performance in the field of autonomous driving (Bojarski et al., 2016). To further improve model performance, this paper proposes an improved algorithm based on multi-feature fusion to build an end-to-end autonomous driving model. Additionally, transfer learning methods have significantly improved the training speed and generalization performance of models in end-to-end applications (Pan & Yang, 2009) [2].

Although end-to-end models have great application prospects in autonomous driving technology, they still face many challenges in practical operations, such as model interpretability, the high quality and diversity of datasets, and decision-making capabilities in complex scenarios (Kiran et al., 2021). With the continuous deepening of computer vision research, how to improve the learning efficiency of autonomous driving systems has become one of the urgent issues to be solved in the field of artificial intelligence. Therefore, the purpose of this study is to construct an efficient end-to-end autonomous driving decision model using deep convolutional neural networks and evaluate its performance on different datasets to provide new perspectives and methods for the further development of autonomous driving technology [3].

2. END-TO-END DECISION MODEL BASED ON DEEP CONVOLUTIONAL NEURAL NETWORKS

Deep Convolutional Neural Networks (DCNNs) are a type of deep learning model that extracts spatial features from input data through convolutional layers, widely applied in the fields of computer vision and autonomous driving. The core of convolutional neural networks lies in reducing the number of parameters by using local connections, shared weights, and pooling operations, thereby improving training efficiency and generalization ability (LeCun et al., 1998). Its basic structure generally consists of convolutional layers, activation functions, pooling layers, and fully connected layers to form a deep network. DCNNs in the field of autonomous driving can efficiently extract spatial features and make decisions from images. For example, Bojarski et al. (2016) proposed an end-to-end learning method that trains a DCNN model to directly predict driving control commands from raw camera images, demonstrating the effectiveness of end-to-end models in complex scenarios. Additionally, DCNNs allow for training on large-scale datasets to enhance the algorithm's performance in real-world environments. At the same time, the feature extraction process of DCNNs is significant as it can recognize multi-level information. The lower layers of the network can capture low-level features such as edges and textures, while the upper layers can combine these features to form more semantic expressions (Krizhevsky et al., 2012) [4]. This characteristic makes DCNNs outstanding in processing complex data, especially suitable for tasks such as image classification and object detection. In recent years, with the improvement of GPU computing power and the availability of large-scale datasets, the application scenarios of DCNNs have become increasingly extensive, especially in the rapid development of intelligent transportation systems and autonomous driving technology, with relevant research emerging continuously (Zhang et al., 2019). Researchers have explored the potential applications of various models in end-to-end autonomous driving technology by combining multiple network frameworks such as VGG, Inception, and ResNet, providing richer and more diverse solutions for the realization of intelligent driving (He et al., 2016). In summary, deep convolutional neural networks, as an efficient feature learning tool, have occupied a core position in autonomous driving technology due to their hierarchical architecture and rich feature representation capabilities [5].

3. EXPERIMENTAL AND ANALYTICAL

In the field of algorithm research, evaluating the superior performance of intelligent vehicle decision methods is a core issue. One common strategy is to use existing datasets for in-depth performance evaluation of these decision methods. Regarding the longitudinal and lateral end-to-end decision models for intelligent vehicles built based on deep convolutional neural networks, this section first outlines the datasets used in the experiment and the selected evaluation criteria, followed by a series of comparative experiments to assess network performance, and finally conducts visual analysis.

Table 1: Common Open-Source Autonomous Driving Datasets

Dataset	Source	Scene	Data Type
DIPLECS	University of Surrey, UK	Rural Roads	RGB Images, Vehicle Speed, Steering Angle
Udacity	Udacity, USA	Highway and Mountain City Roads	RGB Images, Steering Angle, Brake
BDD100K	University of California, Berkeley, USA	Urban Roads	RGB Images, GPS, IMU
Comma.ai	Comma.ai, USA	Highways	RGB Images, Acceleration, GPS
Comma2k19	Comma.ai, USA	Highways	RGB Images, GPS Signal, IMU
ApolloScape	Baidu, China	Highways and Urban Roads	RGB Images, Steering Angle, Brake

Carla	Autonomous University of Barcelona	Virtual City Roads	RGB Images, Radar, Steering, Brake

End-to-end autonomous driving datasets are primarily collected through two methods: one is based on simulated environments, where the core step involves manually configuring driving scenarios on an autonomous driving simulation platform or using specific driving scenarios within simulators (such as CARLA and Udacity). By operating the vehicle using a keyboard or driving simulator, end-to-end driving data is collected. This method is typically used to test autonomous driving systems and provides some reference value for the future development of autonomous vehicles. The other method is real-vehicle driving datasets, which directly collect driving information from actual road driving, including images in front of the vehicle and control data. This paper proposes a new approach based on the front-view imagery to obtain distance-to-road and vehicle speed parameters during driving, thereby achieving end-to-end driving state estimation. The visual environment of the simulation platform is rendered through computer graphics, leading to a significant difference in visual appearance compared to actual driving scenarios. Evidence shows that although the autonomous driving model performs well in simulated environments, its driving effect on real vehicles is unsatisfactory. Therefore, it is particularly important to discover useful knowledge from a large amount of actual driving data. Currently, few publicly available datasets provide front-view images and corresponding driver control commands. Additionally, existing methods are mainly used to study how to improve vehicle active safety or reduce the probability of traffic accidents. Given that end-to-end vehicle decision-making struggles in complex traffic environments with numerous signals, this study only constructs models for highways. To improve simulation accuracy, it is necessary to establish a comprehensive database of different types of road samples for subsequent analysis. Thus, among existing datasets, this study selects two real-vehicle highway driving datasets, the Udacity dataset and the Comma2k19 dataset, for training and testing [16].

3.1.1 Udacity Dataset

In 2016, Udacity launched a project aimed at the development of open-source autonomous vehicles and successfully organized multiple public challenge competitions. The initiative aims to provide technical support for unmanned driving, including testing how to use sensors to perceive environmental information, designing safety systems to ensure pedestrians are not injured, and evaluating driver behavior. The second challenge involves using RGB images from the front of the vehicle to estimate the steering wheel angle in real-time, thereby achieving autonomous driving. This challenge has been successfully completed and published in internationally renowned journals and is currently undergoing testing. The Udacity dataset was collected during the day in Mountain View and surrounding cities in California. This study focuses on extracting features from these datasets to analyze driver intent and control vehicle direction. In the ROS system, we parsed the ROSBAG files to obtain the necessary data. The dataset consists of six video clips with a total playback time of approximately 20 minutes, captured at a rate of 20fps. To obtain more relevant information, we compared it with data collected in a real environment. The recorded data includes video streams from three front-view cameras and various vehicle parameters such as speed, steering angle, throttle, and braking system. To analyze the relationship between these parameters and vehicle speed, we used two sensors to track and record measurements at each capture point. This study only used data from the middle camera, along with corresponding speed and steering angle values, and selected a number of representative frames from the experimental data, as shown in Figure 3.2. These frames were used to identify whether the vehicle was in motion and calculate the corresponding steering wheel angle value. Figure 2 shows the distribution of speed and steering angle label values in the dataset [17].

Figure 1: Example Frames from the Udacity Dataset

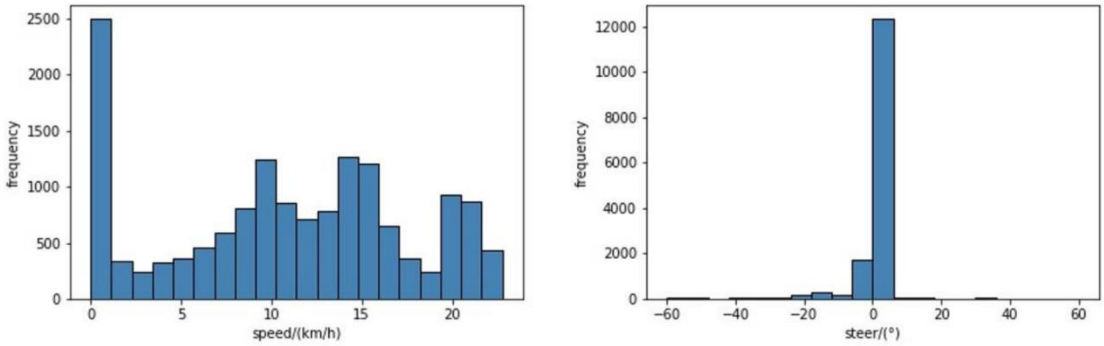

Figure 2: Speed and Steering Angle Data Distribution of the Udacity Dataset

3.1.2 Comma2k19 Dataset

The Comma2k19 dataset is a dataset related to autonomous driving introduced by Comma.ai in 2019. This dataset contains a large amount of information about the operating status of a self-driving car, such as driving speed, acceleration, and position. It records in detail over 33 hours of driving on the California 280 highway, including both daytime and nighttime. The dataset includes a wealth of information about autonomous driving technology provided by car manufacturers and operators, such as driver position, traffic signal status, and surrounding road conditions. The sensor data we collected covers road-facing camera images, raw GNSS, IMU, and CAN bus information emitted by the vehicle. The study divides the data collected while driving on a 20-kilometer stretch of highway between San Jose and San Francisco, California into 2,019 segments, each lasting 1 minute. To analyze the traffic conditions that drivers focus on within this road section, we used a deep learning-based algorithm to identify and calculate the potential number and severity of accidents in each lane. The data is divided into 10 parts, each requiring approximately 200 minutes of driving time. By analyzing this data and using machine learning algorithms to extract the vehicle speed and steering angle, these parameters serve as the basis for judging the target position ahead of the vehicle. Finally, we selected two sets of data from the CAN bus. Since the control information from the CAN bus does not match the front image frames in terms of time, we manually aligned the CAN bus speed and steering angle information with the vehicle's front image information based on the collected timestamps, performing downsampling on the speed and steering angle. Given the high frame rate of the collected images, we can consider the image information to be matched with the labels. By calculating the vehicle speed and steering angle, we can obtain information such as the current distance and target position. Figure 3 presents some selected image examples, and Figure 4 shows the distribution of speed and steering angle in the selected data [18].

Figure 3: Example Frames from the Comma2k19 Dataset

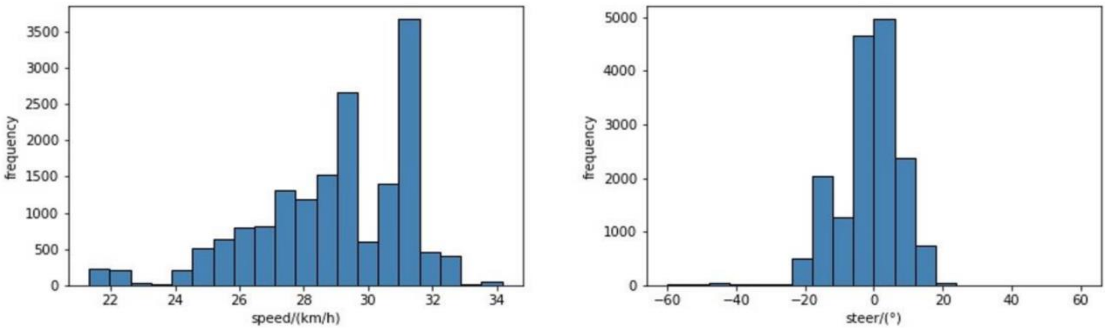

Figure 4: Speed and Steering Angle Data Distribution in the Comma2k19 Dataset

3.2 Data Preprocessing

From Figure 2, we can observe that in the Udacity dataset, most drivers are driving on straight roads (steering angle ±0.05), which is not beneficial for training end-to-end driving models. Therefore, we downsampled the straight-road driving data to one-third of the original amount. Experiments show that under certain conditions, the model obtained after this improvement can better approximate the true values. Additionally, the data distribution for left and right turns is not uniform, with fewer left turns and smaller angles for right turns. To address this issue, we constructed additional samples by swapping the left and right pixels in the images, as shown in Figure 5, and set the corresponding steering angles to negative values. This made the data for left and right turns more balanced, enriched the dataset samples, and enhanced the generalization capability of the trained model.

Figure 5: Example of Left-Right Flipped Augmented Samples

In addition, to enhance the robustness of the system model and the accuracy of predictions, it is crucial to expand the data scale and increase data diversity. Therefore, during the data processing, we performed augmentation on parts of the two datasets based on the variability of the images. Experimental results show that the proposed algorithm in this paper can effectively improve the visual characteristics of the driver. The main augmentation methods include: (1) Cropping. By removing all background pixels from the original scene, we reduce the amount of data. Intuitively, image data such as the sky or mountaintops is not directly related to the driver's decision-making, so we decided to remove these irrelevant contents. This paper trains the network by changing the grayscale value of each pixel in the training samples. (2) Light intensity. To ensure that each pixel correctly reflects the distance variation between pixels in the image, corresponding correction operations are required for each pixel. Adjusting the brightness of the images helps to enhance the robustness of the neural network in various environments. This method utilizes the videos captured by the front and rear cameras of the vehicle to determine the left and right side boundaries and calculate the width of the left and right lanes, then obtains the road information at the current position through a simple matrix transformation. First, each frame is converted to the HSV color space, and then the values of the channels are multiplied by a random value from 0 to 1 to simulate various lighting environments. (3) Flipping operation. By flipping all frames, we obtain their mirror images in the horizontal direction. This method ensures a balance between the number of left and right turn samples, thus avoiding bias in the algorithm for both directions. (4) Upsampling. To address the challenge of data imbalance, we performed upsampling on the images to ensure a balance between positive and negative steering angles. Figure 6 presents several instances of the above data preprocessing methods.

Figure 6: Example Samples of Data Augmentation Preprocessing

Finally, before the training begins, the data is randomly shuffled and divided into training, testing, and validation sets in an 8:1:1 ratio. After normalizing each data sample, a new dataset is obtained. The model is trained using the training set, while the evaluation of the model relies on the testing set, and the adjustment of model parameters is achieved through the validation set. This paper conducts a comparative analysis of the prediction results under different sample sizes. Table 2 presents the specific sizes of the data samples.

Table 2: Number of Samples in the Dataset

Dataset Name	Original Dataset	Augmented Dataset	Training Set	Validation Set	Test Set
Udacity	15212	30532	24424	3053	3055
Comma2k19	16793	37265	29808	3726	3731

3.3 Offline Evaluation Metrics

In the ideal scenario, the evaluation of autonomous driving models should be conducted on real vehicles, comparing their online performance metrics. Online evaluation provides real-time feedback, allowing issues to be detected and resolved promptly, garnering increasing attention from researchers. However, for most researchers, online evaluation on real vehicles is impractical. Therefore, to accurately assess the actual performance of self-driving cars, it is crucial to consider significant variations among different vehicles. An alternative is offline model evaluation, which is based on pre-collected test datasets, achieved by comparing predicted values with label values. Due to limited real-road data and varying vehicle operating conditions, this approach is challenging to implement. Literature points out that current offline evaluation metrics for end-to-end driving models, such as Mean Squared Error (MSE), are not good indicators of autonomous driving system performance, as they have weak correlation with real driving quality; two models with the same prediction error can exhibit significant differences in driving performance. This paper addresses this issue by proposing an online real-time optimization algorithm, using a new evaluation metric—Mean Absolute Error (MAE)—to measure driving quality during vehicle operation [19].

3.4 Experimental Process and Results

In this chapter, we detail the network parameter configuration of the end-to-end decision network model: to better construct a unified convolutional network, we adjust the input image size to $120\times260\times3$. Under these conditions, we compare the experimental results of different parameter combinations to determine the optimal value range for each parameter. In the PilotNet benchmark model, the output dimension is set to 2. Due to significant differences between the training dataset and the test set, parameter optimization is necessary. For transfer learning with deep convolutional neural networks VGG16, Inception V3, and ResNet50, we only selected some convolutional blocks as the feature extraction part. Classifying the features extracted from the three different network structures yielded ideal performance. In the longitudinal and lateral prediction networks, the random dropout-fully connected layer is designed as 4 fully connected layers, with the number of neurons being 100, 50, 10, and 2, respectively. The global average pooling-fully connected layer adds 3 fully connected layers after the global average pooling layer, which are 50, 10, and 2, respectively. During the experiment, we observed that both methods have unique advantages, so we chose the one with the best performance as the model's output result. Comparing the analysis of the above three different types of decision issues with traditional machine learning algorithms shows that the method proposed in this paper has high accuracy and robustness, effectively solving classification tasks in complex data environments. The end-to-end decision model reconstructed based on the deep convolutional network is named VGG16-DNet, InceptionV3-DNet, and ResNet50-DNet decision networks (Decision Networks DNet). These three decision tree models have strong learning capabilities and achieve good classification performance. Some hyperparameters for model training are as shown in Table 3.

Table 3: Hyperparameters for Decision Model Training

batchsize	epochs	Optimizer	Dropout
64	30	Adam	0.5

As shown in Figure 7, the PilotNet baseline model demonstrates training loss curves on two different datasets. Judging from the decrease in loss, the model has already reached a stable convergence state by the tenth epoch. The entire training process is quite smooth, and similar to this, the training of an end-to-end decision model built based on transfer learning also exhibits such characteristics.

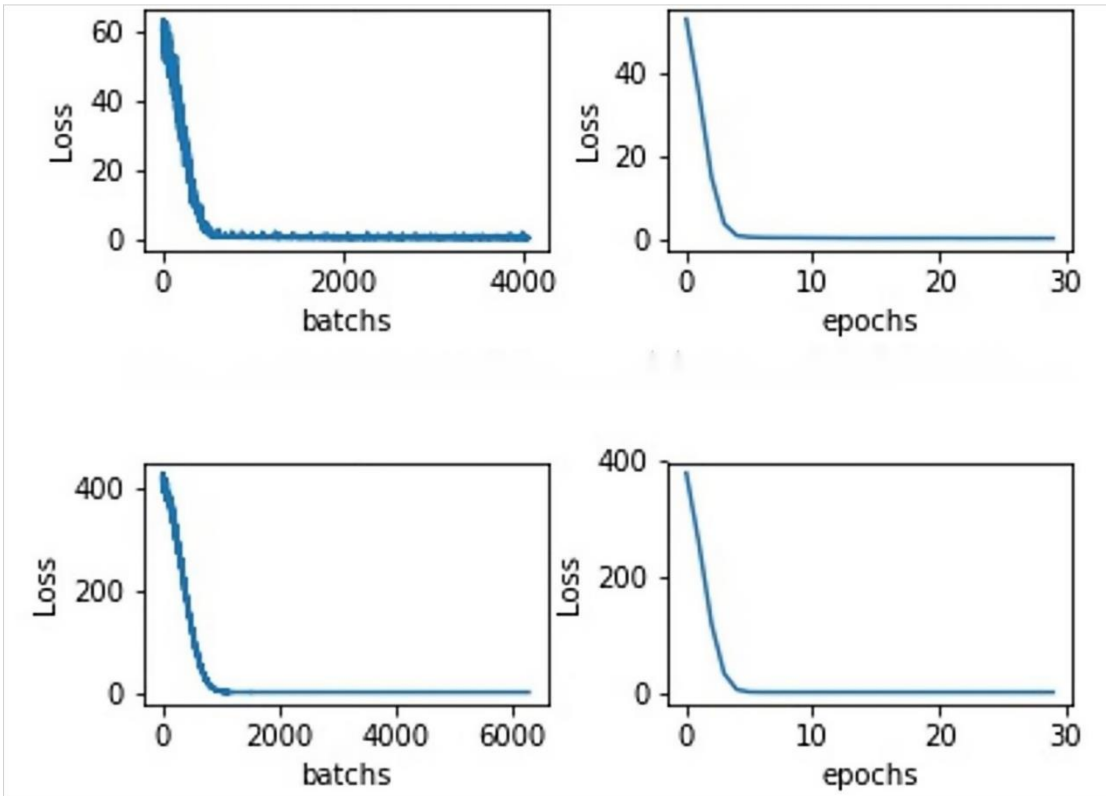

Figure 7: Training Loss Example of the Baseline Model

In the process of constructing the loss function, more emphasis was placed on the accuracy of steering wheel turns, which also applies when calculating evaluation metrics, with weights set at 0.7 and 0.3, respectively. The experimental results of five end-to-end decision models based on convolutional networks, tested on two different datasets, are shown as in Table 4.

Table 4: Experimental Results of Decision Models Based on Deep Convolutional Networks

Model Name	UdacityMAE	UdacityTRE	Comma2k19MAE	Comma2k19TRE
PilotNet	1.972	1.286	2.734	1.831
PilotNet*	1.851	1.260	2.497	1.796
VGG16-DNet	1.429	1.036	1.956	1.442
InceptionV3-DNet	1.483	1.089	1.822	1.390
ResNet50-DNet	1.354	0.993	1.734	1.268

The experimental results reveal that the MAE and TRE performance of the PilotNet* decision model are significantly lower than those of the PilotNet decision model across two different datasets. This indicates that the addition of normalization layers has improved the performance of the end-to-end model. Furthermore, from the perspective of model training loss, it is also observed that the convergence speed of PilotNet* is relatively faster. In addition, compared to the PilotNet* decision model, the end-to-end decision models VGG16-DNet, InceptionV3-DNet, and ResNet50-DNet, constructed based on deep convolutional neural networks, demonstrate better decision-making performance. The performance improvement of these models is significant, indicating that the shallow network PilotNet has limitations in feature representation. However, by increasing the depth of the neural network, we can enhance the model's adaptability, allowing for more accurate predictions of speed and steering angle [20].

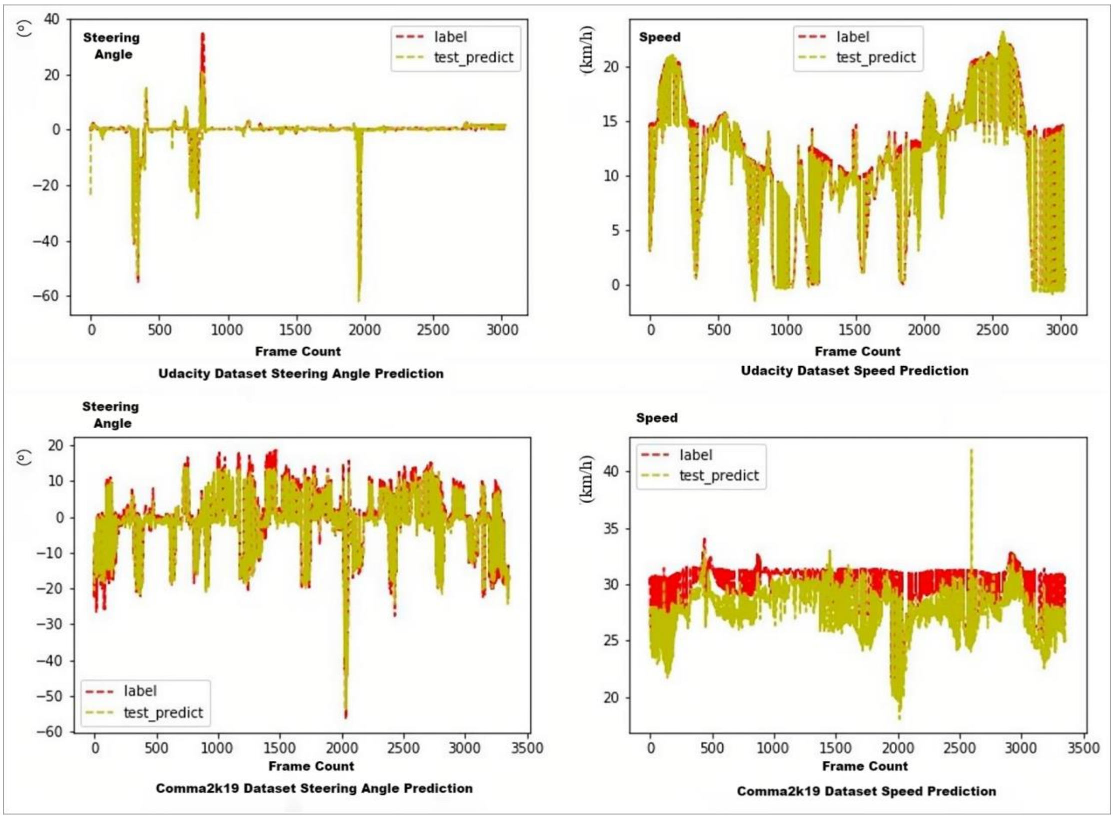

Figure 8 ResNet50-DNet Decision Model Prediction Results

3.5 Feature Visualization Analysis

To further explore the data obtained by deep convolutional networks when extracting spatial features from RGB images, we visualize the shallow features extracted by the deep convolutional network model in this section. This helps us to more intuitively understand the significance of feature extraction by the model, as demonstrated in Figure 9. The first and third rows in the figure show examples of the original RGB images from the Udacity and Comma2k19 datasets, respectively, and the images below are the corresponding feature maps, which have been processed to display high accuracy. From the feature maps, it can be observed that the deep convolutional network has learned information such as lane markings, edge of the lane, and the outline of vehicles ahead when extracting shallow features. This information is crucial for autonomous vehicles to make driving decisions, enabling the end-to-end decision model to make accurate decisions. Since the deep convolutional feature maps become too blurry to be directly analyzed, only the shallow layer features are displayed. After training the neural network on a large number of video samples collected from real-world scenarios, better prediction results can be obtained. The convolutional network has learned how to identify valuable road information, which also enhances the interpretability of the end-to-end decision model.

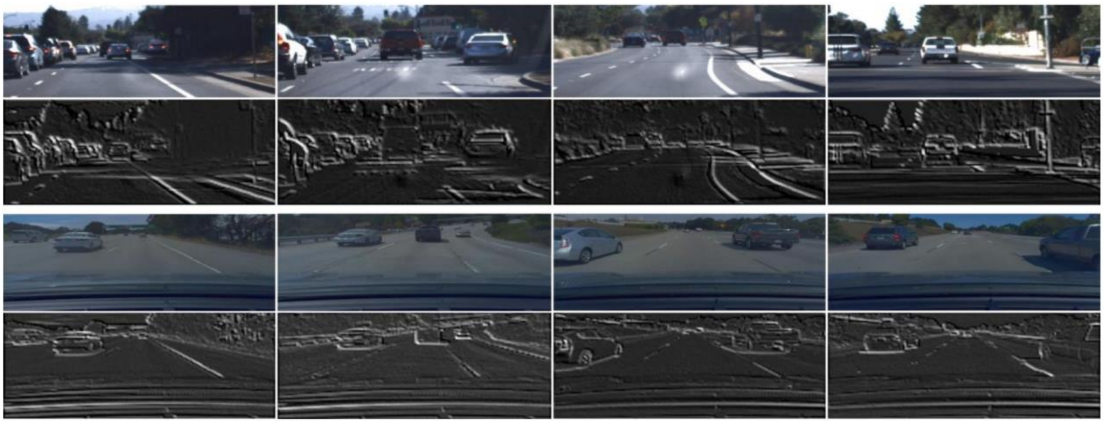

Figure 9: Visualization of Shallow Features in Deep Convolutional Networks

4. CONCLUSION

This study thoroughly explores end-to-end autonomous driving decision models based on deep convolutional neural networks, highlighting their core importance in the field of autonomous driving technology. To address some existing issues in artificial intelligence, a new multi-feature fusion method aimed at autonomous driving scenarios is proposed to enhance system performance. By analyzing existing models (such as PilotNet) and transfer learning-based spatial feature extraction models, we demonstrate the effectiveness and potential improvements of these techniques in handling complex driving environments. Additionally, this study discusses how to construct an end-to-end autonomous driving decision model using various methods and analyzes the advantages and disadvantages of different algorithms in practical applications. Experimental validation shows that end-to-end models for longitudinal and lateral control using deep convolutional neural networks can achieve efficient and safe autonomous driving outcomes, and their performance across various datasets further confirms their excellent generalization capabilities. Furthermore, this study proposes a new algorithm that integrates traditional methods into the endpoint detection process, significantly enhancing vehicle identification accuracy. However, as autonomous driving technology continues to develop, this research exposes a series of challenges, including the gap between simulation data and real vehicle data, the impact of data augmentation techniques on model performance, and the interpretability issues arising from the "black box" nature of end-to-end decision models. Additionally, several potential new problems require further investigation. Future research should focus on enhancing the interpretability of models, improving the quality and diversity of training data, and investigating decision-making processes in unstable environments. Moreover, the feasibility of incorporating deep learning methods into autonomous driving systems to address practical issues should be considered. Despite facing numerous challenges, end-to-end autonomous driving decision models based on deep learning still hold immense application potential in autonomous driving technology, providing a solid foundation for realizing full autonomy in driving.

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