Recognition of Typical Highway Driving Scenarios for Intelligent Connected Vehicles Based on Long Short-Term Memory Network

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Abstract: In the complex traffic environment where intelligent connected vehicles (ICVs) and traditional vehicles coexist, accurately identifying the driving scenarios of a vehicle helps ICVs make safer and more efficient decisions, while also enabling performance evaluation across different scenarios to further optimize system capabilities. This paper presents a typical highway driving scenarios recognition model with extensive scenario coverage and high generalizability. The model first categorizes the constituent elements of driving scenarios and extracts the core elements of typical highway scenarios. Then, based on a long short-term memory (LSTM) network architecture, it extracts features from the ego vehicle and surrounding vehicles to identify the typical driving scenarios in which the ego vehicle is located. The model was tested and validated on the HighD dataset, achieving an overall accuracy of 96.74% for four typical highway scenarios: Lane-change, Car-following, Alongside vehicle cut-in, and Preceding vehicle cut-out. Compared to baseline models, the proposed model demonstrated superior performance.

1 INTRODUCTION

Driving scenario recognition is a fundamental and challenging task in autonomous driving systems, and it is also a key step in understanding traffic environments(Lee et al., 2020). Under different driving scenarios, the parameter settings and operational performance of ICVs vary, making accurate scenario recognition crucial for improving their operational efficiency. Additionally, the environmental and vehicular information contained in these scenarios provides support for the development, testing, and performance evaluation of ICVs. Specifically, the role of driving scenario recognition includes:

- Predicting the scenario in which the autonomous vehicle is located, providing prior knowledge to subsequent decision-making systems, filtering perception system data, providing standardized data to the perception network, and enabling targeted parameter training;
- Identifying the different driving scenarios experienced by the autonomous vehicle, thereby enhancing the efficiency and coverage of open road testing for autonomous driving;
- Evaluating the performance of ICVs in various scenarios through scenario recognition, providing directions for the continuous optimization of autonomous driving systems.

The driving scenarios involved in ICVs typically encompass complex environmental factors, including interactions between dynamic and static traffic participants. A driving scenario refers to the dynamic interaction process between an ICV and surrounding participants over a period of time. For instance, a driving scenario may involve a vehicle rapidly changing lanes from the left lane into the main lane (Lu et al., 2023). Before recognizing this as a Lane-change scenario, the vehicle needs to continuously acquire information about the position, speed, and direction of itself and surrounding traffic participants. The dynamic interaction process among these participants during this time can be defined as a Lane-change scenario.

Detecting real-world traffic conditions and scenarios is a critical area of research in ICVs (Rsener et al.,

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2016; Benmimoun and Eckstein, 2014). In many cases, scenario classification for simple situations can be adequately performed using maneuver-based detection, which considers the goals of the ego vehicle and classifies scenarios in a way that is understandable to humans, such as lane changing, turning or following. For instance, the nuScenes dataset (Caesar et al., 2020) primarily classifies scenarios based on the behavior and status of the ego vehicle, such as "waiting at an intersection," "turning left," "turning right," and "approaching an intersection." However, this method of defining scenarios does not consider the dynamic behavior of other traffic participants, thereby ignoring their influence on the ego vehicle. Analysis of the California autonomous vehicle dataset indicates that the behavior of other vehicles has a significant impact on the safety of autonomous vehicles (Ma et al., 2022). Simply classifying driving scenarios based on the ego vehicle's maneuvers without considering environmental factors results in overly simplistic scenario segmentation and inaccurate classification.

Merely identifying the ego vehicle's maneuvers (such as Lane-change or Turning) does not adequately account for the impact of other vehicles' behaviors on scenario changes, such as a leading vehicle cutting in, resulting in insufficient scenario classification and inaccurate recognition. To address these issues, this paper proposes a typical scenario recognition method based on Long Short-Term Memory (LSTM) networks. The proposed method divides driving scenarios into environmental, roadway, and dynamic driving behavior layers to decouple complex scenarios. By using LSTM networks to consider the interaction characteristics of surrounding vehicles, the method effectively recognizes typical driving behaviors, thereby achieving a comprehensive classification of typical driving scenarios for ICVs.

2 RELATED WORK

2.1 Scenario Definition

Early researchers abstracted the information surrounding a vehicle into a concept called a "scenario" (Ren et al., 2022). Depending on the environmental information and the ego vehicle's data, various definitions of scenarios have been proposed. (Go and Carroll, 2004) described a scenario as a comprehensive representation that includes participants, background information, environmental assumptions, participants' goals or intentions, as well as a sequence of operations and events. In certain applications, some of these elements may be partially omitted or simplified. (Ulbrich et al., 2015) provided a more general definition of a scenario, suggesting that it describes the temporal evolution of multiple situations, each of which has an initial state, and evolves through changes in actions, events, goals, and values. (Zhu et al., 2019) viewed scenarios as a combination of the driving scene and driving context of autonomous vehicles, proposing that a scenario is a dynamic depiction of various elements of the autonomous vehicle and its driving environment over time, with these elements determined by the autonomous driving function being tested.

In the field of autonomous driving, scholars primarily classify scenario elements based on the six-layer scenario model proposed by the German PEGASUS project (Menzel et al., 2018). The PEGASUS project, initiated by relevant companies and research institutions in the German automotive industry, aims to establish testing standards for autonomous vehicles. From the perspective of deconstructing and reconstructing test scenarios, the PEGASUS project proposed a six-layer scenario model:

- 1) Road Layer: Describes the road geometry, dimensions, topology, surface quality, and boundary information;
- 2) Traffic Infrastructure Layer: Describes various fixed facilities associated with the road layer, which constrain the behavior of autonomous vehicles and other traffic participants through traffic rules;
- 3) Temporary Operation Layer: Describes temporary sections of roads and related traffic facilities within the scenario;
- 4) Objects Layer: Describes various dynamic, static, and movable traffic participants within the scenario and their interaction behaviors;
- 5) Environmental Layer: Describes the environmental conditions within the scenario, such as weather and lighting;
- 6) Data Communication Layer: Covers V2X information, digital maps, and other related content.

It can be seen that a scenario encompasses the external road, traffic infrastructure, weather conditions, traffic participants, as well as the driving tasks and status of the vehicle itself. It represents an organic combination and dynamic reflection of the driving environment, traffic participants, and driving behavior over time and space. To clearly delineate different scenario elements and simplify the task of scenario recognition, this paper analyzes and identifies typical driving scenarios of ICVS based on the six-layer element framework.

2.2 Scenario Classification

The German PEGASUS project (Menzel et al., 2018) divides scenarios into three levels of abstraction: functional scenarios, logical scenarios, and concrete scenarios, based on the degree of abstraction of scenario elements. Functional scenarios describe the types of scenario elements and simple parameters, but they are not directly machine-readable. Logical scenarios represent a set of parameterized scenarios, including the types of elements and their value ranges. Concrete scenarios precisely describe a specific situation and the associated chain of events with fixed parameters, and they can be defined in detail using specific languages. In scenario recognition, the focus is generally on recognizing logical scenarios, which facilitates extracting the parameter ranges of specific scenarios for testing and data mining, as well as abstracting functional scenarios to define the operational design domain (ODD) of ICVs, such as Lane Keeping Assist (LKA) and Adaptive Cruise Control (ACC). Therefore, this paper focuses on the extraction and recognition of logical scenarios.

In addition to the aforementioned scenario classifications, there are also types such as hazardous scenarios, edge scenarios, and accident scenarios. These driving scenarios encompass some of the scenario parameters, such as extreme parameters, hazardous parameters, and rare parameters. The vehicle typical driving scenario recognition in this study does not differentiate between these parameter ranges but rather focuses on recognizing scenarios characterized by typical driving behaviors, such as car-following scenarios.

2.3 Scenario Recognition

The recognition of typical driving scenarios for ICVs primarily focuses on detecting vehicle maneuvers, such as Car-following driving and Lane-change driving. Some methods extract similar scenarios through clustering to identify representative driving scenarios. For example, (Nitsche et al., 2017) proposed an algorithm to cluster vehicle collision data based on predefined scenario types, while (Kruber et al., 2018) discussed an unsupervised learning algorithm using random forests to group general traffic data. However, existing methods for obtaining scenario types from driving data often rely on manually crafted features, which may lead to certain situations being overlooked or insufficiently recognized. To address this, (Hauer et al., 2020) proposed a method for extracting scenario types from driving data, primarily extracting speed and distance features and utilizing Principal Component Analysis (PCA) for feature compression.

In addition, neural network methods can also be used to distinguish and recognize driving scenarios. For instance, (Lu et al., 2023) proposed an unsupervised method from a bird's-eye perspective to categorize hazardous scenarios in intelligent driving. (Yang et al., 2022; Sun et al., 2020) extracted ego and surrounding vehicle information, along with the spatiotemporal features of the environment, to identify lane-changing behaviors and predict Lane-change trajectory distribution. (Epple et al., 2020) used an approach that separately handled the temporal and spatial domains to extract and recognize vehicle scenario features.

However, methods based on fixed preset rules are typically limited to extracting a single specific scenario, making it difficult to adapt to increasingly complex real-world driving environments. Moreover, solely identifying the ego vehicle's maneuvers cannot fully capture the dynamic changes of elements within typical driving scenarios. Therefore, in this study, we divided the scenario elements into different dimensions, focusing on analyzing dynamic driving elements that change significantly in a short period. We developed a typical driving scenario recognition model to enhance the comprehensiveness and accuracy of typical scenario recognition.

3 METHODOLOGY

3.1 Task Statement

According to the PEGASUS project, scenarios in intelligent driving systems can be categorized into six constituent elements, which can be further divided into three dimensions: dynamic driving scenarios, road scenarios, and natural environment scenarios. Dynamic driving scenarios include behaviors such as car-following, lane-keeping, ego-vehicle lane changes, alongside vehicle cut-in, and preceding vehicle cut-out. Relevant parameters describe the motion state of the ego vehicle, as well as its relative position and relative motion with respect to target objects. Road information includes descriptions of road type, road class, pavement structure, and infrastructure, such as highways, urban expressways, road classifications (e.g., primary, secondary roads), road curvature, lane width, number of lanes, toll stations, main road entrances and exits, and intersections. These details are generally obtainable through map and positioning data. Natural environment information describes weather conditions, including weather type, time of day, light intensity, and direction, which can

Table 1: Dynamic driving scenarios on highways.

	Vehicle behavior	Behavior decomposition	Notes
1	Lane-keeping driving	Longitudinal (straight road), longitudinal + lateral (curved road)	Single vehicle behavior
2	Car-following driving	Longitudinal (straight road), longitudinal + lateral (curved road)	Two-vehicles interaction
3	Alongside vehicle cut-in	Longitudinal	Two-vehicles interaction
4	Preceding vehicle cut-out	Longitudinal	Two-vehicles interaction
5	Free lane change	Longitudinal (straight road), longitudinal + lateral (curved road)	Single vehicle behavior
6	Forced lane change	Longitudinal (straight road), longitudinal + lateral (curved road)	Two-vehicles interaction
7	Merging from acceleration lane /emergency lane into the mainline	Longitudinal (straight road), longitudinal + lateral (curved road)	Single vehicle behavior
8	Merging from the mainline into the deceleration lane	Longitudinal (straight road), longitudinal + lateral (curved road)	Single vehicle behavior
9	Lead vehicle emergency braking	Longitudinal	Two-vehicles interaction
10	Overtaking	Longitudinal (straight road), longitudinal + lateral (curved road)	Two-vehicles interaction
11	Avoiding speed-conflict vehicles	Longitudinal (straight road), longitudinal + lateral (curved road)	Two-vehicles interaction

typically be obtained from meteorological data.

For the task of recognizing typical driving scenarios, dynamic driving scenarios exhibit significant changes over short time periods. Therefore, the focus is primarily on identifying dynamic driving scenarios within a given time frame, and subsequently overlaying road and weather scenarios to determine the typical driving scenario on the highway. By analyzing the constraint relationships between different road scenario types and dynamic driving scenarios, a coupling relationship can be established between road scenarios and dynamic driving scenarios, categorizing highway dynamic driving scenarios into 11 types, as shown in Table 1.

Excluding specific road types, the aforementioned 11 dynamic driving scenarios can be categorized into five fundamental driving behaviors: Lane-keeping, Car-following, Alongside vehicle cut-in, Preceding vehicle cut-out, and Lane-change. Among these scenarios, lane-keeping has fewer distinct features, so in a highway driving trajectory, once the other four scenarios are identified, the remaining trajectory sequence is classified as lane-keeping. Therefore, the focus of typical driving scenario recognition in this paper is on the identification of four scenarios: Car-following, Alongside vehicle cut-in, Preceding vehicle cut-out, and Lane-change. This approach not only considers the scenario changes caused by ego-vehicle maneuvers but also accounts for those resulting from the maneuvers of surrounding vehicles.

3.2 Definition of Target Vehicle and Environmental Information

The objective of typical driving scenario recognition is to identify the driving scenarios experienced by the target vehicle based on the historical trajectories of both the target vehicle and the surrounding vehicles. The scenario of the target vehicle is influenced by the surrounding vehicles. As shown in Fig. 1, the area around the target vehicle is divided into eight positions: Left-Preceding(LP), Preceding(P), Right-Preceding(RP), Left-Alongside(LA), Right-Alongside(RA), Left-Following(LF), Following(F), and Right-Following(RF). The spatial information from each of these positions serves as an important feature input to the scenario recognition model, thereby improving the accuracy of scenario recognition.

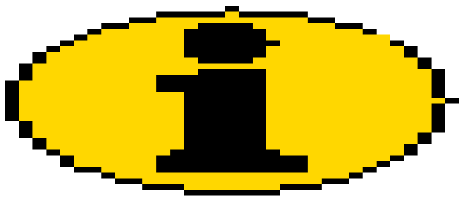

Figure 1: The 8 adjacent positions vehicles of the target vehicle.

As mentioned above, it is necessary to use the spatiotemporal features of the ego vehicle and surrounding vehicles as input sequences. We input a time se-

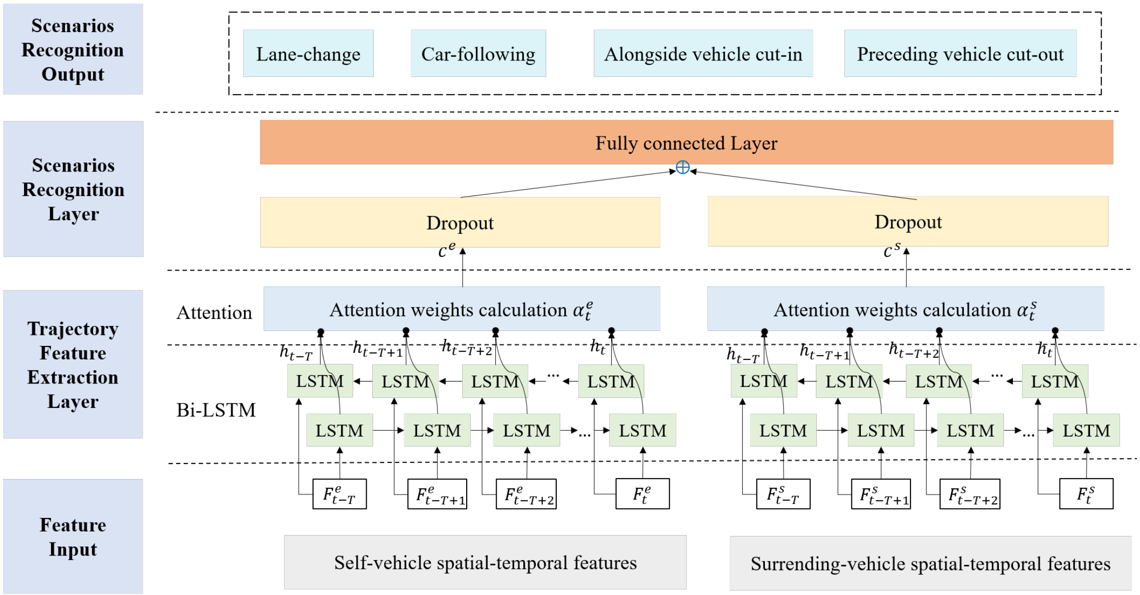

Figure 2: The structure of the proposed dynamic driving scenarios recognition model.

ries consisting of T time steps, as shown in Equation 1.

$$F = (F_1, F_2, ...F_T) \tag{1}$$

where $F_T = (F_T^e, F_T^s)$ represents the trajectory features at time step T, F_T^e represents the ego vehicle trajectory features at time step T, which include ego vehicle coordinates, lateral and longitudinal speeds, and lateral and longitudinal accelerations. F_T^s represents the surrounding vehicle trajectory features at time step T, including the coordinates, lateral and longitudinal speeds, and lateral and longitudinal accelerations of the vehicles at eight surrounding positions. If no vehicle exists in a given surrounding position, the corresponding values are set to 9999 for consistent processing in subsequent steps.

3.3 Dynamic Driving Scenario Recognition Model

In this study, we propose a two-layer LSTM-based dynamic driving scenario recognition model to extract hidden driving features from vehicle trajectories. As shown in Fig. 2, the proposed model consists of a trajectory feature extraction layer and a scenario recognition layer, with the scenario classification score as the output for recognition results.

The trajectory feature extraction layer utilizes a bidirectional Long Short-Term Memory (Bi-LSTM) network combined with an attention mechanism, allowing the model to consider both forward and backward trajectory information while focusing on key features. The LSTM core comprises three gates: a forget gate, an input gate, and an output gate. The forget gate determines which information should be discarded or retained during transmission; the input gate is responsible for updating the cell state; and the output gate determines the output of the cell. In trajectory sequences, the current output may be influenced by both previous and future information, which is why a Bi-LSTM, combining both forward and backward LSTMs, is used to fully leverage sequential information. The corresponding calculation formula is shown in Equation 2 and Equation 3.

$$h_t^e = concat(h_{L_t}^e, h_{R_t}^e) \tag{2}$$

$$h_t^s = concat\left(h_{L_t}^s, h_{R_t}^s\right) \tag{3}$$

where h_{L_t} and h_{R_t} represent the hidden states of the forward LSTM and backward LSTM, respectively. The *concat* function concatenates the forward and backward hidden states. h_t^e and h_t^s represent the ego vehicle state information and the surrounding vehicle information, respectively.

The attention weights α_t are obtained using the Softmax function, as shown in Equation 4:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_k)} \tag{4}$$

where e_t is the attention score at time step t.

The weighted sum of the outputs at each time step can then be calculated as Equation 5 and 6:

$$c^e = \sum_{t=1}^{T} \alpha_t^e h_t^e \tag{5}$$

$$c^s = \sum_{t=1}^{T} \alpha_t^e h_t^s \tag{6}$$

where c^e and c^s represent the weighted sums of the hidden layers for the ego vehicle and surrounding vehicles, respectively.

The scenario recognition layer uses a Dropout function to remove redundant hidden units, preventing the model from overfitting.The context vectors of the ego vehicle and surrounding vehicles are concatenated along the feature dimension to form a comprehensive feature vector, as shown in Equation 7.

$$c = [c^e; c^s] \tag{7}$$

The concatenated feature vector c is fed into a fully connected layer to obtain the raw prediction scores z for each class. Finally, we feed the raw prediction scores z into the Softmax function to obtain the predicted probability for each class, as shown in Equation 8.

$$\hat{y}_i = \frac{\exp(z_i)}{\sum_{k=1}^{K} \exp(z_k)}, \quad i = 1,2,3,4 \tag{8}$$

where y_i represents the predicted probability for class i.

4 EXPERIMENT

4.1 Dataset and Data Processing

The HighD dataset is a large-scale naturalistic vehicle trajectory dataset used to validate scenarios on German highways. The dataset includes approximately 110,000 post-processed trajectories of vehicles (including cars and trucks), which were extracted from videos recorded using drones on German highways near Cologne in 2017 and 2018. A total of 60 recordings were conducted across six different locations, with an average recording duration of 17 minutes, totaling 16.5 hours, covering a highway segment approximately 420 meters in length, as shown in Fig. 3.

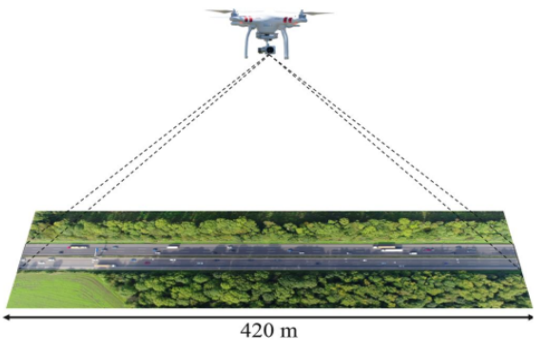

Figure 3: The HighD dataset collection diagram.

The HighD dataset consists of 60 recordings, each containing three files that record vehicle information for each frame, including ID, trajectory coordinates, speed, acceleration, Car-following data, and vehicle type. The dataset was collected across different highway locations and on different dates, encompassing various vehicle types, thus demonstrating diversity. This dataset is representative of typical vehicle characteristics in daily traffic, making it highly valuable for scenario recognition research in ICVs.

4.2 Sample Sequence Extraction

To extract the motion features of the ego vehicle and surrounding vehicles at each frame for the purpose of distinguishing different scenarios, this study first extracts the Lane-change data sequence based on the ego vehicle's lane-change behavior. For lane-change vehicles, the complete trajectory includes the preparation phase, the midpoint of the lane change, and the completion phase. To avoid scene trajectory overlaps and changes in surrounding vehicle IDs, we extract only the preparation and midpoint phases of the lane change, marking these as Lane-change scenarios, and collect the surrounding vehicle trajectories during this phase. The trajectory data extraction method is illustrated in Fig. 4.

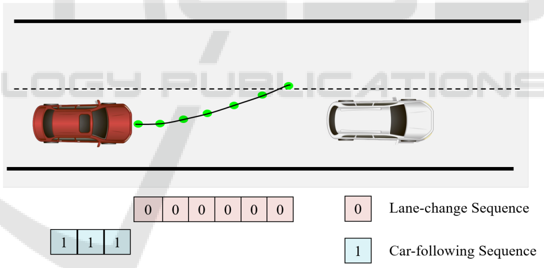

Figure 4: Lane-change and Car-Following Trajectory Sequence Extraction.

Next, we extract trajectories for Alongside vehicle cut-in, Preceding vehicle cut-out from the ego vehicle's lane-keeping trajectory. Initially, we check whether the lead vehicle ID changes. If the ID remains unchanged, the trajectory sequence is labeled as Car-following. If the lead vehicle ID changes, we differentiate between Alongside vehicle cut-in and Preceding vehicle cut-out by comparing the vehicle coordinates before and after the change. To avoid confusion due to changes in surrounding vehicle IDs, we only extract the trajectory up to the successful completion of a lane change, ensuring that vehicle IDs in surrounding positions remain consistent, The trajectory data extraction method is illustrated in Fig. 5 and Fig. 6.

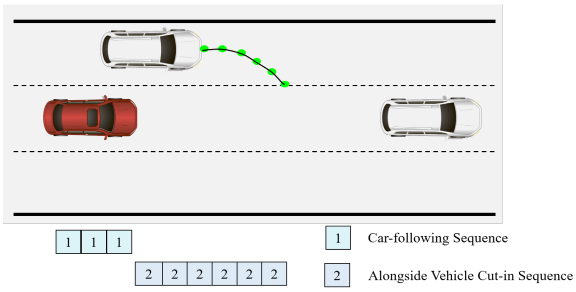

Figure 5: Car-Following and Alongside vehicle cut-in Trajectory Sequence Extraction.

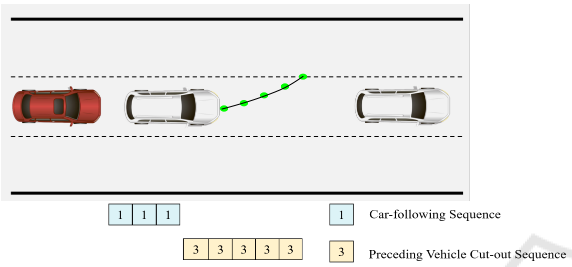

Figure 6: Car-Following and Preceding vehicle cut-out Trajectory Sequence Extraction.

Finally, the sliding window method is used to extract fixed-length sample sequences from all vehicle trajectory segments, with a window length of 1 second. In total, we extracted 11,721 Lane-change scenario trajectories, 7,166 Car-following trajectories, 3,976 Alongside vehicle cut-in trajectories, and 7,669 Preceding vehicle cut-out trajectories. To mitigate the impact of data imbalance on model performance, we applied oversampling to underrepresented scenarios to balance the number of samples across classes. Since the dataset includes multiple types of data, such as position and speed, which have varying scales and units, we performed min-max normalization on all data to reduce interference from different data magnitudes and facilitate the training and convergence of the neural network. The corresponding normalization formula is as shown in Equation 9:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

where x represents the original data, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the data, respectively, and x' is the normalized data.

4.3 Training Parameters and Evaluation Metrics

In this study, the data was randomly divided into a training set and a test set, with the test set comprising 20% of the data. The proposed scenario recognition network was trained using the PyTorch framework. The model consists of a 4-layer stacked LSTM, with each hidden layer containing 64 neurons. Cross-entropy loss was used as the loss function, and the entire model was trained using the Adam optimizer.

We employed precision, recall, and F1-score as evaluation metrics to assess the proposed LSTM-based typical driving scenario recognition model:

Precision refers to the proportion of correctly identified samples for a particular scenario out of the total samples identified as belonging to that scenario category. For detailed calculation, refer to Equation 10.

$$\mathrm{P} = \frac{TP}{TP + FP} \tag{10}$$

Recall refers to the proportion of correctly identified samples for a particular scenario out of the actual total samples of that scenario, as shown in Equation 11.

$$\mathrm{R} = \frac{TP}{TP + FN} \tag{11}$$

F1-score refers to the harmonic mean of Precision and Recall, providing a single measure that balances both. The formula for the F1-score is Equation 12:

$$\mathrm{F1} = \frac{2 * P * R}{P + R} \tag{12}$$

In the above formula, TP (True Positives) represents number of samples correctly identified as belonging to the target class. False Positives (FP) represents the number of samples incorrectly identified as belonging to the target class. False Negatives (FN) represents the number of samples that belong to the target class but were incorrectly identified as not belonging to it.

4.4 Result

The model was trained for 300 epochs, with the training and test losses gradually decreasing.The validation set was used as the test set, and predictions were compared with actual results to generate a confusion matrix, describing the correspondence between the classifier's predictions and actual labels, as shown in Fig. 7. The precision and recall for each class exceeded 95%, indicating that the model can accurately recognize vehicle driving scenarios.

The ROC curve is shown in Fig. 8. The ROC curves for each class, as well as the macro-average and micro-average ROC curves, all have an AUC value of 1, indicating excellent classification performance of the model.

Table 2 demonstrates that the proposed typical dynamic driving scenario recognition model outperforms the baseline models—Support Vector Machine(SVM), Long Short-Term Memory(LSTM), and

Table 2: Comparison of Scenario Recognition Performance Across Different Models.

	SVM			simple-LSTM			Bi-LSTM			Proposed model		
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Lane-change	89.07%	94.1%	91.52%	90.26%	88.14%	89.19%	91.36%	90.7%	91.03%	98.76%	98.72%	98.74%
Car-following	87.8%	94.11%	90.86%	92.79%	92.8%	92.79%	93.48%	94.07%	93.78%	95.97%	95.61%	95.80%
Alongside vehicle cut-in	84.11%	71.1%	77.06%	92.92%	93%	92.96%	92.98%	92.07%	92.52%	96.48%	96.93%	96.7%
Preceding vehicle cut-out	86.48%	80.3%	83.28%	85.95%	87.89%	86.91%	88.61%	89.56%	89.08%	95.73%	95.69%	95.71%
Overall	87.59%			90.45			91.6%			96.74%		

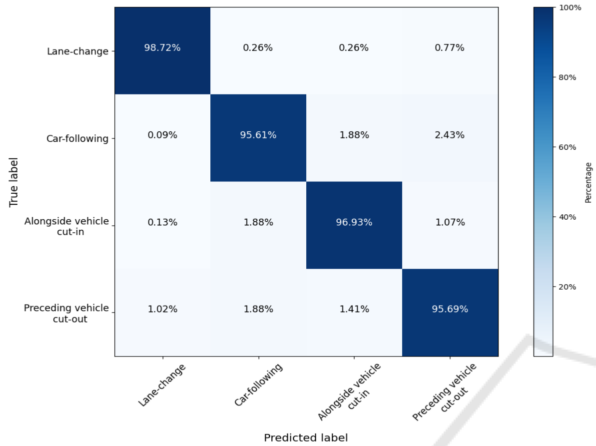

Figure 7: The confusion matrix of the proposed model. (AV:Alongside Vehicle, PV:Preceding Vehicle).

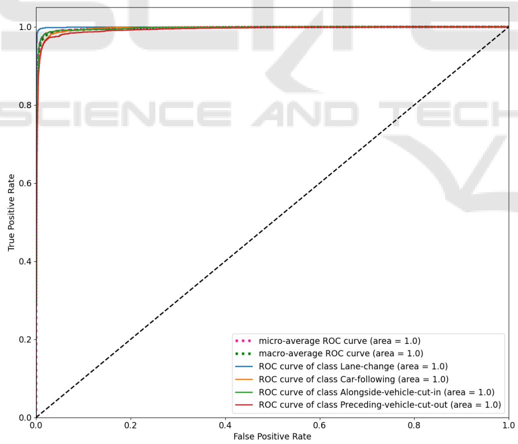

Figure 8: The ROC Curve of the proposed model.

Bi-directional Long Short-Term Memory(Bi-LSTM). The proposed model exhibits significant advantages in terms of accuracy, recall, and F1-score for Lane-change, Car-following, Alongside vehicle cut-in, and Preceding vehicle cut-out scenarios, indicating that the model is highly efficient in recognizing dynamic driving scenarios.

5 CONCLUSIONS

This study addresses the issues of overly simplistic scenario classification and the lack of consideration for overall environmental changes in scenario recognition. We propose an innovative highway typical driving scenario recognition model based on LSTM and attention mechanisms, which extracts features while accounting for scenario changes caused by vehicle interactions and surrounding vehicle maneuvers. Comparative experiments with other baseline models demonstrate the accuracy and reliability of the proposed model, advancing a deeper understanding of driving scenario recognition.

In addition, this task can predict the driving scenarios of vehicles, provide prior knowledge for subsequent decision-making systems, and also filter the perception paradigm data of ICVs to provide standardized data to neural networks, making subsequent parameter training more targeted and improving the safety of intelligent connected vehicles.

However, the method proposed in this article for identifying typical driving scenarios on highways does not cover more road types. In future work, in order to achieve comprehensive recognition of typical driving scenarios, it is necessary to integrate automatic recognition of road and environmental elements to improve the generality of the scenarios, thus covering more types and achieving accurate recognition. Therefore, future research should focus on developing a unified recognition framework to achieve more accurate and comprehensive recognition results.

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