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***Research article***

# Ensemble deep learning-based lane-changing behavior prediction of manually driven vehicles in mixed traffic environments

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**Abstract:** Accurately predicting lane-changing behaviors (lane keeping, left lane change and right lane change) in real-time is essential for ensuring traffic safety, particularly in mixed-traffic environments with both autonomous and manual vehicles. This paper proposes a fused model that predicts vehicle lane-changing behaviors based on the road traffic environment and vehicle motion parameters. The model combines the ensemble learning XGBoost algorithm with the deep learning Bi-GRU neural network. The XGBoost algorithm first checks whether the present environment is safe for the lane change and then evaluates the likelihood that the target vehicle will make a lane change. Subsequently, the Bi-GRU neural network is used to accurately forecast the lane-changing behaviors of nearby vehicles using the feasibility of lane-changing and the vehicle's motion status as input features. The highD trajectory dataset was utilized for training and testing the model. The model achieved an accuracy of 98.82%, accurately predicting lane changes with an accuracy exceeding 87% within a 2-second timeframe. By comparing with other methods and conducting experimental validation, we have demonstrated the superiority of the proposed model, thus, the research achievement is of utmost significance for the practical application of autonomous driving technology.

**Keywords:** traffic engineering; lane change; traffic safety; ensemble learning; deep learning

## 1. Introduction

With the increasing urbanization and continuous improvement of road transportation systems, automobiles have become a vital mode of transportation for the general public, providing convenience and freedom for commuting. However, these advancements also pose significant challenges to traffic safety. Studies have indicated that driver errors in operation or judgment are among the leading causes of traffic accidents, with lane-changing and merging accidents accounting for 18% [1]. Various passive safety systems have saved millions of lives, but they are not designed to prevent accidents; instead, they aim to protect passengers in the event of an accident [2,3]. Autonomous driving technology has emerged as a prominent research focus in academia and industry to reduce and prevent traffic accidents and ensure efficient and safe vehicle operation.

The rapid advancements in deep learning technology and continuous improvement in computer performance are fueling the progress of autonomous driving vehicles. Consequently, the road environment is gradually evolving into a mixed traffic environment, with the coexistence of manual and autonomous vehicles [4]. To ensure the safe operation of autonomous vehicles on the road and minimize the negative impact of erratic lane-changing behavior of vehicles on traffic safety, autonomous driving algorithms need to accurately and timely predict the lane-changing behaviors of surrounding manually driven vehicles [5,6].

Due to the different feature selections, existing models can be loosely categorized into two groups. The first category involves models that utilize driver behavior and control parameters, including data such as driver eye and head rotation parameters captured by onboard cameras, and driver control parameters like steering wheel angle and brake pedal position obtained from onboard sensors [7]. For example, Xing et al. put out a vision-based intention inference system, which records multi-modal information using multiple inexpensive cameras and the VBOX vehicle data gathering system. A unique ensemble bi-directional recurrent neural network (RNN) model incorporating Long Short-Term Memory (LSTM) units is developed to cope with the time-series driving sequence and the temporal behavioral patterns. They deduced an intention 0.5 seconds before the maneuver began with an average accuracy of 96.1% using their approach [8]. On the other hand, Schmidt et al. analyzed 3111 lane changes performed by 51 drivers in a simulated highway scenario. Their findings indicated that the steering wheel angle was the most predictive indicator and the primary sign of lane change preparation [9].

Different methods and models were designed and proposed in the studies above to validate the correlation between driver behavior, driver control parameters, and the lane-changing process. However, data such as the driver's face, steering wheel angle, and brake pedal position contain sensitive information about the driver of a self-propelled vehicle and are limited to simulation experiments, making them unsuitable for real-world road environments. Additionally, the data collected from onboard sensors is only adequate for predicting the behavior of the ego vehicle and not suitable for predicting the actions of surrounding vehicles [10]. In response to this problem, this study introduces an ensemble deep learning-based lane-changing behavior prediction method that validates the proposed algorithm using vehicle natural trajectory data from the highD dataset. The model integrates vehicle motion parameters and surrounding traffic environment features to achieve accurate and timely prediction of driver behavior. The main work of this article is as follows:

(I) The highD dataset is analyzed and processed to extract the necessary feature parameters for the model, considering the relevant characteristics of lane changing. Effective processing and feature extraction from the input data help reduce noise and redundant information, leading to improved learning capability of subsequent models.

(II) We propose a model for predicting lane change behavior based on lane change feasibility judgment, which involves two steps. In the first stage, the Extreme Gradient Boosting (XGBoost) algorithm is used to judge whether the target vehicle can change lanes safely by feeding the model data about the target vehicle's surroundings. The second step involves using a neural network to predict the target vehicle's behavior of changing lanes. The neural network utilizes the target vehicle’s motion state information and the result obtained from the first step as inputs.

(III) Our proposed method is compared and evaluated with other models using the same dataset. It seems that the results indicate that our model achieves earlier prediction of lane change behavior.

The structure of this paper is as follows: Section 2 presents the research progress in the field of vehicle lane change behavior prediction. Section 3 introduces the structure of the proposed model. Section 4 provides an overview of the dataset used in this study and presents the experimental results. Finally, Section 5 summarizes the conclusions of this research and suggests future research directions.

## 2. Related work

As research on vehicle lane change behavior advances, researchers have become increasingly aware of the significant impact of lane change behavior on road safety and traffic congestion. Consequently, it is crucial to study accurate and efficient prediction methods for the lane change behavior of neighboring vehicles to enhance the driving safety of autonomous vehicles.

The field of vehicle lane change behavior prediction has witnessed extensive studies dedicated to exploring effective methods and models. These studies have contributed crucially to driver behavior research and the enhancement of autonomous vehicle safety. Broadly, these studies can be categorized into three groups: generative models, discriminative models, and the increasingly popular neural network models.

### *2.1. Generative models*

Generative models are probabilistic models that predict lane change behavior by modeling driver behavior and generating data samples that adhere to the distribution of driving behavior. Rhder et al. presented a lane change intent prediction method based on a hybrid Bayesian network, which was trained and tested using data collected on German highways, demonstrating good performance [11]. Li et al. presented a lane change behavior prediction method that integrates Hidden Markov Model (HMM) and Bayesian Filter (BF) technologies. The algorithm considers the driving style of the driver in various scenarios to estimate their lane change intentions [12]. Zhang et al. proposed an intent-based adaptive cruise control method based on contextual traffic information. The continuous HMMs integrated with the Gaussian Mixture Models (GMMs) are used to model the behavior of lane change and lane keeping, respectively. The method achieves a recognition accuracy of over 85% for the target vehicle's behavior [13]. Xia et al. proposed a lane change intention prediction model based on HMM. The model replicates the human visual system’s selective attention mechanism, simulating how human drivers prioritize surrounding vehicles and accurately perceive their lane change intentions [14].

### *2.2. Discriminative models*

Whereas generative models focus on describing the lane change process, discriminative methods optimize their model parameters specifically for the classification problem. Consequently, it has the advantages of simplicity and directness [15]. Zhang et al. proposed a three-step XGBoost-based feature learning algorithm for feature selection for lane change prediction [16]. Li et al. utilized the NGSIM natural dataset and chose features including vehicle speed, vehicle acceleration, headway distance, headway time distance, and vehicle lateral and longitudinal positions as input variables. The author has demonstrated through experiments that the gradient boosting decision tree(GBDT) model performs better than random forest (RF) in predicting vehicle lane change [17]. Kim et al. introduced an open-set recognition concept that utilizes the support vector machine (SVM) classification algorithm to cautiously detect the lane change intentions of surrounding vehicles. The objective is to enhance the performance of adaptive cruise control (ACC) and prevent potential accidents [18]. Hu et al. investigated the rear-end collision avoidance behavior of drivers in merging scenarios on three-lane highways and developed a decision tree-based model for predicting maneuvers. The research collected data from 24 participants, conducted 1326 valid trials in a driving simulator, and obtained the participants' personality traits using the revised Eysenck Personality Questionnaire designed for Chinese individuals. The model attained a prediction accuracy of 79.2% on the training dataset and 80.3% on the testing dataset [19]. Feng et al. introduced an SVM model for recognizing lane change behavior using Gridsearch-PSO optimization. In the Matlab environment, the SVM model, optimized through parameter optimization using Gridsearch-PSO, exhibited substantial enhancement in recognition accuracy compared to the SVM model with default parameters [20]. Das et al. employed the SHRP2 database, selected vehicle kinematics, machine vision, driver, and road geometry features, trained various machine learning algorithms, and performed validation, testing, and comparative analysis. The findings demonstrated that the XGBoost model achieved superior overall prediction accuracy and F1 score compared to other models [21].

### *2.3. Neural network models*

Given the recent achievements of deep learning in domains like image classification and speech recognition, numerous researchers have adopted this approach for behavior recognition and prediction [22]. Wei et al. introduced a hybrid prediction model based on RNN and Fully Connected Neural Networks (FC), which was validated through experiments conducted in real traffic scenarios [23]. Guo et al. presented an attention-based Bidirectional Long Short-Term Memory network (AT-BiLSTM) for modeling lane-changing intentions in connected environments. The analysis results demonstrated the model's favorable recognition accuracy [24]. To overcome the challenge of data imbalance that hinders neural network models in predicting lane change behavior, Shi et al. introduced a layered over-sampling bagging method. This method generates a wider range of informative instances from the minority class, which are then used to train the LSTM model [25]. Xue et al. constructed an integrated lane change prediction model incorporating traffic context using machine learning algorithms. The model considers the impact of traffic conditions and vehicle types on lane-changing maneuvers and was validated on the NGSIM dataset, showcasing its ability to accurately predict the entire lane-changing process [26]. Wu et al. introduced an Attention-Enhanced Residual Multi-layer Bi-directional LSTM model for recognizing drivers' lane-changing intentions. This model utilizes trajectory features and vehicle interaction information and was validated using the highD dataset [27]. Zyner et al. presented a vehicle lane-changing intention prediction method that utilizes RNN and validated its effectiveness on a roundabout [28]. Chandra et al. introduced TraPHic, a model that combines a CNN-LSTM hybrid network for predicting the trajectories of traffic participants [29]. Li et al. presented an attention-based LSTM model for predicting highway lane-changing behavior. The model considers the surrounding vehicle information and the historical trajectory data of the target vehicle [30]. Dang et al. redefined the lane-changing prediction problem as lane-changing time prediction, approaching the task as a regression problem to estimate the time it takes for a vehicle to complete a lane change. They employed LSTM to forecast the duration from the current moment until the vehicle crosses the lane boundary [31]. Li et al. took into account the dynamic interaction among surrounding vehicles by incorporating the sequential motion information of these vehicles as inputs. They integrated the target vehicle's state with this information to judge the congestion level across different lanes. Employing RNN, they predicted the lane-changing behavior of highway drivers and designed an intention-aware motion planning controller. The feasibility of the proposed intention inference model was empirically demonstrated [32].

Regarding the above study, although the generative model-based methods have achieved good prediction accuracy, most of the existing HMM-based lane-changing behavior prediction methods assume that the state of a vehicle at any moment depends only on the state of the previous moment and is independent of the state of other moments, which cannot fully exploit the feature information of the traffic context, and has limitations in the prediction of lane-changing behavior. Existing XGBoost-based models and neural network-based models outperform other methods, but related studies rarely consider the relationship between the surrounding environment and vehicle lane changing. Therefore, this study introduces a lane-changing behavior prediction model that considers the influence of the surrounding environment: the information of the surrounding environment is input into the XGBoost model to determine the lane-changing feasibility of the target vehicle; a Bi-GRU network is constructed to combine the information of the target vehicle and the lane-changing feasibility to predict the vehicle's lane-changing behavior.

## 3. Method

To accurately predict the lane-changing behavior of manually driven vehicles in the presence of autonomous vehicles, this paper introduces an ensemble deep learning-based lane-changing behavior prediction method. This model incorporates the analysis of the driving environment and motion state of manually driven vehicles. The model comprises three modules: a data processing module, a lane-changing feasibility judgment module, and a lane-changing behavior prediction module. The cooperative functioning of these three modules enables precise prediction of the lane-changing behavior of neighboring manually driven vehicles and offers decision-making and control guidance for autonomous vehicles. The provided Figure 1 depicts the comprehensive structure of the proposed lane-changing behavior prediction fusion model in this paper.

### *3.1. Data processing*

Figure 2 illustrates a schematic diagram of vehicles driving in high-speed scenarios. The vehicle being predicted, referred to as the target vehicle (TV), is depicted in the diagram. The surrounding vehicles of the target vehicle are denoted as SVs = {PV, LPV, LAV, LFV, RPV, RAV, RFV}. PV refers to the vehicle positioned in front, LPV denotes the vehicle on the left front, LAV represents the vehicle on the left side, LFV stands for the vehicle on the left rear, RPV indicates the vehicle on the right front, RAV symbolizes the vehicle on the right side, and RFV corresponds to the vehicle on the right rear.

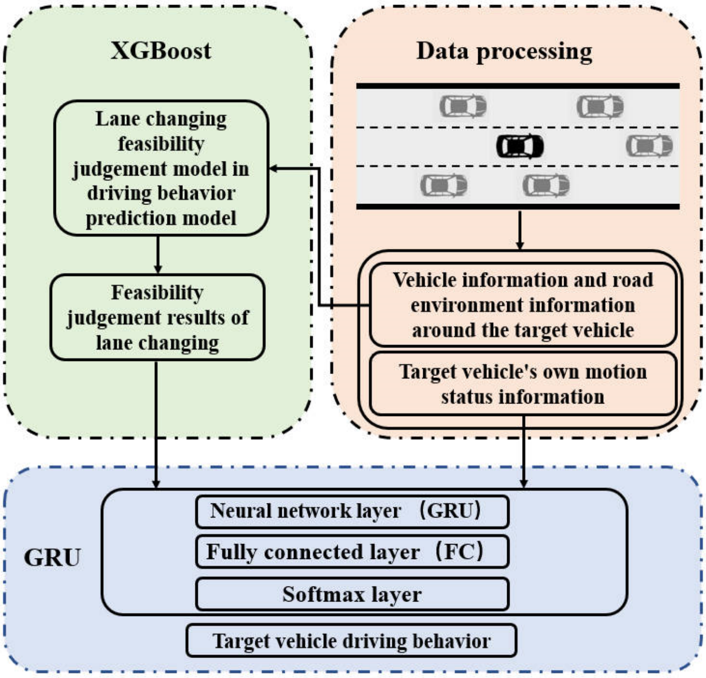


**Figure 1.** The framework of the lane-changing behavior prediction fusion model.

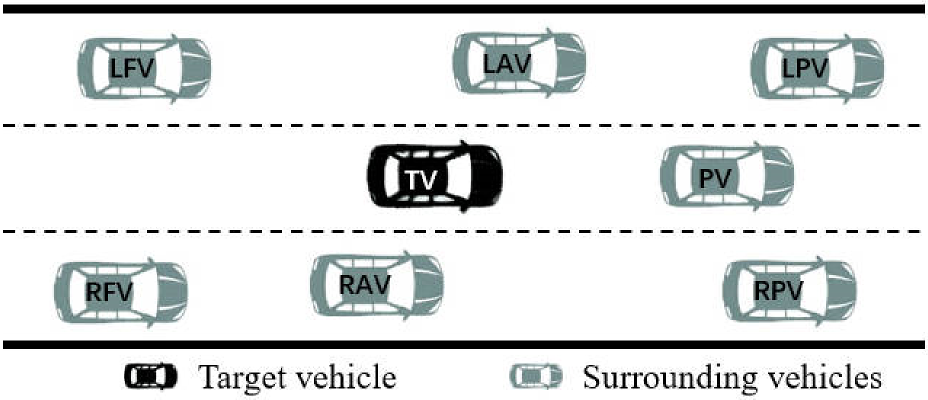


**Figure 2.** Illustration of driving scene.

Prior research suggests that drivers commonly evaluate the viability of a lane change by considering the relative distance and velocity about surrounding vehicles [33,34]. This study initially extracts vehicle trajectory data from the highD dataset. After that, the data processing procedure extracts the relevant information about the target vehicle and its surrounding environment, as specified in Table 1. The target vehicle information includes vehicle location information, speed, acceleration, and vehicle type. The surrounding environment information includes road environment information and surrounding vehicle information. The surrounding environment information is used as input by the lane change feasibility judgment model to assess whether it is feasible for the target vehicle to change lane. The target vehicle's motion state information is then used as input to the lane-changing behavior prediction model, and when combined with the results of the lane-changing feasibility judgment model, the neural network is used to anticipate the vehicle’s lane-changing behaviors.

**Table 1.** Lane change scenario parameter definitions.

| Parameters | | Definition |
|---|---|---|
| Target vehicle information | $x$ | Lateral coordinate of the target vehicle |
| | $y$ | Longitudinal coordinate of the target vehicle |
| | $v$ | Lateral velocity of the target vehicle |
| | $a$ | Lateral acceleration of the target vehicle |
| | $T_{ype}$ | Type of the target vehicle, 1 for car and -1 for truck |
| Road environment information | $R_l$ | Left lane indicator, 1 when there is a left lane next to the target vehicle, otherwise 0 |
| | $R_r$ | Right lane indicator, 1 when there is a right lane next to the target vehicle, otherwise 0 |
| Surrounding vehicle information | $D_p/V_p$ | Difference in distance/velocity between the target vehicle and the preceding vehicle in the current lane |
| | $D_{pl}/V_{pl}$ | Difference in distance/velocity between the target vehicle and the leading vehicle in the left lane |
| | $D_{pr}/V_{pr}$ | Difference in distance/velocity between the target vehicle and the preceding vehicle in the right lane |
| | $D_{al}/V_{al}$ | Difference in distance/velocity between the target vehicle and the adjacent vehicle in the left lane |
| | $D_{ar}/V_{ar}$ | Difference in distance/velocity between the target vehicle and the adjacent vehicle in the right lane |
| | $D_{fl}/V_{fl}$ | Difference in distance/velocity between the target vehicle and the following vehicle in the left lane |
| | $D_{fr}/V_{fr}$ | Difference in distance/velocity between the target vehicle and the following vehicle in the right lane |

### *3.2. Lane change feasibility judgment model based on XGBoost*

Drivers often judge the plausibility of a lane change in real-world lane change scenarios by monitoring the relative distance and speed of other vehicles. The driver will initiate a lane change only when they determine that the conditions are favorable while choosing to remain in the original lane if the conditions are not met. This module's goal is to judge whether a lane change for the target vehicle is feasible by figuring out whether it has enough time and space to carry out the maneuver. In this paper, the surrounding vehicle information and road environment information are selected as input values to determine whether the lane change conditions are satisfied.

Evaluating the feasibility of lane change conditions for vehicles is fundamentally a multi-classification task. Several weak classifiers are combined in ensemble learning to create a strong classifier that builds on the advantages of each weak classifier and performs relatively well. Furthermore, the combination of multiple models can mitigate the influence of outliers and data noise [35]. Thus, this study adopts the XGBoost algorithm to evaluate the feasibility of lane changes for vehicles.

XGBoost is an ensemble algorithm that utilizes boosting and is based on Cart decision trees. It has gained significant popularity as a machine learning model due to its excellent interpretability and efficient parallel processing mechanism [36]. XGBoost is constructed by combining multiple decision trees into an additive model. Therefore, the representation of XGBoost is as follows:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \tag{1}$$

where $x_i$ represents the feature value of the $i$-th sample, $f_k(x_i)$ represents the output result of the $k$-th decision tree, $\hat{y}_i$ represents the prediction result of the $i$-th sample.

In the iterative process, using the forward stepwise algorithm, the prediction result at step t is obtained by combining the result of the newly constructed decision tree with the prediction result from step (t-1):

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \tag{2}$$

The objective of the XGBoost algorithm is to minimize the objective function during training, which is defined as follows:

$$L^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \tag{3}$$

where the training loss function, $l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i))$, quantifies the difference between the training data's true values and the anticipated values. Given that the judgment of lane change feasibility encompasses multi-class classification, the logarithmic loss function is employed. $\Omega(f_t)$ represents the regularization term, which sums up the complexities of all decision trees to control overfitting.

The regularization term for decision tree complexity is specifically represented as:

$$\Omega(f_t) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{4}$$

where $\gamma$ and $\lambda$ are constants, $T$ represents the number of leaf nodes in the decision tree, and $w$ represents the leaf weights. As a result, the decision tree's overall leaf node count as well as its leaf weights define the complexity of the loss function.

### *3.3. Lane change behavior prediction based on Bi-GRU*

The goal of this work is to construct a Bi-directional Gated Recurrent Unit (Bi-GRU) model for forecasting the lane change behavior of the target vehicle by integrating the projected findings from the lane change feasibility judgment model and the target vehicle's motion state information. This module can accurately forecast the target car's lane change behavior, including left lane change, staying in the current lane, or right lane change, by learning the driver's behavioral patterns and vehicle motion patterns, Figure 3 displays the structure of the model. The target vehicle's motion status information and the XGBoost prediction results are included in the first layer, which is the input layer of time series features. The second layer comprises the Bi-GRU layer. Unlike traditional GRU networks that propagate information solely in one direction, capturing only the preceding context and lacking access to future trajectory information, this study employs a bi-directional GRU network. This approach enables comprehensive utilization of traffic context information and enhances data utilization. The third layer consists of the fully connected layer, followed by the fourth layer comprising the softmax layer. The softmax function is applied to process the output, generating the lane change behavior probability matrix.

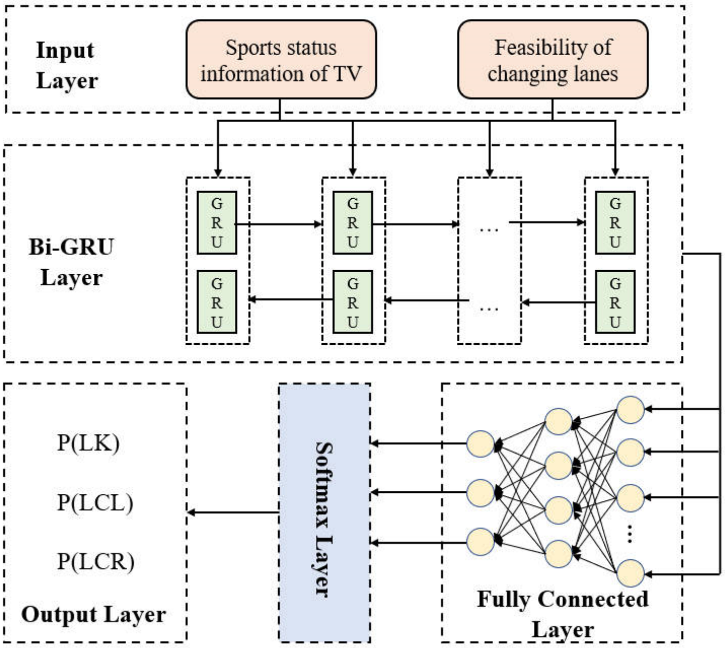


**Figure 3.** Lane change behavior prediction structure.

GRU is a specialized type of RNN. Similar to LSTM, GRU is designed to overcome the challenges associated with vanishing and exploding gradients during the training of sequential data. Unlike LSTM, GRU exhibits a simpler structure (as depicted in Figure 4), offering improved training efficiency while maintaining performance, thereby making it well-suited for real-time driving behavior prediction tasks.

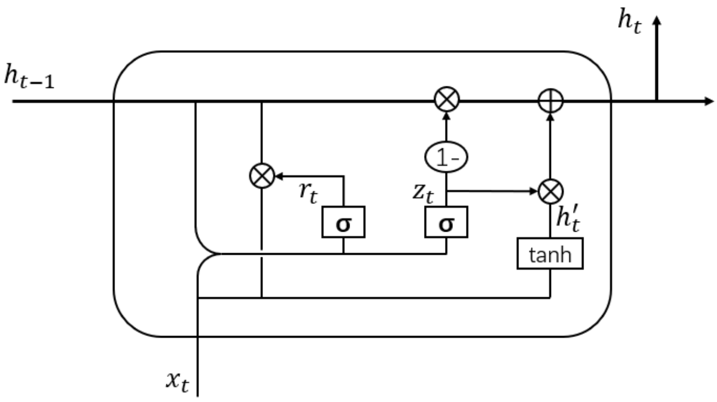


**Figure 4.** Structure of GRU unit.

The input of the GRU unit consists of the current time step's feature $x_t$ and the previous time step's hidden state $h_{t-1}$; $h_t'$ represents the candidate state at the current time step; $h_t$ represents the hidden state at the current time step; $r_t$ and $z_t$ denote the reset gate and update gate, respectively.

In traditional unidirectional GRU, the state is propagated solely from past to future, capturing information solely from the previous context and lacking access to the future context. Conversely, Bi-GRU comprises two GRUs with opposing directions: the lower GRU propagates in chronological order, while the upper GRU propagates in reverse order. Hence, during the propagation process, both the previous and subsequent contexts are taken into account. Figure 5 illustrates the structure of Bi-GRU.

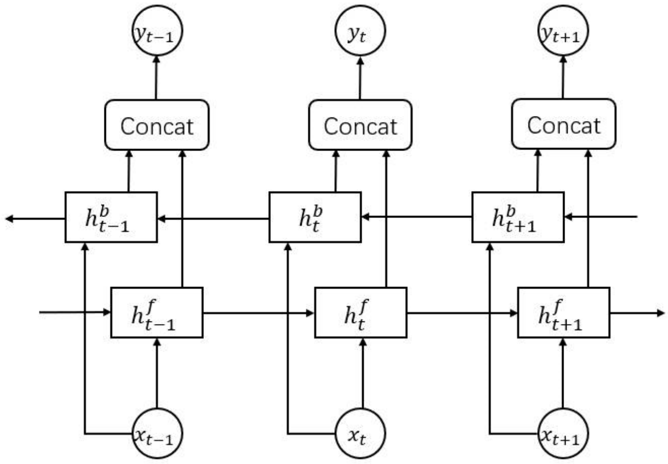


**Figure 5.** Structure of Bi-GRU.

From Figure 5, as can be observed, the present forward hidden state $h_t^f$ and backward hidden state $h_t^b$ are used to determine the hidden state $y_t$ of the Bi-GRU at time t. The forward hidden state $h_t^f$ at time t is determined by the current input $x_t$ and the previous forward hidden state $h_{t-1}^f$, while the backward hidden state $h_t^b$ at time t is determined by the current input $x_t$ and the next backward hidden state $h_{t+1}^b$. The specific mathematical expressions are as follows:

$$h_t^f = GRU(x_t, h_{t-1}^f) \tag{5}$$

$$h_t^b = GRU(x_t, h_{t+1}^b) \tag{6}$$

$$h_t = f(W_{h_t^f} h_t^f + W_{h_t^b} h_t^b + b_t) \tag{7}$$

where $b_t$ is the bias of the hidden state at time t and $W_{h_t^f}$ and $W_{h_t^b}$ are the weights of the forward and backward hidden states at time t, respectively.

## 4. Results and analysis

### *4.1. Data preparation*

The Institute of Automotive Engineering at RWTH Aachen University in Germany provided the highD open dataset, which was used as the source for the car trajectory data used for this work [37]. The dataset comprises post-processed trajectories of 110,000 vehicles captured by drones on six distinct highways in the Cologne, Germany area between 2017 and 2018, encompassing a collection range of 420 meters. The original dataset has a sampling frequency of 25 Hz; however, in practical driving scenarios, such a high level of precision in vehicle information is not always required. To minimize computational costs and ensure safety, the experimental data is sampled at a frequency of 5 Hz. Figure 6 illustrates the shooting locations and scenes depicted in the dataset.


**Figure 6.** The shooting locations and scenes of the highD dataset.

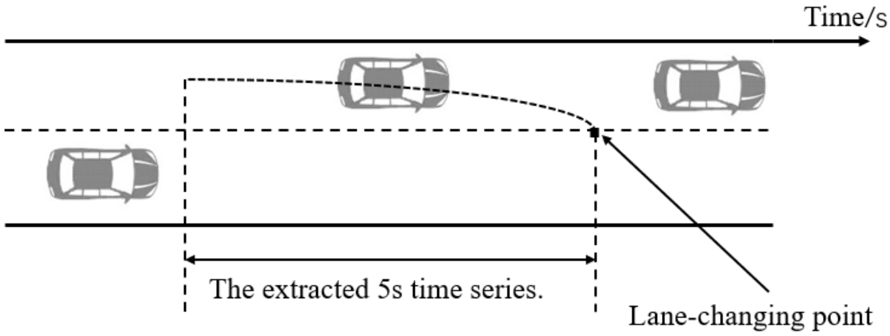


**Figure 7.** Illustration of the extraction of the target vehicle's lane-changing time series.

This study primarily concentrates on vehicles' voluntary lane-changing behavior on the road and does not take into account forced lane changes. Hence, during the data extraction process, only vehicles that have engaged in one lane-changing behavior are taken into consideration. Based on the research of Xue et al., this paper specifies the lane change moment as the instant at which a vehicle's lane number changes the lane change moment in the data processing stage, and the vehicle's position at that time is utilized as a representation of the lane change point [26]. Lane change duration is defined as the time required for continuous lateral moving during the lane change process, nearly 95% of the vehicles had a duration of less than 5 seconds before the lane change point [38]. Therefore, this study employs the 5 s time series to exclude various noises and irregular behavior. Commencing from the lane-changing point, the time series data for the target vehicle's preceding 5 seconds before the lane-changing moment is extracted. The motion data of nearby vehicles within a 5-second time window is then retrieved using the ID of the target vehicle. Figure 7 shows how to retrieve the target vehicle's lane-changing time series.

### *4.2. Model training and result analysis*

#### 4.2.1. Evaluation metrics

When evaluating the performance of lane-change prediction algorithms for vehicles, accuracy, precision, recall, and F1 score are widely regarded as the key metrics [30]. Specifically, accuracy (ACC) denotes the ratio of correctly predicted samples to the total number of samples and can be defined as follows:

$$ACC = \frac{TP + TN}{TP + TN + FN + FP} \tag{8}$$

where TP represents the count of samples with true positive labels and positive predicted results, whereas FP represents the count of samples with true negative labels but positive predicted results. Similarly, TN represents the count of samples with true negative labels and negative predicted results, and FN represents the count of samples with true positive labels but negative predicted results.

Precision (P) is defined as the ratio of correctly identified positive samples to the total number of samples predicted as positive. It can be defined as follows:

$$P = \frac{TP}{TP + FP} \tag{9}$$

Recall (R) represents the proportion of correctly predicted class samples to the total number of true samples in that class. It can be defined as follows:

$$R = \frac{TP}{TP + FN} \tag{10}$$

The F1 score, introduced as a comprehensive evaluation metric, balances the impact of precision and recall by calculating their harmonic mean. It provides a more holistic assessment of the model's performance. The F1 score is defined as follows:

$$F1 = 2 \times \frac{P \times R}{P + R} \tag{11}$$

#### 4.2.2. Performance analysis of the lane-changing feasibility judgment module

The data processing stage resulted in the extraction of trajectory data from 1933 vehicles, which included lane-keeping trajectory data for 640 vehicles, left lane-changing trajectory data for 632 vehicles, and right lane-changing trajectory data for 661 vehicles. Among them, 1520 vehicles' trajectory data were chosen as training samples, constituting a training sample size of 38,000. For experimental validation, a test data sample size of 10,325 was utilized. The lane-changing feasibility judgment model is defined as:

$$y = \{v, T_{ype}, R_l, R_r, S_v\} \tag{12}$$

where y represents the possibilities of three driving behaviors, corresponding to lane-keeping (LK), left lane change (LCL), and right lane change (LCR), denoted as $y_{LK}$, $y_{LCL}$ and $y_{LCR}$, respectively. $S_v$ represents the relative position and velocity between the target vehicle and the surrounding vehicles, $S_v$=$\{D_p, V_p, D_{pl}, V_{pl}, D_{pr}, V_{pr}, D_{al}, V_{al}, D_{ar}, V_{ar}, D_{fl}, V_{fl}, D_{fr}, V_{fr}\}$. The relative speed and distance between the TV and the surrounding vehicle are defined as 0 and 150, respectively, in situations when the surrounding vehicle may not be present [39].

The predictive performance of the lane change feasibility judgment model relies on its hyperparameters, which play a crucial role in model construction. Different hyperparameters can produce varying results even with the same model, and adjusting them can enhance the model's prediction accuracy. In this study, a random search algorithm is employed to fine-tune the model's hyperparameters. Random search is a randomized method that explores hyperparameter combinations through random sampling, offering a balance between computational efficiency and the ability to find optimal configurations. To evaluate the model's performance, 5-fold cross-validation is conducted, involving dataset partitioning into multiple subsets for training and validation. This approach provides a comprehensive understanding of the impact of different parameter combinations. The hyperparameters to be optimized are detailed in Table 2.

**Table 2.** The hyperparameters that need to be optimized for XGBoost.

| Hyperparameters | Explanation of hyperparameters | Optimization scope | Optimal hyperparameter |
|---|---|---|---|
| n_estimators | The number of decision trees. | [50,300] | 300 |
| learning_rate | Learning rate. | [0.01,0.3] | 0.05 |
| max_depth | Maximum depth of each tree. | [3,12] | 6 |
| min_child_weight | The minimum leaf weight for each tree. | [0,20] | 20 |
| subsample | The proportion of data used for training each tree in relation to the entire training set. | [0.6,0.9] | 0.9 |
| colsample_bytree | The proportion of features used when training each tree in relation to the total number of features. | [0.5,0.9] | 0.6 |
| reg_alpha | L1 regularization weight term to prevent overfitting of the model. | [0,1] | 1 |
| reg_lambda | L2 regularization weight term to prevent overfitting of the model. | [0,1] | 0.4 |

In order to validate the predictive performance of the lane-change feasibility judgment model, we applied the optimal hyperparameters obtained through random search to the XGBoost model. Subsequently, the model's accuracy, precision, recall, and F1 score were calculated using the evaluation metrics discussed in the previous section. Table 3 displays the outcomes of the evaluation metrics.

**Table 3.** Model performance evaluation.

| Category | P (%) | R (%) | F1 (%) | ACC (%) |
|---|---|---|---|---|
| LK | 87.72 | 70.07 | 77.91 | |
| LCL | 79.94 | 89.25 | 84.34 | 83.20 |
| LCR | 82.89 | 90.08 | 86.33 | |

The model performance evaluation results presented in Table 3 demonstrate that the optimized XGBoost model achieved an overall accuracy of 83.20%. The model shows a precision of approximately 80% in predicting left lane changes, whereas the precision for maintaining straight and predicting right lane changes both surpass 80%. According to these results, the target vehicle's lane change conditions are accurately identified by the lane change feasibility judgment model. Additionally, the recall rates for detecting left and right lane change behaviors approach 90%, which is higher than the recall for maintaining straight behavior. This discrepancy may be attributed to cases where the conditions for lane change are met but the driver opts to continue driving straight. As a result, the model exhibits strong recall in capturing actual lane change behaviors.

In order to further validate the performance of the lane change feasibility judgment model, this study chooses to establish separate lane change feasibility judgment models using the Random Forest

(RF) and AdaBoost algorithms. These algorithms are optimized using the random search algorithm. The comparison results of the model performances are presented in Figure 8, while more detailed performance metric data can be found in Table 4.

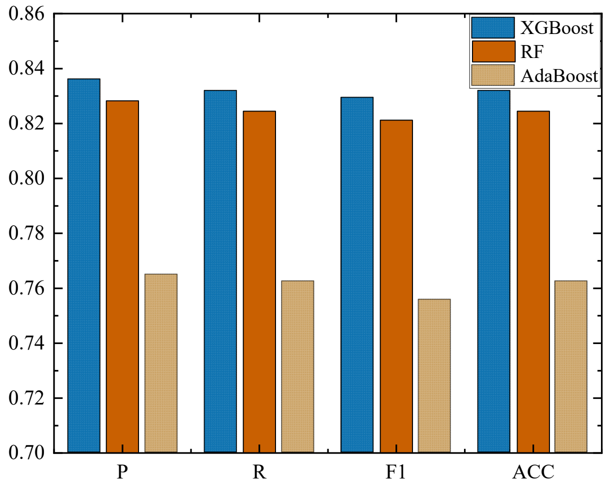


**Figure 8.** Comparison of the three models' performance.

**Table 4.** Model performance evaluation.

| Algorithms | Class name | P (%) | R (%) | F1 (%) | ACC (%) | Time (s) |
|---|---|---|---|---|---|---|
| | LK | **87.72** | **70.07** | **77.91** | | |
| XGBoost | LCL | **79.94** | 89.25 | **84.34** | **83.20** | **0.047** |
| | LCR | 82.89 | **90.08** | **86.33** | | |
| | LK | 86.07 | 67.62 | 75.74 | | |
| RF | LCL | 78.99 | **89.97** | 84.12 | 82.45 | 0.183 |
| | LCR | **83.01** | 89.69 | 86.22 | | |
| | LK | 78.25 | 56.73 | 65.78 | | |
| AdaBoost | LCL | 76.42 | 85.74 | 80.81 | 76.25 | 0.078 |
| | LCR | 75.00 | 86.10 | 80.17 | | |

Upon observing the results in Figure 8, it is evident that the XGBoost model surpasses RF and AdaBoost in terms of average precision, average recall, average F1 score, and accuracy. This demonstrates the XGBoost model's effectiveness in judging lane-changing conditions and providing precise information for the lane-change prediction module. In real-world driving scenarios, real-time judgments on vehicle behavior are essential, necessitating a model with prompt recognition. Table 4 further supports the conclusion that the XGBoost model, utilizing ensemble learning, not only achieves superior prediction accuracy for various lane-changing behaviors but also exhibits higher operational efficiency. This implies that the XGBoost model excels not only in performance but also in meeting the requirements of real-time processing.

#### 4.2.3. Performance analysis of the lane-change prediction module

In this investigation, driving trajectory data from 2352 automobiles were gathered, including 851 right lane changes, 722 left lane changes, and 779 lane-keeping samples. The training set consisted of 80% of the extracted samples, while the remaining 20% constituted the test set. The feature set, denoted as $X = \{x, y, a, v, y_{LK}, y_{LCL}, y_{LCR}\}$, represents the lateral and longitudinal position, acceleration, velocity, lateral velocity, lane-keeping feasibility, left lane-change feasibility, and right lane-change feasibility of the target vehicle. The time series data containing the feature set is input into the Bi-GRU neural network model and then processed by the softmax function to obtain the lane-changing behavior probability matrix:

$$P = \{p_1, p_2, p_3\} \tag{13}$$

where $p_1$, $p_2$, and $p_3$ represent the probability of lane-keeping, left lane-changing, and right lane-changing, respectively.

The recognition algorithm utilized in this study is developed using Python 3.9.7 and the PyTorch 1.12.1 framework. The network architecture comprises a three-layer Bi-GRU structure with a learning rate of 0.001 and a batch size of 64. Gradient descent optimization is performed using the Adam algorithm, and the categorical cross-entropy loss function is employed.

**Table 5.** Results of the approach for predicting lane change behavior in vehicles.

| Predicted time | Evaluation index | Algorithms | | |
|---|---|---|---|---|
| | | GRU (A) | GRU (B) | XGBoost-GRU |
| 0.5 s | ACC (%) | 94.66% | 88.23% | 94.66% |
| | P (%) | 94.92% | 90.32% | 94.69% |
| | R (%) | 94.59% | 88.88% | 94.79% |
| | F1 (%) | 94.48% | 88.33% | 94.72% |
| 1 s | ACC (%) | 89.56% | 73.54% | 90.53% |
| | P (%) | 89.79% | 83.35% | 90.99% |
| | R (%) | 89.58% | 75.14% | 90.94% |
| | F1 (%) | 89.23% | 71.60% | 90.67% |
| 1.5 s | ACC (%) | 72.82% | 65.90% | 88.83% |
| | P (%) | 77.26% | 80.68% | 89.58% |
| | R (%) | 73.85% | 67.82% | 89.31% |
| | F1 (%) | 72.38% | 61.14% | 88.95% |

The primary objective of predicting the lane change behavior of neighboring vehicles is to accurately anticipate and forecast their lane change actions. As an integral part of the decision-making process in autonomous driving, the lane change prediction system plays a crucial role in making timely decisions and allowing sufficient time for their execution. Accurate and proactive lane change behavior prediction of adjacent vehicles is crucial to ensuring driving safety for autonomous vehicles. Accuracy, Precision, Recall, and F1-score are used in this study to assess the model's performance. To demonstrate the significant impact of the lane change feasibility judgment model's prediction results on the output, two additional lane change prediction models, GRU(A) and GRU(B), are introduced for comparative analysis. GRU(A) only makes use of the target vehicle's trajectory information as features, represented by $X_1 = \{x, y, a, v\}$. On the other hand, GRU(B) employs all the feature data from Table 1 without undergoing XGBoost processing. The experimental outcomes are presented in Table 5 and Figure 9.

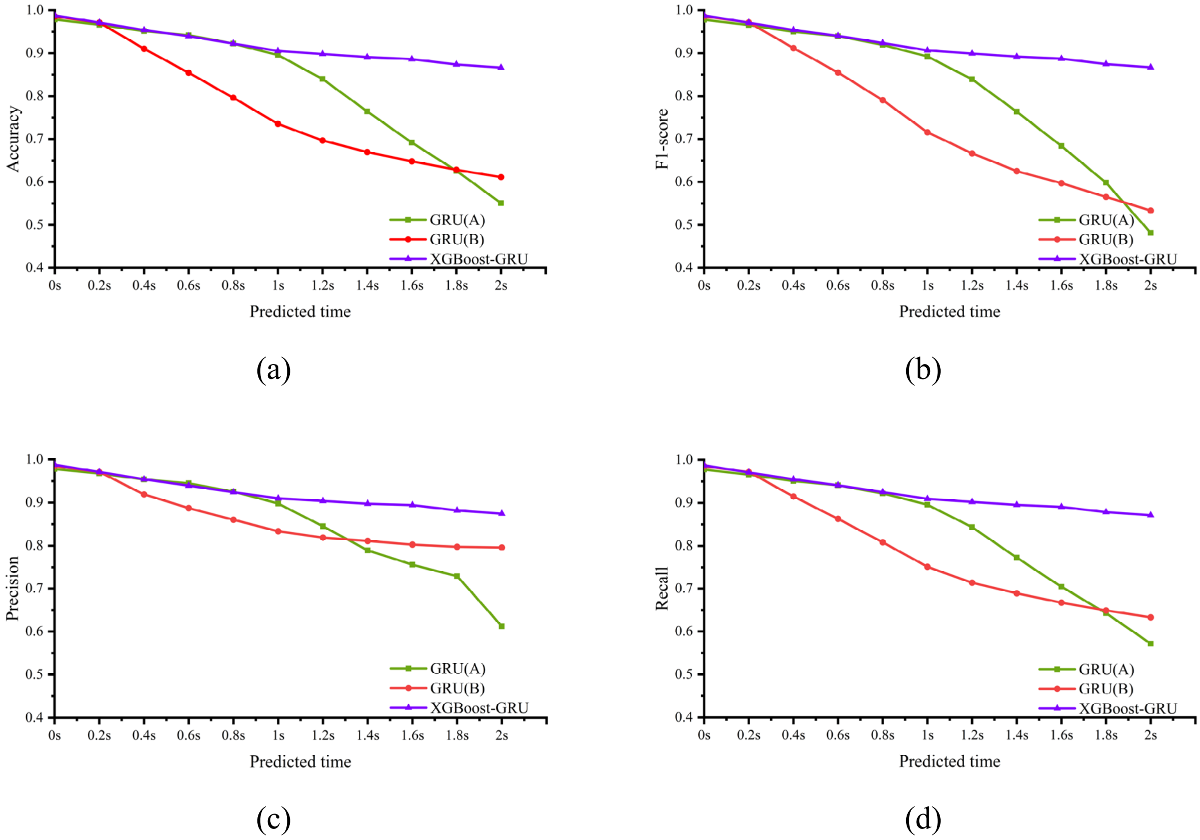


**Figure 9.** Recognition results at different prediction times.

From Table 5 and Figure 9, it is evident that when the vehicle approaches the lane change point, the prediction accuracy of model GRU(A), which utilizes only the target vehicle's trajectory data as input features, is comparable to the suggested model. All evaluation metrics exceed 89% at a prediction time of 1 second. However, as the prediction time extends, the accuracy of model GRU(A) declines rapidly. This decline can be attributed to the limited input feature data, which fails to provide sufficient information to the model. As the prediction time increases, the presence of data noise rises, leading to a reduction in model accuracy. On the other hand, excessive input characteristics that introduce significant noise and have an impact on the model's prediction outcomes are the cause of the model GRU(B)'s poor prediction accuracy. The XGBoost-GRU model that is suggested in the present work uses XGBoost to judge the target vehicle's surrounding environment data at first. Subsequently, the output of XGBoost is utilized as input features for Bi-GRU, effectively leveraging the valuable information contained in the data. The proposed model achieves accurate identification of the target vehicle's lane change behavior with high precision. It can detect lane changes as early as 2 seconds before they occur, with all evaluation metrics surpassing 86%. Furthermore, the model achieves a prediction accuracy of over 90% when predicting lane changes 1 second in advance. Consequently, the proposed model offers precise prediction results for autonomous vehicles, contributing to their safe driving.

## 5. Conclusions

This article aims to improve the driving safety of autonomous vehicles in areas with complex highway traffic. It introduces a vehicle lane change prediction method that incorporates lane change feasibility judgment, comprising a lane change feasibility judgment module and a lane change behavior prediction module. The proposed prediction method undergoes training and testing using the highD dataset. The lane change feasibility judgment model can be used using the target vehicle's environmental data as input to determine if it is feasible to change lanes. The experimental results demonstrate that the XGBoost-based model can accurately evaluate the vehicle's lane change environment, achieving an overall accuracy exceeding 83% in predicting lane change behavior. The target vehicle's lane change behavior can be precisely predicted by the lane change behavior prediction module based on GRU by taking into account the prediction findings of the lane change feasibility judgment module and the target vehicle's motion status information. The model outperforms the performance of the model that ignores the prediction findings, exhibiting an accuracy in lane change behavior prediction that is greater than 87%, specifically 2 seconds before the lane change. The proposed method offers valuable information regarding vehicle lane change for autonomous vehicles, thereby ensuring enhanced driving safety.

Given that the dataset utilized in this study was gathered from highways, where the impact of surrounding environments on vehicle movement is relatively less pronounced in contrast to urban roads, the model's applicability is constrained. Subsequent research will concentrate on enhancing the model's suitability for the intricate road conditions found in urban environments. In addition, in future research, we will conduct an in-depth study of the risk of lane changing to understand in detail how it affects lane-changing behavior to improve the prediction accuracy of our model.

## Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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## Conflict of interest

The authors declare there is no conflict of interest.

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