2022 CARSP Conference
June 20, 2022
Sudbury

A Proactive Lane-changing Risk Prediction Framework Considering Driving Intention Recognition and Different Lane-changing Patterns

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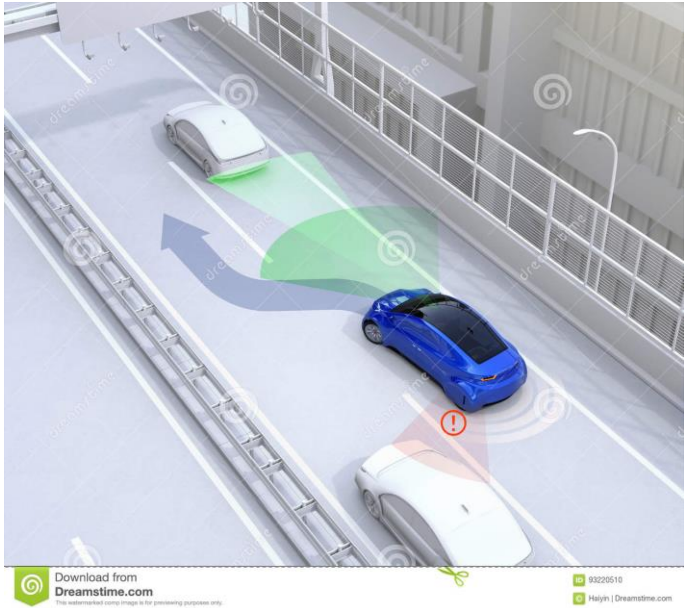
1. INTRODUCTION

INTRODUCTION - Background



- Risky lane-changing (LC) maneuvers can often trigger turbulences in traffic flow
- About 5% traffic crashes and 7% fatalities in US are caused by lane-changing
- Proactive lane-changing risk prediction framework could be implemented in ADAS for improved driving safety

INTRODUCTION - Literature Review

Lane-changing risk analysis

- ☐ **LC risk quantification**
  - ✓ Surrogate safety measure
  - ✓ Field theory
- ☐ **LC risk causation**
  - ✓ LC risk with traffic flow
  - ✓ LC risk with driving behavior
- ☐ **LC risk prediction**
  - ✓ Vehicle trajectory data
  - ✓ Machine learning models

Lane-changing intention

- ☐ **Machine learning models**
  - ✓ Support vector machine
  - ✓ Bayesian network
  - ✓ Hidden Markov model
  - ✓ Decision tree
  - ✓ ……
- ☐ **Deep learning models**
  - ✓ Long Short-term Memory neural network
  - ✓ Convolutional Neural Network

INTRODUCTION – Objectives

Research gaps

- LC intention recognition and different LC patterns (LC to left lane or LC to right lane) are ignored in existing risk prediction studies
- Suitable time window length to predict LC risk is still determined by prior knowledge
- Models are developed based on the driving data at a specific moment

Objectives

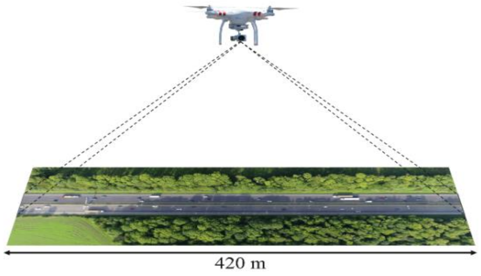
- A framework which combined LC intention recognition and LC risk prediction will be proposed
- The optimal time window length for LC intention recognition and risk prediction will be selected via grid search
- The key factors that influencing LC risk prediction will be analyzed

2. DATA PREPARATION

DATA PREPARATION

highD dataset

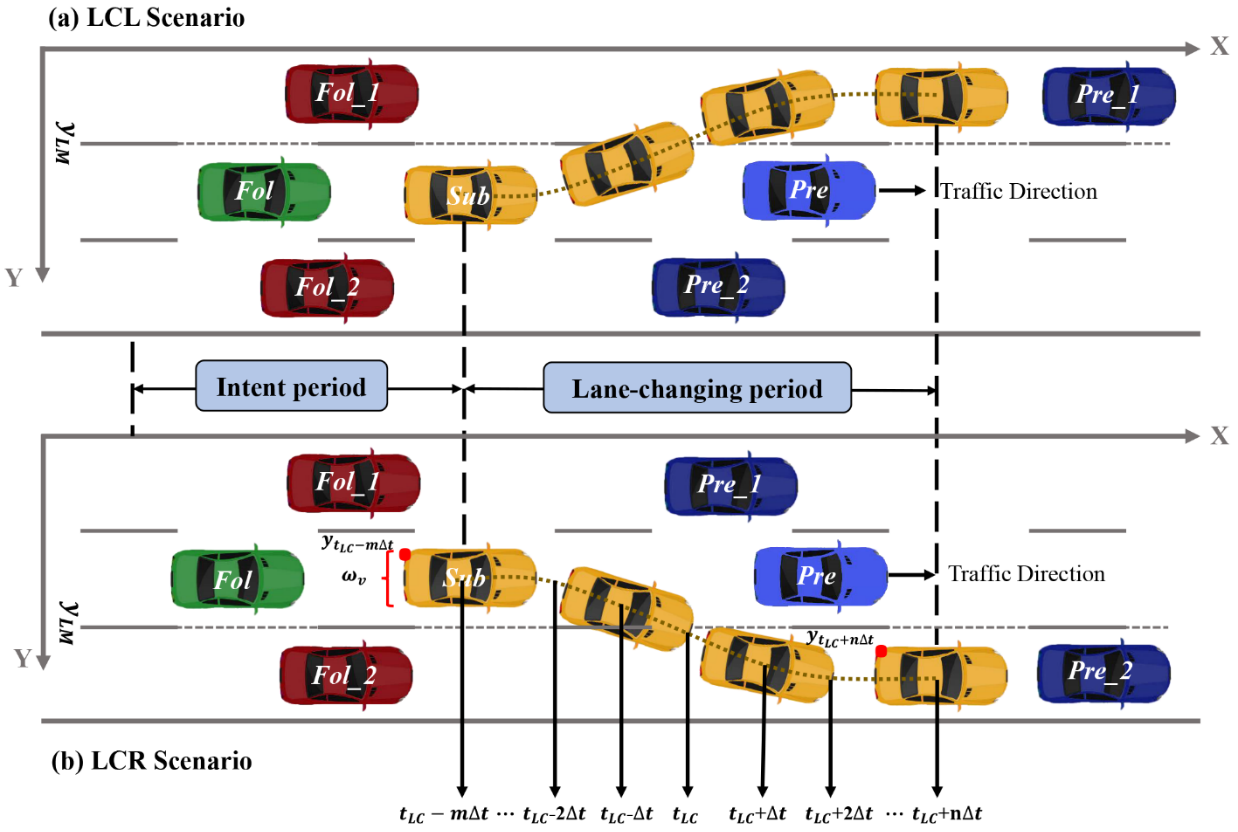
A naturalistic vehicle trajectories recorded on German highways using drone



www.highd-dataset.com

- 110,500 vehicles
- 147 driven hours
- 44,500 driven kilometers
- Six different recording locations
- Typical positioning error <10 cm

DATA PREPARATION

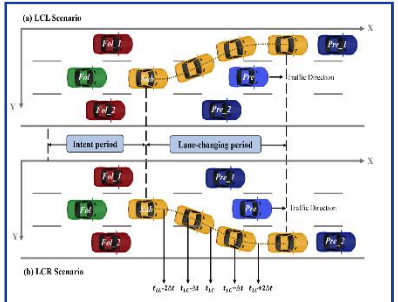


LC events extraction

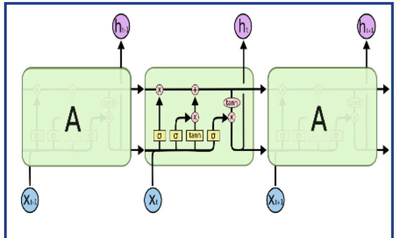
1. Determine the moment that lane ID changes.
2. Extract a whole LC event based on the y position
3. Remove the incomplete LC events
4. Extract the trajectory data of surrounding vehicles

3. METHODOLOGY

METHODOLOGY - Whole Framework



Feature extraction



LSTM model for LC intention recognition

Intention Recognition Module

Extracted Features

Basic Features
Vehicle type, LaneID, Velocity, Acceleration, Exist or not

Interactive Features
Gap distance, Velocity difference, Acceleration difference

Utility Features
Safety utility features, Efficiency utility features, Comfort utility features

Intention Recognition Model

Sequence Input Layer
LSTM Layer
Fully Connected Layer
Softmax Layer
Classification Layer

Driving Intention {LCL, LCR, LK}

Lane-changing Risk Prediction Module

Dataset Construction

Basic Features
Vehicle type, LaneID, Velocity, Acceleration, Exist or not

Interactive Features
Gap distance, Velocity difference, Acceleration difference

Risk Quantification
Fault Tree Analysis (FAT)

Risk Classification
Fuzzy C-Means (FCM)

Risk Variables

LC Risk Prediction

Dataset Spilt + Dataset Scaling
(train_test_split function + Minmax standardization)

Imbalanced Data Resampling
(SMOTE)

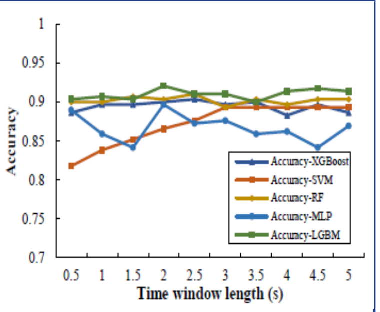
Model Performance Comparison
(**Prediction model:** LGBM, SVM, RF, MLP, XGBoost)
(**Evaluation indicator:** Accuracy, Precision, Recall, F1 Score)

Feature Importance

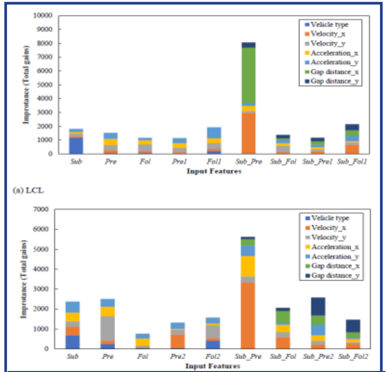
Key Features Analysis
(LGBM- Feature Importance)

Feature Importance (LCL)

Feature Importance (LCR)

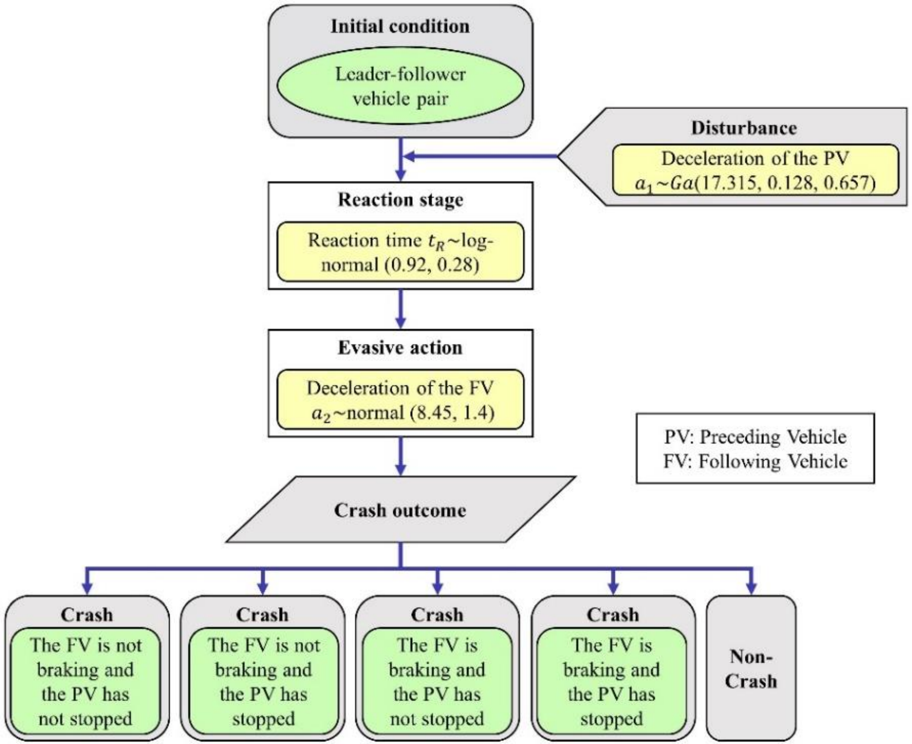


LC risk prediction



Key feature analysis

METHODOLOGY - LC Risk Level

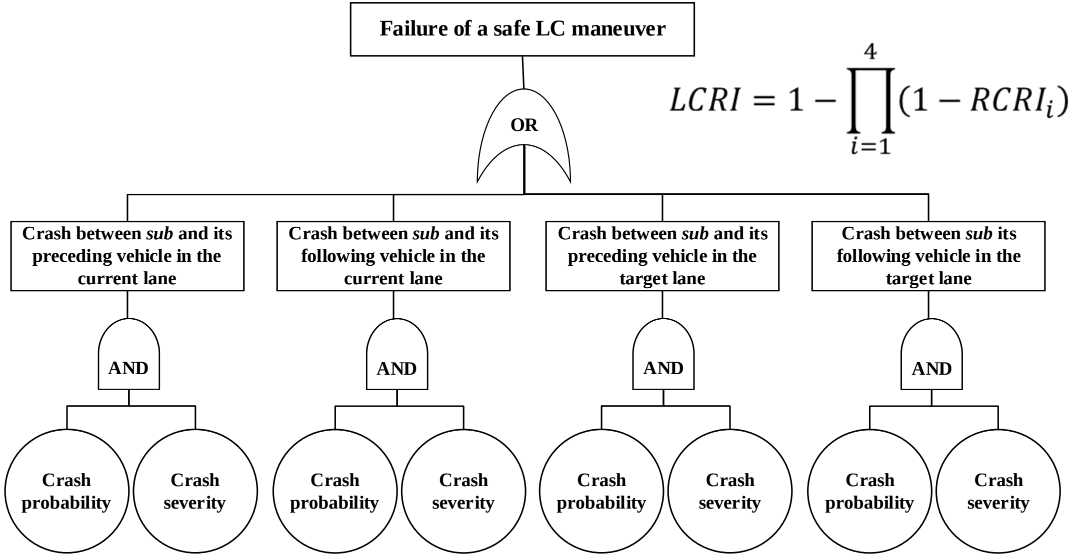


- **Considering the whole process of rear-end crash**
  - ✓ Disturbance of preceding vehicle
  - ✓ Driver's reaction stage
  - ✓ Evasive action
- **Considering the possibility and severity of rear-end crash**
  - ✓ Monto Carlo simulation method
  - ✓ $$RCRI_i = \frac{\sum_{j=1}^{N} crash_{ij} \times SASD_{ij}}{N}$$

Shangguan, Q., Fu, T.*, Wang J., Jiang R. & Fang, S. (2021). Quantification of rear-end crash risk and analysis of its influencing factors based on a new surrogate safety measure. *Journal of Advanced Transportation*, 2021.

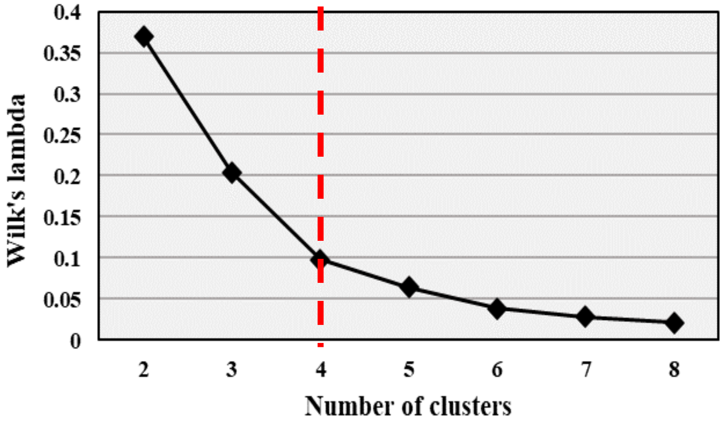
METHODOLOGY - LC Risk Level

Fault tree analysis



$$LCRI = 1 - \prod_{i=1}^{4}(1 - RCRI_i)$$

Fuzzy C-means clustering



Shangguan, Q., Fu, T., Wang J.* & Fang, S. (2021). Quantification of cut-in risk and analysis of its influencing factors: a study using random parameters ordered probit model, *Journal of Transportation Safety & Security*, 2021: 1-26.

METHODOLOGY - LC Risk Level

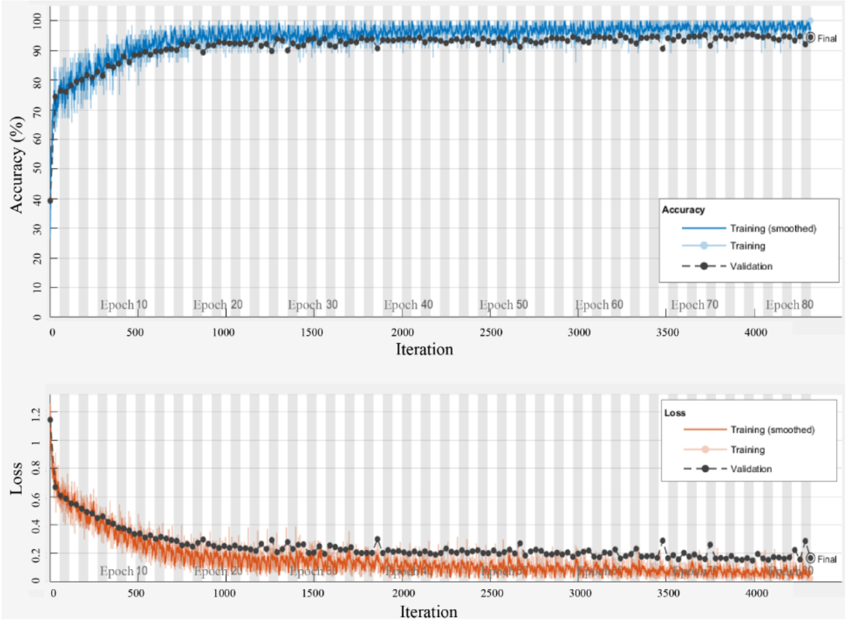
LC risk labelling criteria

Category	Criteria	LC type	Count (Proportion)
Low-risk	LCRI ≤ 0.03	LCL	846 (38.93 %)
		LCR	878 (40.41 %)
Medium-risk	0.03 < LCRI ≤ 0.11	LCL	285 (13.12 %)
		LCR	77 (3.54 %)
High-risk	LCRI > 0.11	LCL	72 (3.31 %)
		LCR	15 (0.69 %)

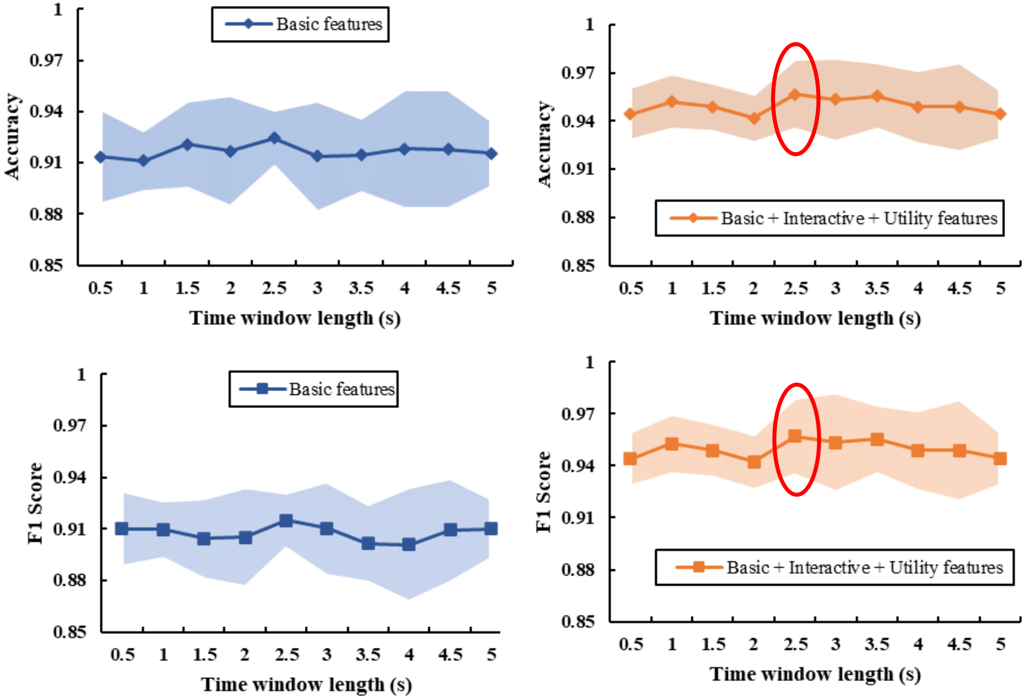
4. RESULTS AND DISCUSSION

RESULTS AND DISCUSSION

LC intention recognition



Training process of LSTM neural network



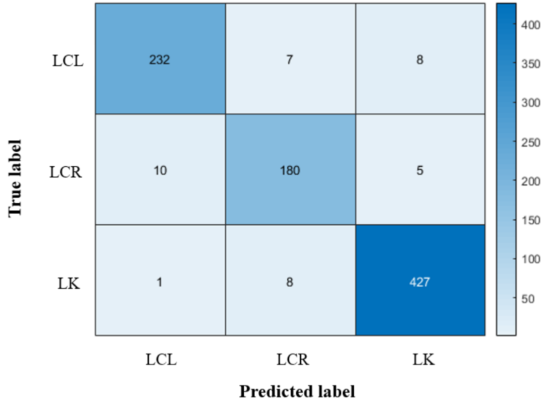
Accuracy and F1 score of LC intention recognition by time window length

RESULTS AND DISCUSSION

Comparison of intention recognition performance when time window length is 2.5 s

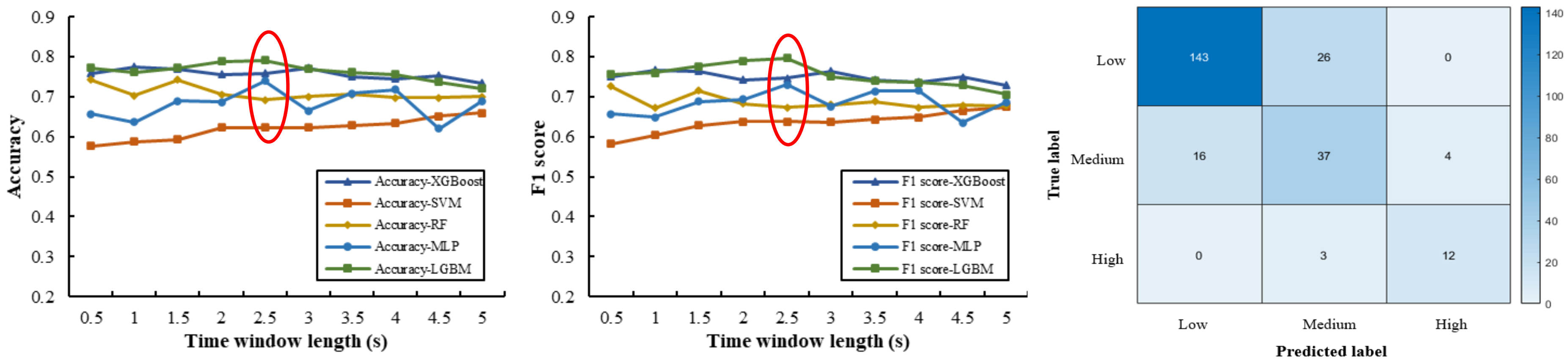
Model	Input features	LC intention	Accuracy	Precision	Recall	F1 score
CNN	Basic features	LCL	0.94	0.89	0.89	0.89
		LCR	0.93	0.82	0.88	0.85
		LK	0.95	0.96	0.92	0.94
		Overall Accuracy = 0.91	Overall F1 score = 0.89			
	Basic features + Interactive features + Utility features	LCL	0.95	0.90	0.90	0.90
		LCR	0.95	0.87	0.88	0.88
		LK	0.97	0.97	0.97	0.97
		Overall Accuracy = 0.93	Overall F1 score = 0.92			
LSTM	Basic features	LCL	0.96	0.93	0.91	0.92
		LCR	0.95	0.82	0.91	0.86
		LK	0.95	0.97	0.94	0.95
		Overall Accuracy = 0.92	Overall F1 score = 0.91			
	Basic features + Interactive features + Utility features	LCL	0.97	0.95	0.94	0.94
		LCR	0.96	0.92	0.92	0.92
		LK	0.97	0.97	0.98	0.97
		Overall Accuracy = 0.96	Overall F1 score = 0.95			

- LCL: Lane-changing to left lane
- LCR: Lane-changing to right lane
- LK: Lane-keeping



RESULTS AND DISCUSSION

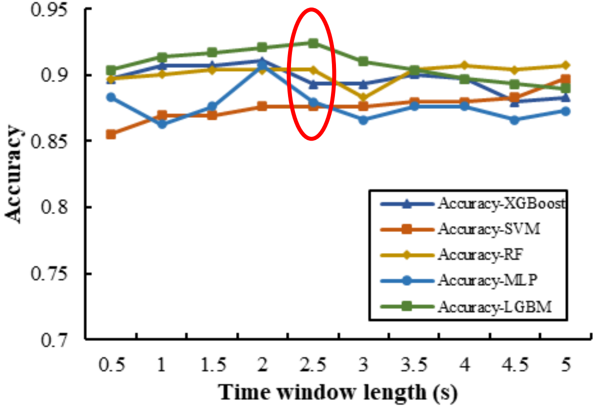
LC risk prediction – LC to left lane (LCL)

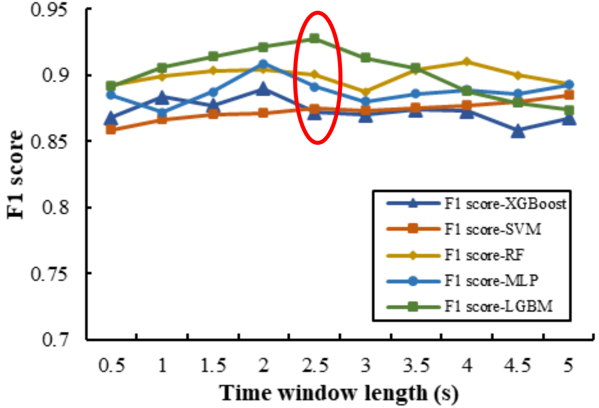


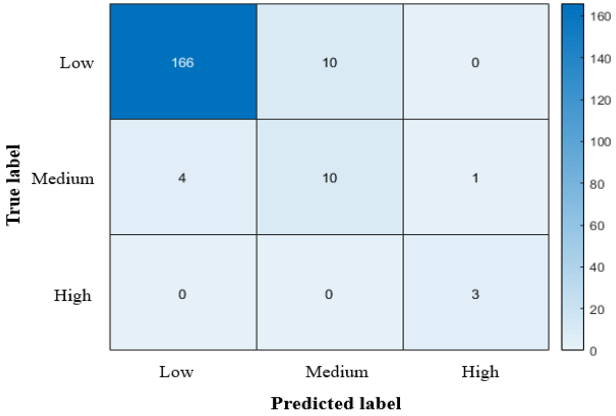
- ✓ Compared to several other machine learning algorithms, the Light Gradient Boosting Machine (LGBM) algorithm achieves higher prediction accuracy
- ✓ Except the Support Vector Machine (SVM) algorithm, other algorithms are not sensitive to the time window length

RESULTS AND DISCUSSION

LC risk prediction – LC to right lane (LCR)



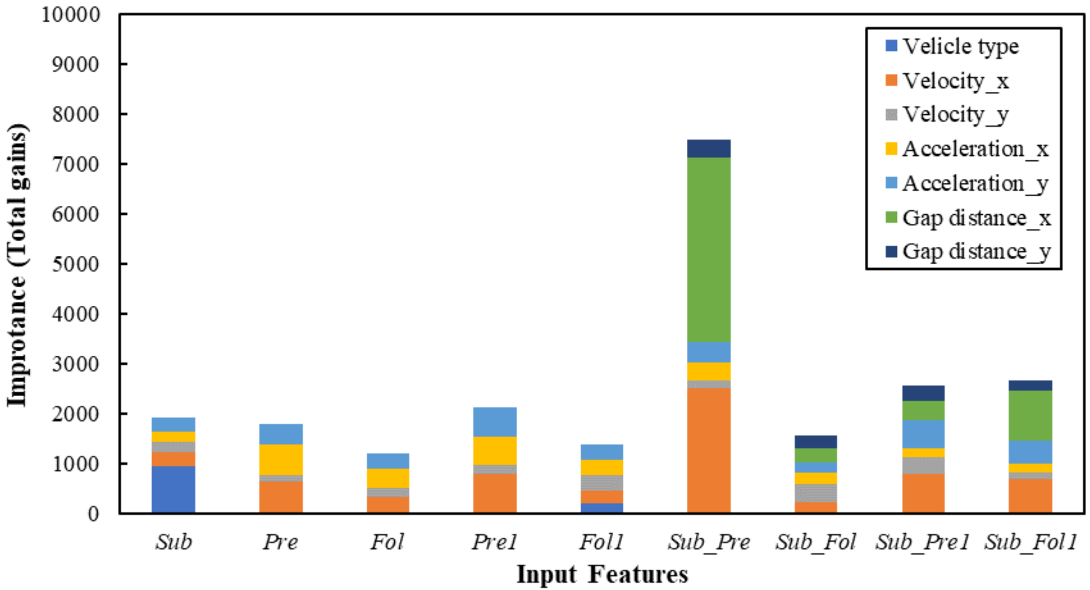




- ✓ When the time window length is 2.5 s and the LGBM algorithm is applied, the accuracy and F1 score of LCL and LCR risk prediction reach the highest value

RESULTS AND DISCUSSION

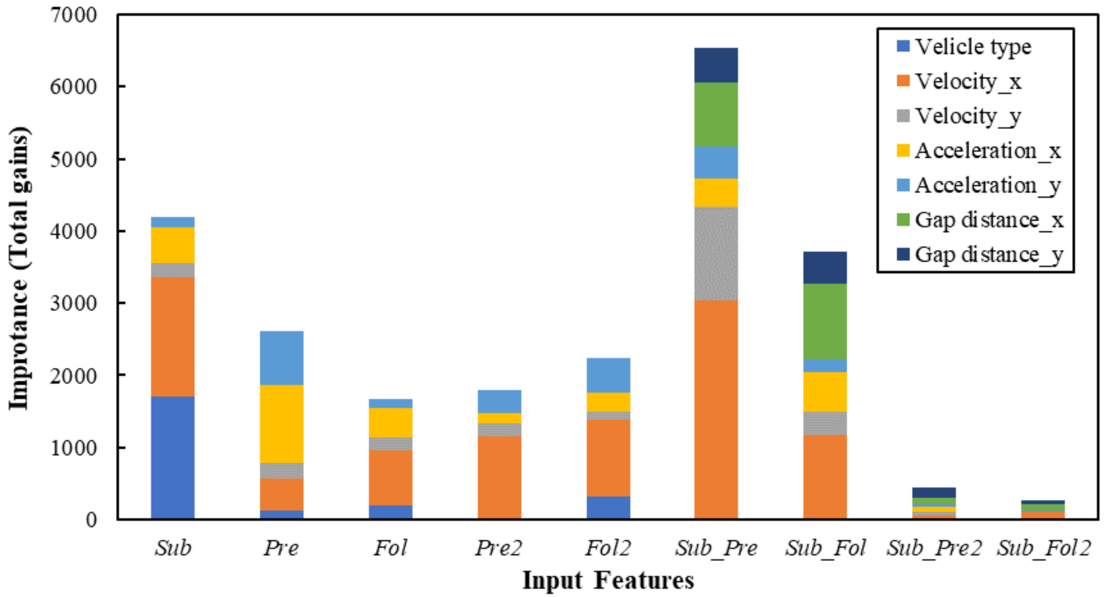
Analysis of LCL risk influencing factors



- ✓ The interactive features between *Sub* and *Pre* have the highest feature importance
- ✓ The driver should pay more attention to the motion state of the preceding vehicle and following vehicle in the target lane

RESULTS AND DISCUSSION

Analysis of LCR risk influencing factors



- ✓ The interactive features between *Sub* and *Pre* have the highest feature importance
- ✓ Driver also needs to avoid sudden deceleration to ensure the safety of the following car in the current lane

5. CONCLUSION

CONCLUSION

- LSTM performs better than CNN in driving intention recognition. When the input time window is 2.5 s, the prediction accuracy of LCL, LCR and LK are 97 %, 96 % and 97 %, respectively.

- Compared with several other machine learning models, the LGBM model is more suitable for LC risk prediction.

- During the LC process, the interaction characteristics of the LC vehicle and its preceding vehicle in the current lane have the greatest impact on the LC risk.

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THANKS FOR YOUR ATTENTION
Q&A

Shangguan, Q., Fu, T., Wang, J., & Fu, L. (2022). A proactive lane-changing risk prediction framework considering driving intention recognition and different lane-changing patterns. *Accident Analysis & Prevention*, *164*, 106500.

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