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Personalized driving assistance algorithms: Case study of federated learning based forward collision warning

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ABSTRACT

Current designs of advanced driving assistance systems (ADAS) mainly developed uniform collision warning algorithms, which ignore the heterogeneity of driving behaviors, thus lead to low drivers' trust in. To address this issue, developing personalized driving assistance algorithms is a promising approach. However, current personalization systems were mainly implemented through manually adjusting warning trigger thresholds, which would be less feasible for overall drivers as certain domain expertise is required to set personal thresholds accurately. Other personalization techniques exploited individual drivers' data to build personalized models. Such approach could learn personal behavior but requires impractical large-scale individual data collections. To fill up the gaps, self-adaptive algorithms for personalized forward collision warning (FCW) based on federated learning were proposed in this study. A baseline model was developed by long short-term memory (LSTM) for FCW. Federated learning framework was then introduced to collect knowledge from multiple drivers with privacy preserving. Specifically, a general cloud server model was trained by collecting updated parameters from individual vehicle server models rather than collecting raw data. Besides, a driver-specific batch normalization (BN) layer was added into each vehicle server model to address the heterogeneity of driving behaviors. Experiments show empirically that the proposed federated-based personalized models with the BN layer showed to have the best performance. The average modeling accuracy has reached 84.88% and the performance is comparable to conventional total data collection training approach, where the additional BN layer could increase the accuracy by 3.48%. Finally, applications of the proposed framework and its further investigations have been discussed.

1. Introduction

Advanced driving assistance systems (ADAS), such as driving assistance systems and collision warning systems, are playing key roles in improving traffic safety, drawing more and more attention from both the governments and industrial communities (Ledezma et al., 2021). In the United States, ADAS helped prevent approximately 9900 fatalities and 30% crashes annually (Mosquet et al., 2016). And in Europe, fatalities and injuries were decreased by 15.2% and 8.9% respectively (Kyriakidis et al., 2015). Encouraged by beneficial government policies, vehicle companies actively promoted the commercialization of ADAS. Mercedes Benz, Tesla, Volvo etc. considered ADAS as an essential safety utility and planned to increase the ADAS equipment rate to 93% or higher by 2022 (NHTSA, 2017).

Despite of high equipment rate, the applications of ADAS are facing the problem of low drivers' trust in (Fleming et al., 2019; Govindarajan et al., 2018). Specifically, there were significant gaps between the collision warnings provided by ADAS and the drivers' subjective risk perception, and thus, drivers might not follow the ADAS suggestions. One possible explanation for this issue is that current designs of ADAS mainly focused on building uniform collision warning algorithms (Yuan et al., 2020), while the driving risk perception and driving capability among drivers are heterogeneous (Yu et al., 2020a; Zhao et al., 2021). The ignored heterogeneity has led to failures in drivers' compliance with ADAS (Iranmanesh et al., 2018). To solve the abovementioned issue, developing personalized driving assistance algorithms is a potential

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solution (Panou, 2018; Martínez et al., 2015).

The driving assistance algorithms for collision warnings were mainly developed from two approaches: (1) threshold-based algorithms and (2) collision risk quantification models. The first approach implemented through calculating safety surrogate indicators, such as time to collision (TTC), time headway etc., based upon vehicle kinematic data (Vogel 2003; McLaughlin et al., 2008; Zhu et al., 2020). Warnings were triggered when the metrics below preset threshold values. Then, thresholds for different drivers can be adjusted manually based on their personal parameters (e.g., reaction time) to achieve personalization (Panou, 2018; Govindarajan et al., 2018; Reinmueller et al., 2020). However, such adjustment requires complex expertise in transportation engineering, human factors engineering and etc. Thus, setting personal thresholds accurately is hard for non-domain experts.

The second approach quantified collision risks mainly utilized sequential driving environment data. These risk analysis models were commonly being developed based upon deep learning methods such as deep neural network (DNN) (Formosa et al., 2020), long short-term memory (LSTM) (Mishra et al., 2020) and etc. Then, collision risk posterior probabilities were estimated and warnings were triggered when there indicated high-risk. To develop personalized deep learning models, generally acknowledged approach is to exploit individual drivers' data and establish personal models respectively.

However, deep learning modeling requires large sample sizes to provide accurate and stable prediction (Anaby-Tavor et al., 2020; Shams, 2014). Thus, to train personalized collision risk quantification models for drivers, large number of crashes and near-crash events are required (Wulfe et al., 2018). For instance, given the ratio of crash and near-crash is approximately 1:10 (Klauer et al., 2006) and the crash rate is about 0.54 per million miles (NHTSA, 2020). More than one million miles historical driving data are needed to develop the individual models assuming that 10 near-crashes are needed for model training. Therefore, model development based upon individual driver's data is not feasible. To achieve accurate personalized modeling, knowledge from multiple drivers' data should be combined during model training, and then adapted to each driver according to their personal behaviors.

With the research gaps mentioned above, in this study, a federated learning approach was proposed to develop personalized driving assistance algorithms. The empirical analyses were conducted using FCW algorithm development as a case study. Main contributions of this study are summarized as follows:

(1) Proposed a self-adaptive federated learning framework that could be used to develop personalized driving assistance models with the benefits of individual drivers' data privacy protecting and accurate collision risk prediction.
(2) Trained LSTM based FCW models under the federated learning framework through collecting model parameters rather than data per se from individual vehicle servers to a cloud server. Empirical analyses showed the model has reached 81.40% accuracy and the accuracy was only reduced by 1.16% compared to conventional total data collection training approach which violated drivers' privacy.
(3) Introduced a driver-specific batch normalization (BN) layer to allow models learning heterogeneous driving behaviors, which improved the average modeling accuracy by 3.48%.

The remainder of this paper is organized as follows: in the *Related Work* section, pervious researches focused on personalization methods for deep learning models and privacy-preserving techniques have been presented and discussed. In the *Data Preparation* section, the form of the empirical analysis data is illustrated. In the *Methodology* section, the LSTM based FCW model, federated learning setting for privacy-preserving and batch normalization for personalization are introduced. In the *Modeling Results* section, experimental results are presented and the performance comparison among models is conducted. Finally, conclusions and future work outlooks are provided.

2. Related work

In order to develop personalized driving assistance algorithms, both the suitable personalization method and personal data privacy issue (Martin and Palmatier, 2020) should be considered. In this section, existing methods to allow deep learning models adapting to data heterogeneity and the common privacy-preserving techniques have been discussed.

2.1. Personalization methods for deep learning models

Personalization methods for deep learning models were mainly conducted to address the issue that the uniform model trained on a dataset could not adapt well to novel personal datasets due to the heterogeneity of data (Tzeng et al., 2017). Domain adaptation and data regularization are two frequently used approach for deep learning model personalization. The first approach classified differently distributed data into the target domain and the source domain, then mapped the former into the feature space of the latter to allow models adapting to heterogeneous data. Common methods included maximum mean discrepancy (Tzeng et al., 2014), correlation distances (Sun and Saenko, 2016), generative adversarial networks (GAN) (Bousmalis et al., 2017) etc. However, this complex approach is hard to apply in real time, since additional discriminator pre-training is needed to fit the mapping relationship between domains which significantly increases computing time cost.

As for the second approach, feature regularization transformations were learned to project differently distributed data onto a common space. The regularization was mainly conducted adding a batch normalization (BN) layer to the model. Lange et al. (2020) provided local data adaptation by adding a BN layer for user models under a novel dual user-adaptation framework. Chen et al. (2021a) proposed a weighted federated transfer learning and used BN to modify the basic model trained on federated learning setting for personalized healthcare. This approach based on only the model structure modification for personalization is more efficient.

2.2. Privacy-preserving techniques

The current privacy-preserving techniques for model training were mainly conducted from two approaches: (1) data encryption methods and (2) distributed training approach. As for the first approach, data were anonymized to prevent raw information leakage by adding noise or obscuring certain sensitive attributes. And the common anonymization algorithms included k-Anonymity (Ghasemzadeh et al., 2014), l-Diversity (Machanavajjhala et al., 2007), t-Closeness (Li et al., 2007), differential privacy (Wasserman and Zhou, 2010) and etc. However, this approach essentially is hard to guarantee privacy under attacks since there is still data sharing (Yang et al., 2019).

To avoid data sharing, the second approach analyzed private data through distributed learning frameworks. Among which, federated learning is the most popular setting in recent years. Bonawitz et al. (2016) applied federated learning to decentralized learning of mobile phone devices without privacy leakage. Hard et al. (2018) utilized federated learning framework to train language models on client devices without exporting sensitive user data to servers for mobile keyboard prediction. Liu et al. (2020) used federated learning based gated recurrent unit neural network algorithm for traffic flow prediction while protecting privacy. Chen et al. (2021b) proposed a communication-efficient federated learning framework than enables edge devices to efficiently train and transmit model parameters. This approach could train a high-quality centralized model based on training data sets that remain distributed over local clients (Konečný et al., 2016). In this study, federated learning was employed for privacy-preserving.

3. Data Preparation

In this study, the commercial vehicle naturalistic driving data collected in Shanghai were utilized for the empirical analyses. Data were recorded through mounted cameras with resolution of 655 × 268 pixels, and the image updating frequency is 4 frames per second. Fig. 1 shows a sample image.

Events were captured when the vehicle performed brake operations at a deceleration more than 0.4 g (g: gravitational acceleration) (Gao et al., 2018). Limited by the crash cases during the data collection period, high-risk events have been utilized as crash surrogate. And the event data have been divided into high-risk and non-conflict by traffic safety analysis experts, according to the definitions and descriptions shown in Table 1 (Yu et al., 2020b).

A total of 643 high-risk events were collected from 41 drivers. Among which, the majority of drivers had less than 10 events. To consider data size requirement of model training, only the top 3 drivers with frequent high-risk event occurrence were utilized, which contains 168 high-risk events in total. Furthermore, to keep the balance of sample size, 168 non-conflict events were randomly selected. Table 2 shows the number of events used for each driver (named as 1, 2, 3 respectively).

For each event data, a 6-second window data was used, and a 2-second time gap (acceptable response time (Riener, 2010)) before hard braking is reserved as a warning time to provide FCW. Fig. 2 shows an example of the video information utilization.

Due to the complex driving conditions (Yu et al., 2021), YOLOv3 target detection algorithm (Redmon and Farhadi, 2018) was utilized to pre-process the video and extract features of the interactive object. Specifically, with the YOLOv3 algorithm, the contour of the front vehicle contained in the original image were extracted. Then the horizontal pixel distance and the vertical pixel distance between front vehicle and ego vehicle can be calculated, which means the position of front vehicle was extracted. The example of the front vehicle position extracted procedure is shown in Fig. 3. The position of ego vehicle was assumed to be at the midpoint of the bottom edge, marked as "O". The position of front vehicle was assumed to be at the two-thirds point of the bottom edge of the YOLO box. Then the horizontal/vertical distance depended on the horizontal/vertical pixel distance between front vehicle position point and the point O. When the front vehicle position point was to the left of point O, the horizontal distance was negative.

Besides, motion states of the ego vehicle (speed, acceleration, and jerk) were also being collected by the three-axis vehicle sensor. Finally, the positions of front vehicle and characteristics of the ego vehicle corresponding to the 6-second window data are utilized for modeling. Summary statistics of the 5 modeling variables are shown in Table 3, and the structure of modeling data is shown in Fig. 4.

4. Methodology

In this section, long short-term memory (LSTM) was first introduced. Then settings for federated learning and batch normalization have been presented.

Fig. 1. Sample picture captured by the camera.

Table 1
Definition of severity level in driving.

Level	Description
High-risk	Any circumstance that requires a read-end collision avoidance response on the front vehicle.
Non-conflict	Any circumstance that affects normal driving and requires driver's reaction. But no vertical conflict objects and potential read-end collision exist.

Table 2
Number of events for the top 3 drivers.

Driver	High-risk events	Non-conflict events	Total events
1	78	78	156
2	77	77	154
3	13	13	26
Total	168	168	336

4.1. LSTM based FCW model

LSTM is one kind of recurrent neural network (RNN), which has powerful ability to process time series data since its unique design (Hochreiter and Schmidhuber, 1997). In this study, LSTM was employed to establish FCW models. Specifically, LSTM extracted temporal features from the input sequential modeling data, then one dense layer was used as a classifier to process the extracted features and finally output each event as a binary class (high-risk and non-conflict). The structure of the LSTM model is shown in Fig. 5. Details of the model architecture are shown in Table 4.

Fig. 6 shows the structure of a LSTM cell at each time step. LSTM captures the long-term dependency features from the input sequence vectors by calculating the LSTM cell activations at each time step using the following equations (Varsamopoulos et al., 2018):

$$\mathrm{i_t} = \sigma(\mathrm{x_t U^i} + \mathrm{h_{t-1} W^i}) \tag{1}$$

$$f_t = \sigma(\mathrm{x_t U^f} + \mathrm{h_{t-1} W^f}) \tag{2}$$

$$o_t = \sigma(\mathrm{x_t U^o} + \mathrm{h_{t-1} W^o}) \tag{3}$$

$$C_t = \tanh(\mathrm{x_t U^g} + \mathrm{h_{t-1} W^g}) \tag{4}$$

$$C_t = \sigma(\mathrm{f_t}{*}\mathrm{C_{t-1}} + \mathrm{i_t}{*}C_t) \tag{5}$$

$$h_t = \tanh(C_t){*}o_t \tag{6}$$

where σ and tanh are activation functions. $\mathrm{x_t}$ is the input sequence vector, i_t is the input gate, f_t is the forget gate, o_t is the output gate, h_t is the hidden state. W is the recurrent connection between the previous hidden layer and current hidden layer. U is the weight matrix that connects the inputs to the hidden layer. C_t is a candidate hidden state and C_t is the internal memory of the cell.

4.2. FCW model under federated learning setting (Fed-LSTM)

The main idea of federated learning setting was derived from the distributed learning system consisting of parameter servers and computational workers (Yao et al., 2019). Considering a learning system containing one parameter server and K computational workers. At each epoch t, the parameter server distributes the global model parameters w_t to each worker, then worker k updates the parameters w_t^k locally by computing:

$$w_{t+1}^k = w_t^k - \alpha \sum_k \nabla_{w_t} \mathscr{L}\left(w_t^k, x^k, y^k\right) \tag{7}$$

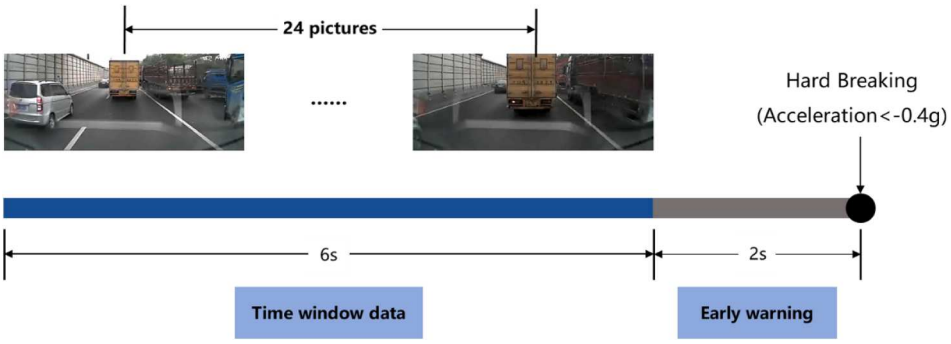


Fig. 2. Timeline of driving event recorded in a video clip.

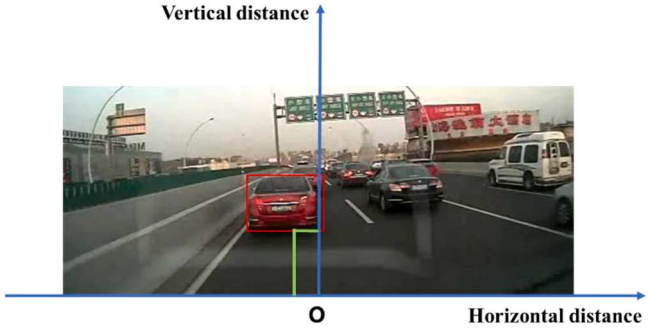


Fig. 3. Example of front vehicle position extraction.

where α is the learning rate, $\mathscr{L}$ is the loss function, x^k and y^k are the local worker training data and the ground truth labels. Next, K workers upload the local updated parameters w_{t+1}^k to the parameter server, and the global model on the parameter server updates by aggregating all parameters as formula (8) and formula (9), where n^k is the local worker training data size.

$$n = \sum_k n^k \tag{8}$$

$$w_{t+1} = \sum_k \frac{n^k}{n} * w_{t+1}^k \tag{9}$$

In this study, the LSTM model, drivers and the cloud server can be regarded as the global model, computational workers and the parameter server respectively. The Fed-LSTM is summarized in Algorithm 1. First, all vehicle servers downloaded the parameter of the latest global model from the cloud server. Then, the vehicle servers updated the parameter based on their local data by formula (7). The learning rate α was set as 1×10^{-4}. The loss function $\mathscr{L}$ was binary cross entropy and the formula is as follows:

$$loss = \sum_{i=1}^{N} y_i log(p_i) + (1 - y_i) log(1 - p_i) \tag{10}$$

where p_i is the predicted possibility and y_i is the ground truth label with 1 as high-risk and 0 as non-conflict. Finally, all vehicle servers uploaded their locally updated parameter back to the cloud server. Uploaded parameters were gathered an aggregation on the cloud server by formula (8) and formula (9).

Algorithm 1. Fed-LSTM based FCW algorithm

Input: K is the number of drivers, α is the learning rate, x^k and y^k are the local training data and target labels for driver k
Output: Parameters w
***CloudServerUpdate*:**
1: Initialize w_0 (the parameters of LSTM model)
2: **for** each epoch t = 0, 1, … **do**
3: **for** each driver $k \in \{1, 2, \cdots, K\}$ **do in parallel**
4: $w_{t+1}^k \leftarrow$ ***LocalUpdate***(k, w_t^k)
5: **end for**
6: $w_{t+1} \leftarrow \sum_k \frac{n^k}{n} * w_{t+1}^k$ // aggregation
7: **end for**
LocalUpdate(k, w_t^k): // run on driver k
1: **for** each batch b = 0, 1, … **do**
2: $w_t^k \leftarrow w_t^k - \alpha \sum_k \nabla_{w_t} \mathscr{L}(w_t^k, x^k, y^k)$ // update LSTM
3: **end for**
4: Return w_t^k to cloud server

4.3. Personalized FCW via batch normalization

In this study, batch normalization (BN) was utilized to provide personalized FCW models by adapting each distinguished local distribution to a normal distribution, as shown in Fig. 7. Details of the model architecture are shown in Table 5. A BN layer was added between the LSTM network and the dense layer to collect batch normalization

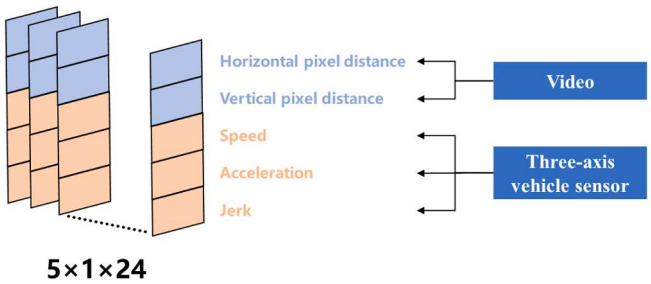


Fig. 4. The structure of modeling data.

Table 3
Summry statistics for the modeling variables.

Variables	Description	Mean	Std	Min	Median	Max
Horizontal distance	Horizontal distance between front vehicle and ego vehicle (pixel)	−6.85	51.89	−207.01	0.00	217.15
Vertical distance	Vertical distance between front vehicle and ego vehicle (pixel)	164.70	82.07	1.00	162.00	268.00
Speed	Speed of ego vehicle (km/h)	44.81	23.57	0.01	45.62	124.78
Acceleration	Acceleration of ego vehicle (g)	−0.02	0.11	−0.62	−0.01	0.50
Jerk	Jerk of ego vehicle (g/s)	−0.01	0.30	−4.08	0.00	3.72

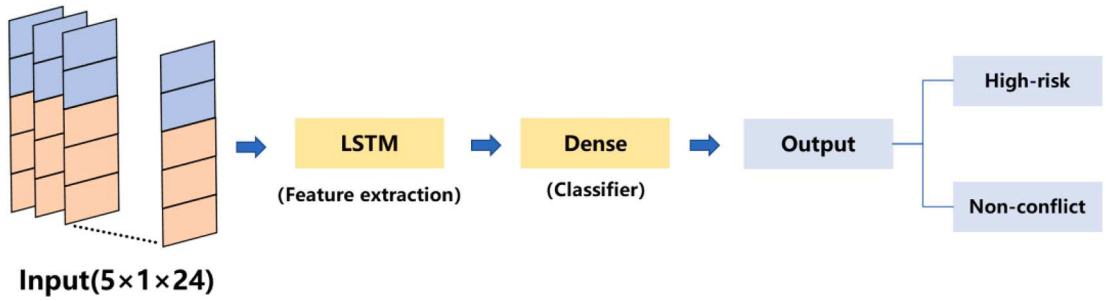


Fig. 5. The structure of LSTM model.

Table 4
The architecture of LSTM model.

Layer	Name	Details
1	LSTM	Input size = 5, hidden size = 64, number of layers = 3
2	Dense	Dimension of input features = 64, dimension of output features = 2

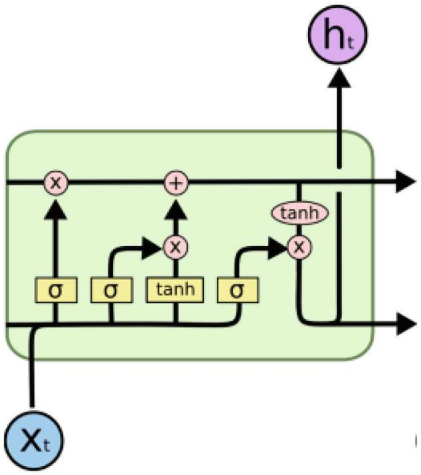


Fig. 6. The structure of LSTM cell (Varsamopoulos et al., 2018).

statistic data. The BN layer can adapt the input features into zero mean and unit variance with the following formula:

$$x^{'} = \frac{x - \mathrm{mean}[x]}{\sqrt{\mathrm{Var}[x] + \epsilon}} * \gamma + \beta \tag{10}$$

where x is the input of the BN layer and $x^{'}$ is the output, ϵ is a very small constant to avoid a zero denominator, γ and β are learnable parameter vectors of size C (C is the size of x). During training, the layer calculates the mean and variance of each input in a mini-batch and performs a moving average, the momentum value of the moving average is 0.1. Each vehicle server had a BN layer. The parameters of BN layer of different vehicle servers were not shared, which allowed each vehicle server to train its own BN layer parameters.

The algorithm of the modified model under federated learning setting (named as Fed-BN-LSTM) was achieved by following a three-step protocol at each epoch illustrated in Fig. 8, including (1) downloaded parameters from cloud server, (2) updated parameters in vehicle servers locally, and (3) uploaded parameters and aggregated in cloud server. The parameters sharing between the cloud server and the vehicle server were only parameters of LSTM and dense layer. And the parameters of BN layer were always preserved locally. Due to the differential BN layer parameters ($W_t^k, k \in \{1, 2, \cdots, K\}$) of different drivers, each driver had a personalized FCW model that could adapt to the local data distribution.

5. Modeling results

5.1. Basic LSTM models

Collision warning models that developed based upon individual data could well fit the drivers' behavior heterogeneity. In this study, models were first developed for the 3 drivers individually. To be specific, each FCW model was trained by LSTM for 100 epochs and evaluated using

Table 5
The architecture of modified LSTM model.

Layer	Name	Details
1	LSTM	Input size = 5, hidden size = 64, number of layers = 3
2	BN	Dimension = 64
3	Dense	Dimension of input features = 64, dimension of output features = 2

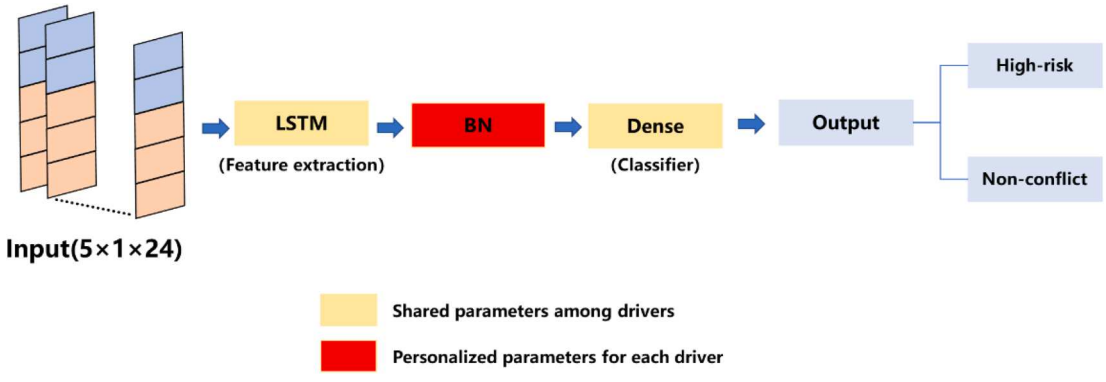
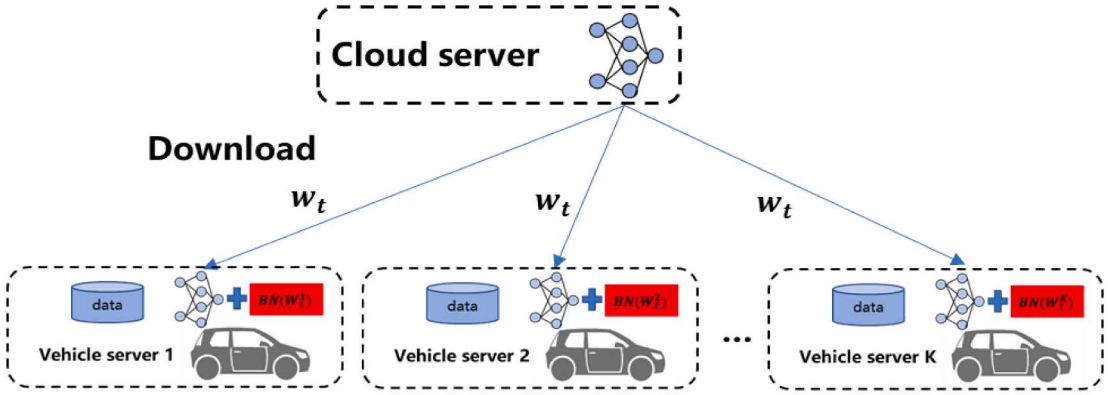
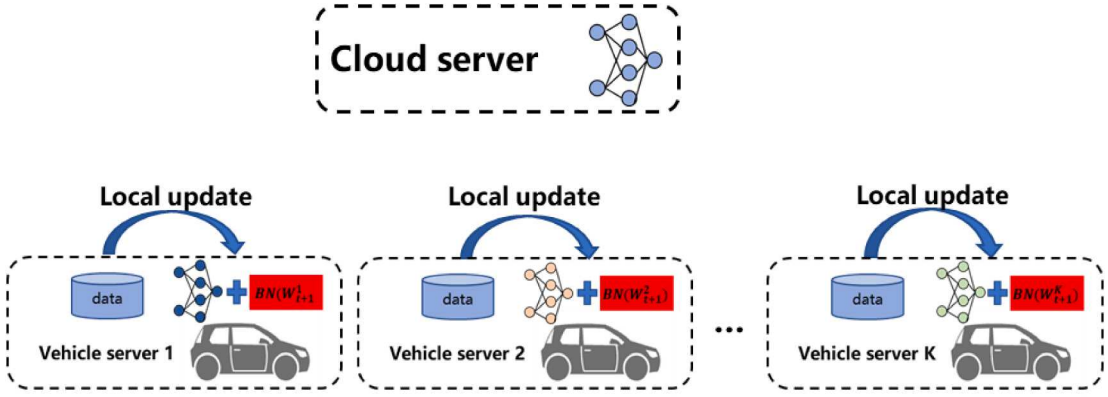


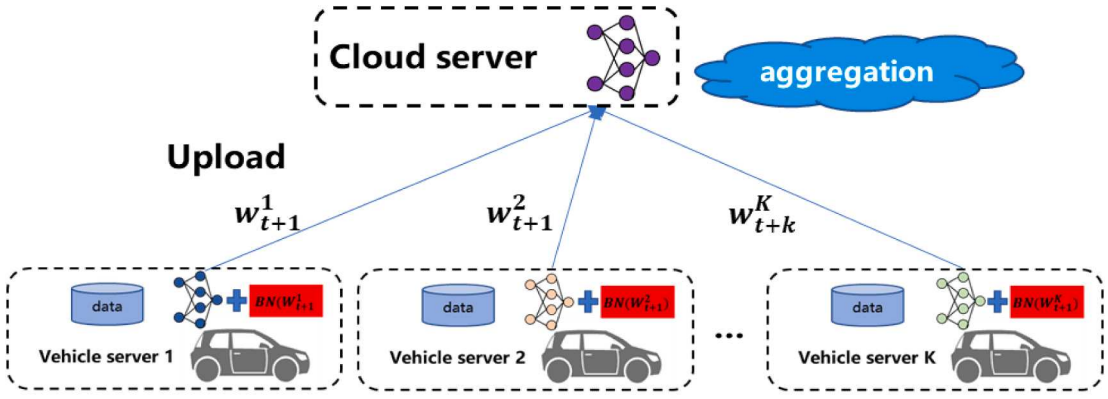
Fig. 7. The structure of modified LSTM model.



(a) Downloaded parameters from cloud server



(b) Updated parameters in vehicle servers locally



(c) Uploaded parameters and aggregated in cloud server

Fig. 8. The three-step protocol of Fed-BN-LSTM at each epoch.

testing data. Table 6 shows the data statistic and test accuracy of each driver's model. None of the model accuracies has exceeded 80.00% and the model accuracy increase in accordance with the training data size.

To further explore the impacts of data sample size on model performance, a model using three drivers' data totally was then developed. The loss and accuracy of training and testing are shown in Fig. 9. The model converges around the 60th epochs, and the testing accuracy reaches 82.56%, which is 4.48% improvement compared to the average accuracy (78.06%) of the LSTM models trained on individual drivers' data. To conclude, modeling with total data of all drivers can improve

Table 6
The data statistic and modeling accuracy of each driver.

Driver	Training data size	Testing data size	Testing accuracy
1	118	40	80.00%
2	114	38	76.67%
3	18	8	75.00%
Average	–	–	78.06%

individual models especially when the driver's data sample size is limited.

5.2. Fed-LSTM model compared with LSTM model using total data

However, collecting raw data from individual drivers violated the data privacy issue. In this section, Fed-LSTM was utilized to train LSTM model under federated learning setting by distributing the model to each driver and collecting model parameters updated locally instead of collecting total raw data. The model loss and model accuracy of Fed-LSTM model compared with the basic LSTM model are shown in Fig. 10. The best testing accuracies are 81.40% and 82.56% respectively. Compared with LSTM model trained on total raw data conventionally, Fed-LSTM protects drivers' data privacy at the expense of 1.16% accuracy.

5.3. Fed-BN-LSTM models compared with Fed-LSTM model

As mentioned above, Fed-LSTM could address the privacy issue with good model performance but the model was still the same for all drivers. In this section, personalized models were developed base on Fed-BN-LSTM and the model performance was evaluated compared with Fed-LSTM model. The model structures were modified by adding a learnable BN layer for each driver. Weighted average of results of Fed-BN-LSTM models was calculated at each epoch. And the comparison results are shown in Fig. 11. The best testing accuracies of Fed-BN-LSTM and Fed-LSTM are 84.88% and 81.40% respectively. This phenomenon implies that on total drivers' data, personalized models with the adaptive BN layer for individual drivers would improve the average accuracy by 3.48%.

5.4. Model performance comparisons

Table 7 summarized the performance of (1) LSTM trained on data of individual drivers (named as LSTM (individual)); (2) LSTM trained on total data (named as LSTM (total)); (3) Fed-LSTM; and (4) Fed-BN-LSTM for individual drivers and the weighted average accuracy. Comparing the model performance, the following conclusions can be drawn. First, the results of LSTM (individual) are relatively worst and Fed-BN-LSTM are the best. Besides, the performance of Fed-LSTM is close to LSTM (total). Fed-BN-LSTM models have the highest accuracy (85.00%, 81.58%, 100%) on three drivers, and the increasements are 2.50%, 2.63%, 12.50% respectively compared with Fed-LSTM. Even compared to LSTM (total), Fed-BN-LSTM improves the model performance on driver-1 and driver-3. Therefore, Fed-BN-LSTM could provide personalized forward collision warning models for heterogeneous drivers and ensure better accuracies.

5.5. Analysis of features extracted by LSTM

To better understand the effects of driving data heterogeneity, the 64-dimensional features extracted by LSTM were outputted and reduced to 2 dimensions by t-distributed stochastic neighborhood embedding (t-SNE) (Linderman and Steinerberger, 2019) for visualization, as shown in Fig. 12. Box plots for 2-dimensional features of individual drivers' features in both high-risk events and non-conflict events are shown in Table 8. The features of different drivers' data varied significantly, especially in high-risk events, which would mislead the classifier aimed at output each event (high-risk and non-conflict) as a binary class. As mentioned above, the BN layer adapted features of different drivers to the same normal distribution which means the influence of varying driving behaviors among drivers was removed. Therefore, the classifier could only concentrate on distinguishing features of high-risk and non-high-risk events rather than features with different distributions from different drivers, and the model performance was improved.

6. Conclusions and discussions

Personalized driving assistance algorithms which provide self-adaptive functions for the heterogeneous driving behaviors hold the benefits of improving drivers' trust in ADAS. Current personalized systems were mainly implemented through adjusting thresholds manually based on drivers' personal parameters, which have low efficiency. In this study, collision risk warning models that could self-adapt to the heterogenous behaviors have been developed. Besides, traditional individual modeling based on single driver's data could provide personalized models while the performance is limited to the data sample size. Therefore, in this study, a federated learning modeling approach has been proposed, *for the first time,* to develop personalized warning models which combined knowledge from multiple drivers' data with privacy-preserving.

FCW algorithm development was utilized as an example to conduct empirical analysis. Specifically, the empirical data included positions of front vehicles extracted by YOLO algorithm based on video data and motion states of the ego vehicle collected by the three-axis vehicle sensors. Then models were trained to learn how human experts classify events in driving videos as either risky or not when hard braking is involved, and thus could help realize FCW function. Time series feature mining for FCW was conducted by LSTM model. And the training method of the model was based on federated learning setting which trained model through collecting model parameters rather than raw data. Thus, the limitations of the data size and preserved privacy were overcome. Furthermore, a driver-specific BN layer was employed to modify the LSTM model structure for minimizing gaps among extracted features of different drivers and reach personalization with better model performance. Finally, LSTM (individual), LSTM (total), Fed-LSTM and

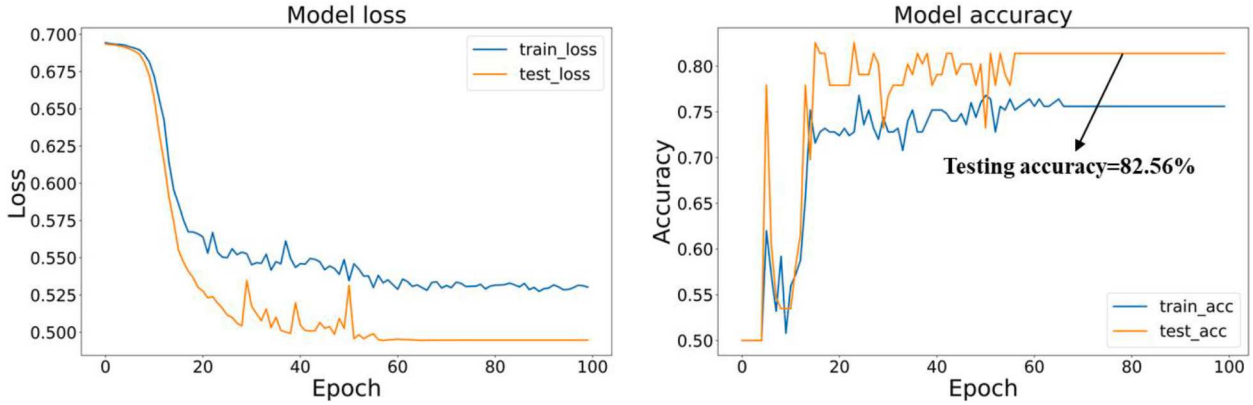


Fig. 9. Loss and accuracy for LSTM model using total data.

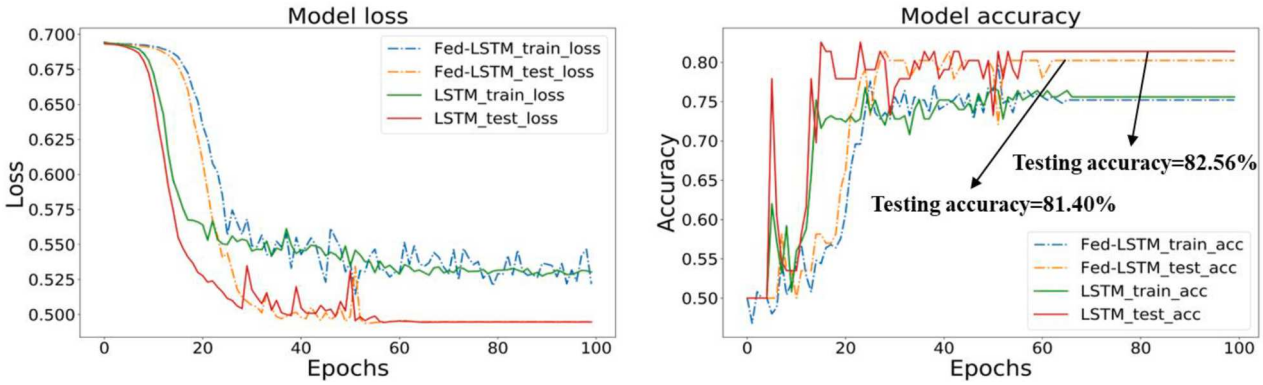


Fig. 10. Loss and accuracy of Fed-LSTM model compared with LSTM model.

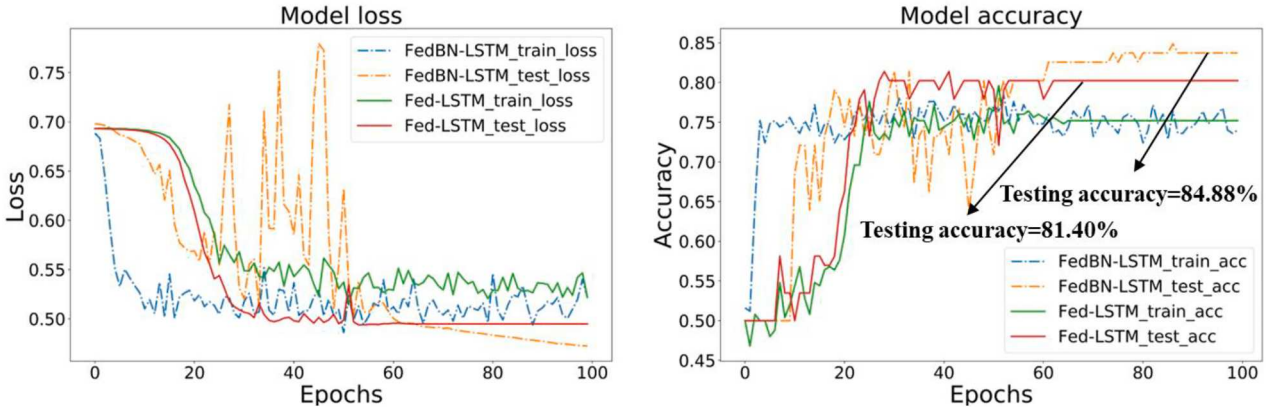


Fig. 11. Loss and accuracy of Fed-BN-LSTM models compared with Fed-LSTM model.

Table 7
Summary of testing accuracy for individual drivers with different models.

Driver	Testing data size	LSTM (individual)	LSTM (total)	Fed-LSTM	**Fed-BN-LSTM**
1	40	80.00%	82.50%	82.50%	**85.00%**
2	38	76.67%	81.58%	78.95%	**81.58%**
3	8	75.00%	87.50%	87.50%	**100%**
Average accuracy	–	78.06%	82.56%	81.40%	**84.88%**

Fed-BN-LSTM were compared on individual drivers' testing data.

The modeling results show that: (1) the larger training data sample size could improve the performance of LSTM model. (2) The model trained by collecting model parameters updated locally in vehicle servers can reach 81.40% accuracy while privacy-preserving, and the accuracy was only reduced by 1.16% compared to the model trained base on collecting total raw data. (3) The added BN layer for each driver allowed models adapting to the personalized driving behaviors could further improve the average modeling accuracy by 3.48%. (4) For individual drivers, Fed-BN-LSTM which provided personalized models reached the best performance on driver-1 and driver-3. As for driver-2, Fed-BN-LSTM also achieved the highest accuracy in common with LSTM

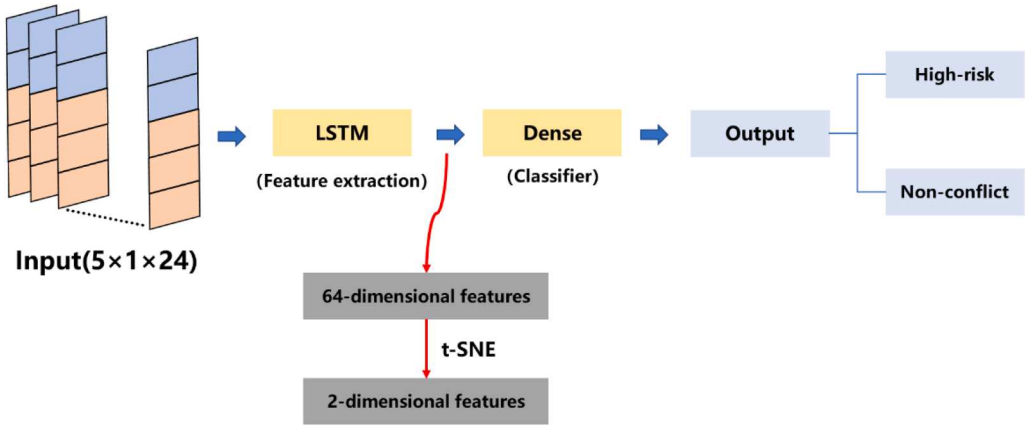
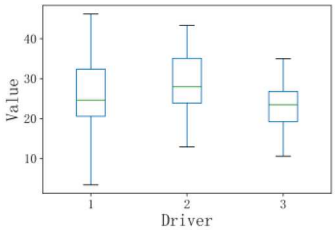
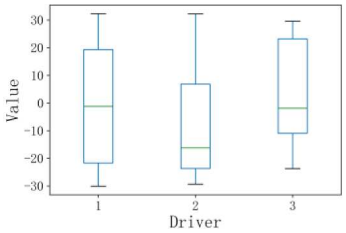
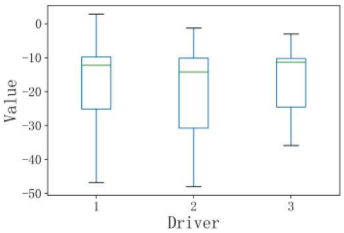
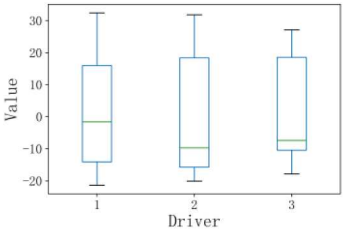


Fig. 12. The extraction and dimensionality reduction of features output by LSTM.

Table 8
2-Dimensional features of different drivers in different events.

Dimension	1	2
High-risk events		
Non-conflict events		

(total), and thus could help to improve the effectiveness of ADAS.

However, the number of drivers for empiric analyses used in this study was limited. The majority of drivers held few high-risk events within the observational period, and only data from 3 drivers who had large sample size of high-risk events were utilized. Such issue might make the proposed personalized algorithms more suitable to develop personalized driving assistance algorithms for the risky drivers rather than the overall driver group.

Besides, there is still plenty of room for future studies as this is the very first attempt to develop personalized driving assistance algorithms based on federated learning. First, in order to explore the effectiveness of the proposed algorithms for general drivers, sufficient samples are required to be collected to meet the modeling needs, especially for the drivers with low frequency of high-risk events. Second, to optimize the personalized modeling algorithms, combinations of federated learning and other personalization methods (e.g., domain adaptation) should also be considered. Meanwhile, to apply the developed algorithms for ADAS, employed self-supervision learning (Zhang et al., 2021) to classify data automatically rather than experts labeling for improving the update efficiency of the algorithms is required.

CRediT authorship contribution statement

Rongjie Yu: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision. **Ruici Zhang:** Investigation, Methodology, Writing – original draft, Writing – review & editing, Visualization. **Haoan Ai:** Investigation, Supervision. **Liqiang Wang:** Methodology, Supervision. **Zihang Zou:** Methodology, Writing – original draft, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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