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RESEARCH ARTICLE

A Privacy-Preserving Learning Method for Analyzing HEV Driver's Driving Behaviors

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ABSTRACT The driving behaviors of electric vehicle (EV) and hybrid electric vehicle (HEV) drivers have received considerable attention in the literature. The use of image recognition in combination with GPS and driving data has emerged as a popular approach to improving driver safety. However, such methods often generate sensitive personal information, including driver images, names, and GPS locations, which may risk the safety of the driver's privacy. To address this issue, a privacy-preserving approach for identifying driver behavior characteristics is necessary. To achieve this, we utilize on-board diagnostic (OBD) interface vehicle-mounted devices to collect and analyze data from an electronic control unit (ECU), thereby collecting only onboard data for data processing and analysis. In this work, we propose deep learning models such as long short-term memory (LSTM) networks and gated recurrent units (GRUs), which enable the learning of specific behavior patterns and represent the state-of-the-art model to classify and predict driving behavior that potentially leads to dangerous accidents. The predictions were then converted into alarm signals and transmitted to the dashboard of vehicle. Our experiments showed that our proposed system model achieved excellent results with an excellent kappa score of 96.5%, demonstrating that it can accurately identify unique driving behaviors in a privacy-preserving manner.

INDEX TERMS Driving behavior, deep learning model, privacy-preserving approach, prediction, safety diagnostic system.

I. INTRODUCTION

Due to various factors such as the driver's habits, emotions, and driving preferences, the driver has become the most unsafe part of the driver-vehicle system. Moreover, every driver has unique driving behavior characteristics. To understand the driver's behavior characteristics, most driver behavior recognition research is mainly based on head movement and facial features (such as eye movement recognition) that can identify the driver's driving state (fatigue/drunk/drowsy/distracted) to provide advanced warning to avoid driving accidents [1], [2], [3]. However, some behavioral studies on car use focus on tracking vehicles daily for several weeks, and the global positioning system (GPS) captures the geographic location once a second. Using GPS to collect travel behavior data, researchers can figure out the dynamic characteristics of travel behavior. Unfortunately, the above methods generate a lot of sensitive information, including driver images, driver names, GPS locations, etc., which makes it difficult to protect driver privacy. GPS location information can expose drivers' activities, personal habits, social relationships, health status, and other private information. For example, the length of time the vehicle stays in the hospital and the frequency of visits may reveal the health of the user. The leakage of the driver's trajectory and the exposure of personal habits is an issue that drivers are very concerned about, which has caused many controversies about track exposure [4], [5], [6].

Many studies have analyzed vehicle driving behavior and established recognition models to detect abnormal driver operation for safer driving, such as using the visual method of monitoring [7], [8], [9], [10]. However, to effectively recognize driver behavior while preserving privacy, it is necessary to select feasible metrics that can describe driver

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TABLE 1. Recent studies of using the visual feedback of driving behavior.

References	Year	Method of Prediction	Behavior Pattern	Model Evaluation
Kashevnik et al. [18]	2019	Mobile application of a smartphone system with sensors	Drowsiness, distraction, high pulse rate, drunk driving, aggressive driving, and stress	The experiment shows flagships and mid-range devices effectively identify dangerous states within 1.5 seconds.
Wang et al. [19]	2022	Graph construction approach-based regression model (logistic regression)	Normal and aggressive behavior	Accuracy 99%
Xiao et al. [20]	2022	Attention-Based Deep Neural Network (ADNet)	AUC label (safe driving, drinking, texting right, texting left, phone right, phone left, reaching behind, adjusting the radio, hair makeup, and talking to passengers) and NHU label (Normal, doze, phone, smoke, and yawn)	AUC (accuracy 90.22%), NHU (accuracy 98.42%)
Hou et al. [21]	2022	EDVR restoration algorithm, CNN-MobileNet-V2	Driver mask detection, bus driver motion	Mask detection (CNN-MobileNet-V2 97.87%), bus driver motion (EDVR TSN flow 96.3%)
Chen et al. [22]	2023	CNN-Transfer Learning	Acceleration, deceleration, turning, lane changing, and lane keeping	Accuracy 80%

characteristics. Additionally, the measurement system representing driver characteristics should be properly utilized by expressing and validating it using measurable parameters [11], [12], [13], [14], [15], [16], [17]. In this study, we utilized OBD interface vehicle-mounted devices to communicate with an ECU. Only onboard data collected from the ECU was communicated to the onboard device for data processing and analysis. In contrast to previous approaches, we utilized machine learning methods, including various deep learning models, to calculate the driving pattern. This approach provided more accurate results from a larger number of diverse and related characteristics, predicting the driving mode for different characteristics from a macroscopic perspective. The model can determine the current driving pattern and decide whether the driver is engaging in unsafe or dangerous driving behaviors while protecting driver privacy by not requiring sensitive driver and vehicle information such as driver images and GPS location data.

In this work, we developed a model for predicting dangerous driving behavior and conducted experiments using various deep learning methods to analyze both the driving mode of the vehicle and the driver's habits. Feedback is provided to the warning system, which is integrated with a website API and delivers notifications to the car dashboard system in front of the driver.

II. RELATED WORK

In recent years, there has been a growing interest in developing systems that utilize visual feedback or visually monitor driving behavior to enhance driver safety. This trend is summarized in Table 1. Kashevnik [18] proposed a technique and mobile application for driver monitoring, analysis, and recommendations based on observed risky driving behavior. The approach utilizes the smartphone's cameras and built-in sensors, including an accelerometer, gyroscope, GPS, and microphone, to monitor the driver's behavior. It includes a reference model, a classification of risky states, and the detection of dangerous states. Wang [19] proposed a method for modeling aggressive driving behavior by utilizing graph construction based on time-series data. The study employed raw data to construct graphs representing specific driving trips, incorporating driver characteristics, environmental information, and driving behavior variables. The performance of regression models was evaluated, demonstrating the suitability of a 5-second time window. Eleven significant variables, such as speed, acceleration, gender, age, distractions, and time-to-collision, were selected. Xiao [20] introduced the Attention-Based Deep Neural Network (ADNet) as a method for driver behavior recognition. The framework incorporates a channel attention (CA) block to capture inter-channel dependencies within the ADNet. Additionally, a spatial attention block is combined with the CA block to enable adaptive feature extraction. Data augmentation techniques are applied during the data processing stage to enhance recognition performance. Notably, the ADNet method achieves an impressive Top-1 accuracy of 98.48%. Hou [21] presented a lightweight framework aimed at detecting abnormal driving behavior. This framework leverages the capabilities of edge intelligence, empowering IoT devices to efficiently process and understand data. It encompasses four crucial modules: mask detection for bus drivers, detection of abnormal driver motion, fatigue driving detection, and video recovery. Chen [22] proposed a recognition method that combines Convolutional Neural Network (CNN) and transfer learning. The model leverages multi-source data fusion, including natural driving GPS data and drivers' facial expression data from online car-hailing services, to accurately identify five driving behavior patterns: acceleration, deceleration, turning, lane changing, and lane keeping. Experimental results demonstrate the superior performance of the transferred model, which achieved an accuracy score of 0.80. The literature discussed presents promising approaches for improving driver safety through visual feedback and monitoring of driving behavior. However, it is important to address privacy concerns related to the use of personal driver data, which can impact the reliability and ethical considerations of such research.

On the other hand, numerous researchers have been investigating how driving habits or behaviors influence the configuration of vehicular systems, specifically in the context of electric vehicles. Lv et al. [23] focused on the codesign optimization approach for adapting the automatic control of an intelligent electric vehicle to driving styles. It proposed a cyber-physical system (CPS)-based framework to optimize the plant and controller parameters of the vehicle, considering dynamic performance, drivability, and energy efficiency in relation to different driving styles. Wang et al. [24] conducted a study to investigate the eco-driving behaviors and motivations of EV drivers compared to internal combustion engine vehicle (ICEV) drivers. The researchers analyzed survey data and applied statistical analysis methods. The findings of the research indicate that EV drivers exhibit calming driving maneuvers and fuel-efficient driving habits, demonstrating their willingness to save energy during travel time. Rahmati et al. [25] identified a potential mismatch between the braking decisions of Connected and Automated Vehicles (CAVs) and the expectations of human drivers. The study revealed systematic differences in their braking trajectories, prompting the adoption of a Markovian decision modeling framework to design a CAV braking profile that aligns with human expectations and facilitates safe and comfortable maneuvers in mixed driving environments. Oh et al. [26] developed the Vehicle Energy Dataset (VED), a large-scale dataset tailored for research on vehicle energy consumption. This dataset enables the identification of driving behaviors that protect the personal information of the driver while also providing insights into eco-driving approaches based on fuel consumption. By leveraging this extensive dataset, researchers can gain valuable insights into both privacy-preserving driving behavior and eco-friendly driving strategies correlated with fuel consumption. These studies have shed light on various aspects of vehicular systems and driving behaviors, particularly in the context of electric vehicles.

The emerging method of artificial intelligence (AI) enhances the results and aids in achieving the goal of investigating driving behavior [27], [28]. Shahverdy et al. [29] proposed a classification method that utilizes deep learning for analyzing driving behavior. The method employs a 2D Convolutional Neural Network (CNN) with imaging features and utilizes the recurrent plot technique to recognize driving signals. The classifier model has 21.5k parameters and a computational complexity of 0.043 MFLOP, which results in low computational costs. Despite this, the model achieves a high accuracy rate of 99.76%. Specifically, Lu et al. [30] analyzed the factor of stress while driving a vehicle without using psychological data. The extreme gradient boosting (XGBoost) algorithm outperformed traditional machine learning models such as support vector machine (SVM) and achieved an accuracy range of 91.18% to 93.25%. On the other hand, Sethuraman et al. [31] elaborated on the use of the AdaboostMSVM algorithm paired with the CMO algorithm for anomaly detection in the Advanced Driver Assistance System (ADAS). The hyperparameters of the CMO algorithm significantly boosted the performance of the model, resulting in an accuracy of 91.45%, an F-score of 94.45%, a precision of 93.38%, and a recall of 94.90%. These results outperform other existing methods that handle specific tasks. Ping et al. [10] introduced a method for recognizing distracted behavior utilizing the Temporal-Spatial double-line DL network (TSD-DLN) and causal And-or graph (C-AOG). The TSD-DLN combines attention features from dynamic optical flow information with spatial features from single video frames to accurately identify distracted driving postures. The proposed model outperforms other state-of-the-art methods on two public datasets as well as a collected dataset specifically focused on distracted driving behavior. Meanwhile, Liu et al. [32] introduced a novel framework called DSDCLA, which combines attention-based hybrid convolutional neural network (CNN) and LSTM models. DSDCLA aims to extract local spatial features from multi-modal driving sequences and utilizes LSTM and multi-head attention mechanisms to capture long-term temporal relationships between timesteps. Additionally, the researchers designed three variants with different fusion levels, which not only demonstrate the advantage of selecting components but also improve interpretability. The proposed DSDCLA framework was evaluated on two public real-world datasets, and the experimental results showcased its superiority over current state-of-the-art methods, achieving impressive F1-scores of 97.03% and 97.65%. Furthermore, Song et al. [33] proposed a method to reduce the complexity of the model by utilizing lightweight deep learning image classification models. The proposed model increases the speed of model operations without degrading performance, as compared to traditional deep learning models. Ma et al. [9] proposed the LSTM-R algorithm for real-time detection of abnormal driving behavior. The research demonstrated that LSTM-R outperforms other algorithms, achieving a maximum F1-score of 0.866. The evaluation of the model showed that LSTM-R is effective even with a small proportion of abnormal driving behavior in the training set, indicating relaxed requirements for labeled data. The findings highlight the potential application of LSTM-R in enhancing roadway safety through real-time detection, driving risk assessment, and behavior improvement. The rapidly developing field of AI has a lot of potential for advancing studies on driving behavior. In particular, numerous deep learning-based methodologies have demonstrated noteworthy improvements in terms of accuracy and efficacy, playing a significant role in the ongoing effort to understand and improve driving behavior by utilizing AI techniques.

This literature review examines advancements in analyzing driving behavior, particularly in the context of EV. The reviewed studies emphasize the identification of abnormal driving patterns using methodologies such as data mining,

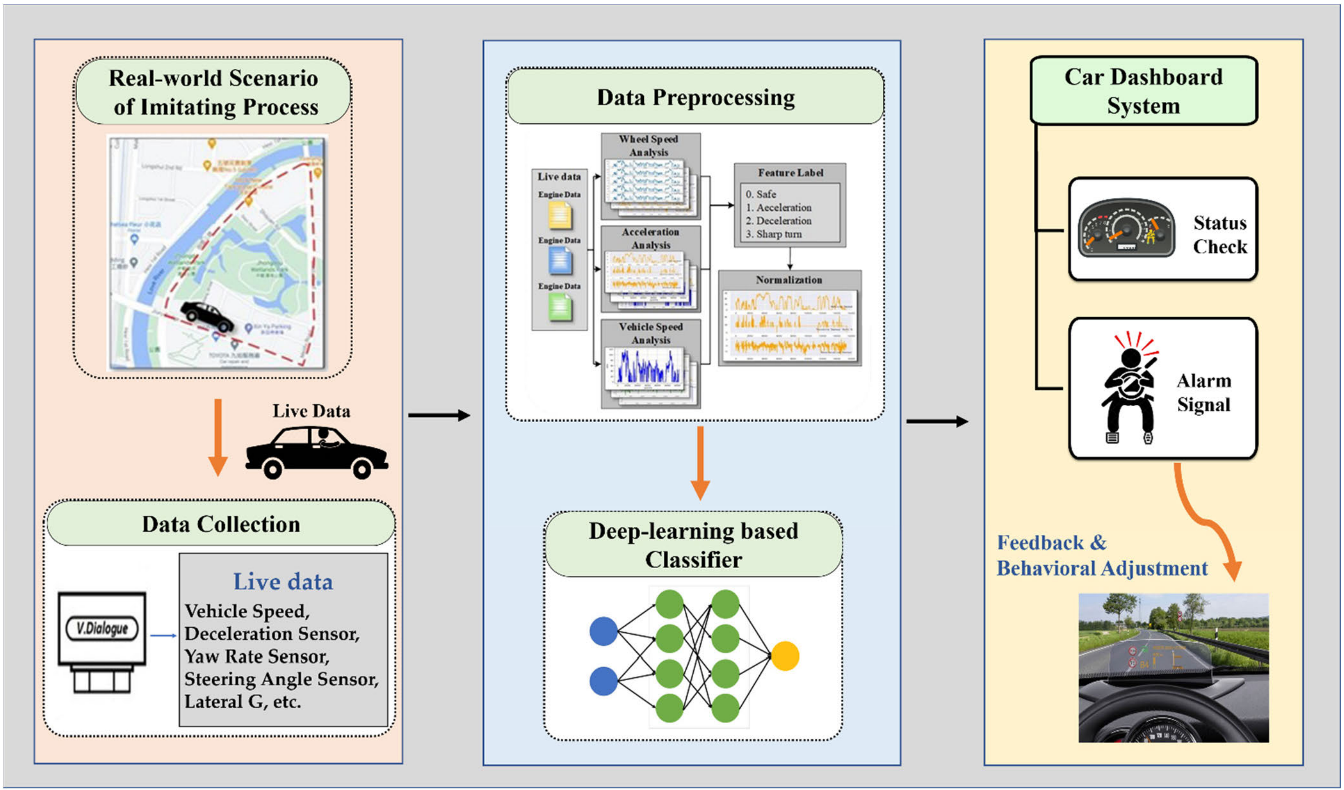

FIGURE 1. System Framework.

machine learning, and deep learning. However, there is a lack of literature specifically focusing on electric vehicle study cases and utilizing AI models to achieve state-of-the-art analysis of abnormal driving behavior. Overall, the field of AI shows great potential for advancing the study of driving behavior, with deep learning-based methodologies playing a significant role in improving accuracy and effectiveness.

III. SYSTEM MODEL

A. SYSTEM FRAMEWORK

Based on the previous study by Hung [34], which presented an approach for analyzing safe and dangerous driving behavior. In this work, we expand the previous work to incorporate the proposed model by strengthening the behavior model and enhancing the feedback mechanism. In this study, we employ deep learning methods to detect and predict unsafe driving patterns using OBD vehicle data. We also investigate the impact of various influencing variables on different levels of dangerous driving, such as aggressive acceleration and sharp turn driving, in real-time environments. Fig. 1 illustrates the framework of our proposed system, which involves collecting telematic data from the vehicle and extracting driving labels. The preprocessed data is then aggregated to create an experimental dataset, and labels are assigned based on their corresponding values. A deep learning classification model, specifically LSTM and GRU methods as supervised learning techniques, is utilized for training and testing purposes to learn driving behavior. Feedback is provided to the warning system, which is integrated with a website API and delivers notifications to the car dashboard system in front of the driver. The details of the system framework are depicted in Fig. 1.

B. DATA SOURCE

1) DATA ACQUISITION

The vehicular data for the driving records were obtained from six drivers using the same car, a Toyota Prius V 2ZR-FXE. Real-time scenarios were applied to imitate safe and unsafe driving behaviors in a real-world environment. The data was collected using a cloud fleet management system, which recorded driving parameters such as steering angle, speedometer readings, acceleration, deceleration, gear information, vehicle speed, and steering wheel angle. The collected data was stored on a local hardware device and transmitted to a cloud platform for analysis. Approximately 1.5 million real-time data points were collected, covering 60 hours of driving time. A total of 76,948 pieces of data were collected after the data were cleaned and compiled. After being labeled according to driving behaviors, these datasets were saved in CSV format for further processing.

2) BEHAVIOR MODELING

As shown in Fig. 1, we simulated various driving behaviors, including safe driving (Safe), aggressive acceleration (Ace), rapid deceleration or hard braking (Dece), and sharp turns (Turn). Each driver performed these behaviors on the same track and car to ensure the complexity of the data.

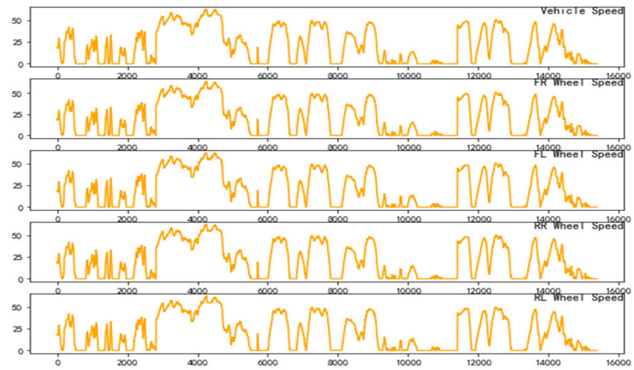

FIGURE 2. Vehicle speed data sample confirmed by connection of the vehicle wheels.

Furthermore, the drivers imitated real-time scenarios of safe and unsafe driving behaviors. For aggressive acceleration, the drivers accelerated rapidly during the straight sections of the track, achieving a higher acceleration rate compared to normal driving. A sudden deceleration or hard braking was imitated by rapidly reducing the vehicle's speed during the straight sections or when approaching a turn, applying the brakes forcefully for quick deceleration. Sharp turns were imitated by taking specified turn angles with higher steering input, requiring a significant change in the vehicle's direction. Safe driving behavior was simulated by following the track without abrupt accelerations, decelerations, or aggressive turns. The drivers maintained a steady speed, followed the designated path, and adhered to traffic rules and regulations. By controlling the acceleration, braking, and steering inputs during each section of the track, the drivers imitated different driving behaviors according to the specified scenarios for aggressive acceleration, sudden deceleration or hard braking, sharp turns, and safe driving.

3) VEHICLE DIAGNOSTIC DATA

Table 2 presents the data obtained from the onboard vehicle, which served as the foundation for further processing [34]. This dataset consists of 21 variables labeled with driving behaviors such as safe driving, aggressive acceleration, rapid deceleration or hard braking, and sharp turns. These variables were utilized in the training process to construct a classifier model for driving behavior analysis.

C. VALIDATION OF THE PATTERNS BASED ON SAMPLE TELEMATICS DATA

In this work, we verified data correctness using interactive numerical calculations on specific selected features, as shown in Fig. 2.

Subsequently, we verified the relationships between engine speed, throttle voltage, and acceleration and deceleration by performing driving tests, as shown in Fig. 3. Generally, throttle voltage and acceleration increase as vehicle speed increases [34].

According to the driving test results, we found that the value of the deceleration will change drastically when there

TABLE 2. The variables in the vehicle data [34].

List of OBD data	Description
Date (yyyy/mm/dd)	Data collection date
Time (h:mm:ss)	Data collection time of day at microsecond granularity
BAT (V)	Current battery output voltage
Vehicle speed (km/h)	Instantaneous vehicle speed
Calculated load (kg)	Engine load (i.e., default vehicle engine load weight)
MAF (ratio)	Air-fuel combustion mixing ratio
Coolant temperature (°C)	Engine water temperature (water tank temperature)
Throttle voltage (%)	Throttle valve position
Deceleration (m/s^2)	Vehicle acceleration and deceleration (positive and negative, respectively)
Yaw (deg)	Vehicle steering angle
Steering angle (deg)	The rotation angle of the vehicle steering wheel
Lateral acceleration	Lateral acceleration: positive is toward the left, negative toward the right, relative to vehicle forward motion.
Forward and rearward acceleration (m/s^2)	Vehicle acceleration and deceleration (positive or negative, respectively) $V_a = (V_2 - V_1 \times 1000 \times t)$
FR wheel speed (km/h)	Vehicle front right wheel speed
FL wheel speed (km/h)	Vehicle front left wheel speed
RR wheel speed (km/h)	Vehicle rear right wheel speed
RL wheel speed (km/h)	Vehicle rear left wheel speed
FR wheel acceleration (m/s^2)	Vehicle front right wheel acceleration
FL wheel acceleration (m/s^2)	Vehicle front left wheel acceleration
RR wheel acceleration (m/s^2)	Vehicle rear right wheel acceleration
RL wheel acceleration (m/s^2)	Vehicle rear left wheel acceleration

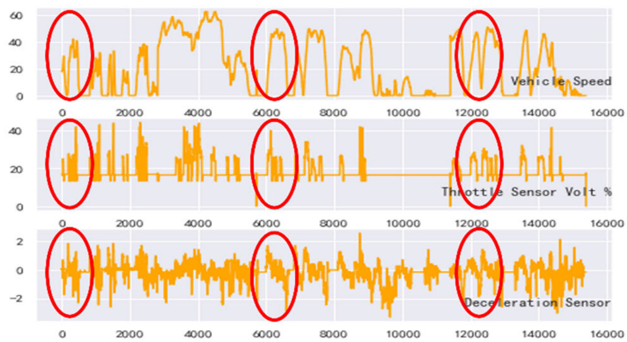

FIGURE 3. Validation relationships among engine speed, throttle voltage, and deceleration [34].

is a sudden acceleration and rapid deceleration when driving. There are positive and negative values in this field. If the value is positive, it means that the value is forward acceleration, which means that the actual driving action is the accelerator action. The larger the value, the faster the speed. If the value is negative, it means that the actual driving action is backward acceleration, and the actual driving action is a braking action. The larger the value, the greater the braking force. Here, we define the former driving behavior as rapid acceleration

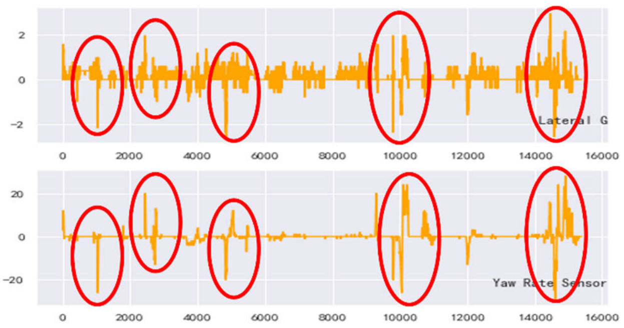

FIGURE 4. **Validation of sample data on steering angle and lateral acceleration [34].**

driving behavior and the latter driving behavior as rapid deceleration driving, which is used as a label for data labeling.

Fig. 4 shows that yaw increases when lateral acceleration increases, and lateral acceleration increases as steering angle increases. According to the actual driving-test results, the changes in the values can be observed from Fig. 4, and the driving actions and patterns can be found from them. We found that when driving into a sharp turn, the value of the Lateral G acceleration field will change drastically. For example, at the red circle, there are positive and negative values in the field. A positive sign indicates that the value is acceleration to the right, indicating that the actual driving action is turning the vehicle to the right. If the value is negative, it means that the actual driving action is turning the vehicle to the left. The larger the value, the faster the speed, which is used for subsequent labeling of the data.

D. EXPERIMENTAL DESIGN

The development of a prediction model for driving behavior is described in Algorithm 1, which outlines the steps for building, training, and evaluating an LSTM or GRU model for multi-class classification. Firstly, the input data, consisting of 21 variables along with the driving behavior label, is normalized using Min-Max normalization. The normalized data is then divided into training and testing sets with an 80/20 split. Next, the model architecture is defined, incorporating specific input layers, hidden layers, and a final output layer that utilizes Softmax as the activation function for multi-class output. ReLU activation functions are applied to the hidden layers, and dropout layers with a rate of 0.2 are inserted between each layer to mitigate overfitting.

In this work, the model is compiled with a categorical cross-entropy loss function and accuracy as the metric. It is then fitted to the training data and computed for 500 and 1000 epochs for comparison. Once trained, the model is evaluated on the testing data, and benchmarking metrics are calculated. Finally, the trained model, model accuracy and loss, and evaluation metrics are outputted for further analysis and comparison with other models. Overall, Algorithm 1 provides a clear and structured framework for developing a prediction model for driving behavior.

Algorithm 1 The Development and Evaluation of Learning Models

Input:
- Vehicle OBD data (training and testing data)
- *Bidirect* // The parameter times two

Output:
- Trained model
- Model accuracy and loss
- Evaluation metrics (accuracy, recall, precision, F1-score, and kappa score)

Steps:
1. Normalize the input data using Min-Max Normalization
2. Split the data into training and testing sets (80/20)
3. Define the *LSTM* or *GRU* model architecture with the following parameters:
   - Input layers: *128*
   - Hidden layers:*128*Bidirect* and *64*Bidirect* layers
   - Activation function: *ReLU* // for hidden layers
   - Final output layer: *Softmax* (4 class label)
   - Optimizer: *Adam*with a *learning rate*$1e^{-3}$
   - Batch size: *128*
   - Dropout layer: *0.2* in each layer // prevent overfitting
4. Compile the model with *categorical cross-entropy* loss function
5. Fit the model to the training data with a specified number of epochs (e.g., 500 and 1000)
6. Evaluate the model on the testing data and calculate the accuracy and loss
7. Calculate the following evaluation metrics on testing data
8. Output the trained model, model accuracy and loss, and evaluation metrics

IV. RESULTS AND DISCUSSION

A. EVALUATION METRICS

First, we explain the method and criteria for model evaluation in the experiments. In this work, we use three classification metrics as review and evaluation criteria for the numerical model's effectiveness in predicting specific driving behaviors. Prior knowledge contained in the confusion matrix incorporates various critical measures, including precision and recall rates for each class, which express the classifier's recognition ability for each class. Accuracy, recall, precision, and F1-score were defined as follows:

$$Accuracy = \frac{TP + TN)}{(TP + FP + FN + TN)} \tag{1}$$

$$Recall = \frac{TP}{(TP + FN)} \tag{2}$$

$$Precision = \frac{TP}{(TP + FP)} \tag{3}$$

TABLE 3. Kappa coefficient strength.

Kappa statistic	Agreement strength
<0.00	Poor
0.00-0.20	Slight
0.21-0.40	Fair
0.41-0.60	Moderate
0.61-0.80	Substantial
0.81-1.00	Almost perfect

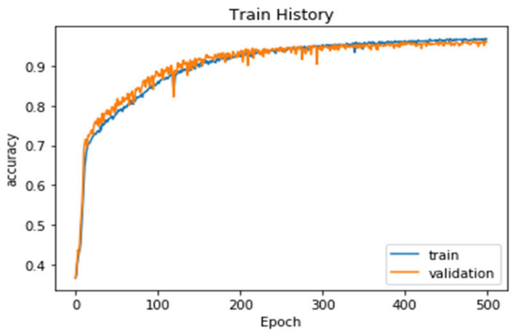

FIGURE 5. Accuracy for LSTM model training.

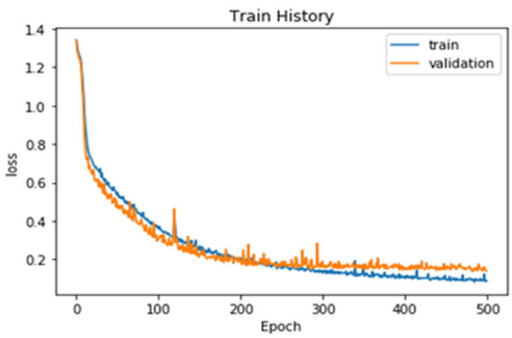

FIGURE 6. Loss for LSTM model training.

$$F1 - Score = \frac{(2 * Precision * Recall)}{(Precision + Recall)} \tag{4}$$

Subsequently, we introduce the concept of Kappa Coefficients. The Kappa coefficient is a statistical measure of reliability or consistency between evaluators.

$$K = \frac{P_o - P_e}{1 - P_e} \tag{5}$$

Kappa coefficients are commonly used to evaluate qualitative documents and determine consistency between two evaluators, and they provide a useful benchmark for comparing specific methods. K = 1 if the evaluators agree completely, and K = 0 if there is no agreement between the evaluators. Table 3 shows the Kappa statistic ranges and corresponding descriptors.

B. EXPERIMENTAL RESULTS OF LEARNING MODELS IN 500 EPOCHS

1) LSTM MODEL

The smooth and converging curves of the training and verification data for LSTM are depicted in Figs. 5 and 6 [34]. The accuracy and loss metrics show rapid improvement up to around epoch 80, followed by a slower but steady improvement until around 250 and 400 epochs, respectively. Beyond these epochs, the metrics become relatively stable, indicating that increasing the number of epochs can enhance the model's accuracy.

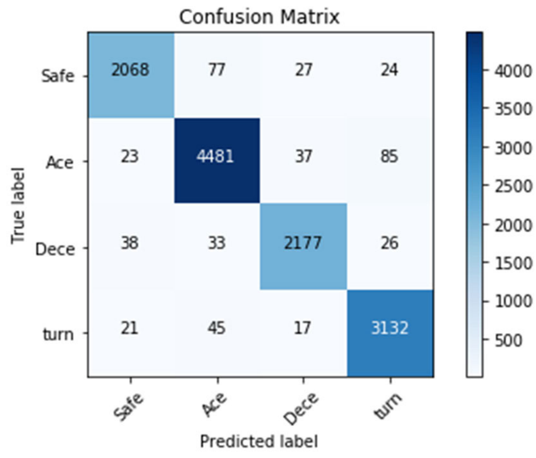

FIGURE 7. Confusion matrix for training LSTM model.

TABLE 4. Evaluation model of LSTM.

	Precision	Recall	F1-score	Support
Safe	0.949	0.949	0.949	2196
Ace	0.961	0.969	0.965	4626
Dece	0.961	0.958	0.960	2274
Turn	0.972	0.962	0.967	3215
Accuracy	0.962	0.962	0.962	0.962
Kappa score	0.947			

Fig. 7 indicates that all categories have high accuracy, with Ace achieving the highest accuracy among the categories, indicating that it is the least likely to be confused with other categories [34]. Safe, which has 2068 records, is the category that is most frequently confused with other categories, most often with Ace. Conversely, Ace is often misclassified as a turn.

Table 4 shows that the precision and recall for all categories are similar, resulting in an overall accuracy of 0.962 and a kappa score of 0.947. Therefore, the LTSM model provides excellent classification performance.

2) GRU MODEL

Figs. 8 and 9 indicate that the training of GRU starts relatively smoothly and that accuracy and loss vary rapidly up to 40 and 90 epochs, respectively [34]. Although the rate of change gradually decreases as the epoch increases, the model never reaches stability. Therefore, by increasing the number of epochs, further improvements in accuracy and loss can be achieved.

Fig. 10 shows Ace has the highest accuracy (4367 records) and is hence least likely to be confused. Safe (2013 records) is the most easily confused category, most commonly with Ace, whereas Ace is most misjudged as turn [34].

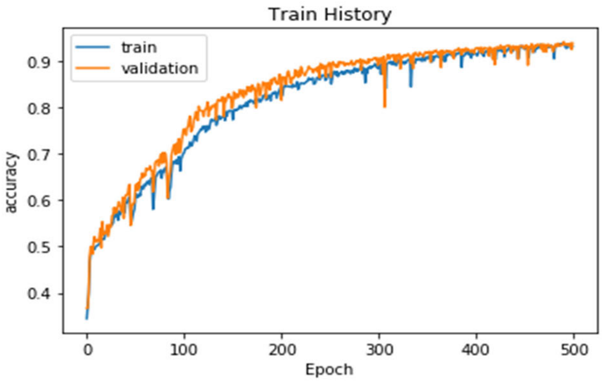

FIGURE 8. Accuracy for training GRU model.

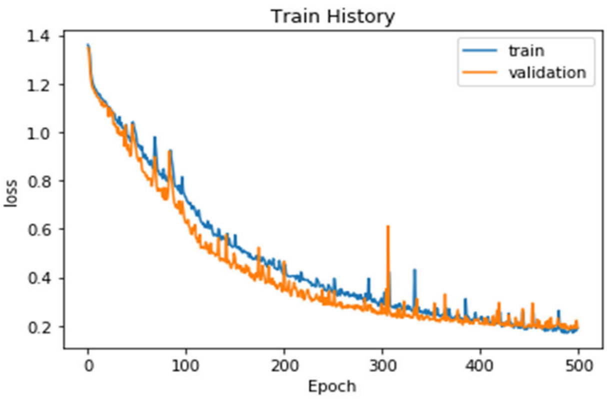

FIGURE 9. Loss for training GRU model.

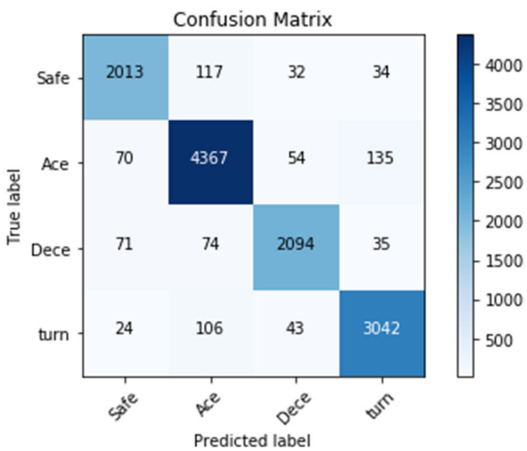

FIGURE 10. Confusion matrix for GRU training 500 epochs.

TABLE 5. GRU training 500 epochs classification performance.

	Precision	Recall	F1-score	Support
Safe	0.924	0.917	0.920	2196
Ace	0.936	0.944	0.940	4626
Dece	0.942	0.921	0.931	2274
Turn	0.937	0.946	0.942	3215
Accuracy	0.935	0.935	0.935	0.935
Kappa score	0.911			

Table 5 validates the alignment between precision and recall, exhibiting an overall accuracy of approximately 0.935 and a kappa score of 0.911. This suggests that GRU can serve as an exceptional classification model, although it may not offer as exceptional a performance as the LSTM model.

TABLE 6. Evaluation and classification performance for the considered models, 500 epochs.

Learnin g Model	Clas s	Precisio n	Recall	F1-Score	Kappa Score
LSTM	Safe	0.917	0.935	0.926	**0.947**
	Ace	0.925	0.902	0.914	
	Dece	0.919	0.940	0.929	
	Turn	0.919	0.919	0.919	
GRU	Safe	0.954	0.845	0.896	0.911
	Ace	0.924	0.945	0.934	
	Dece	0.917	0.943	0.930	
	Turn	0.926	0.951	0.938	

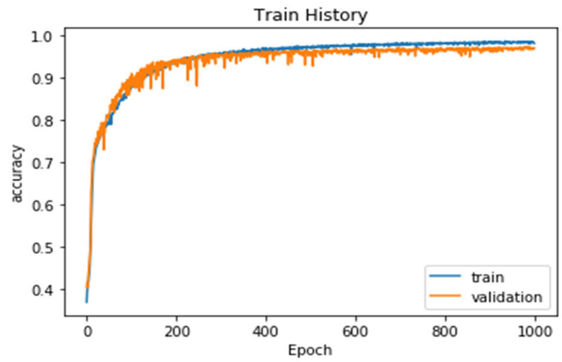

FIGURE 11. Accuracy for LSTM model training to 1000 epochs.

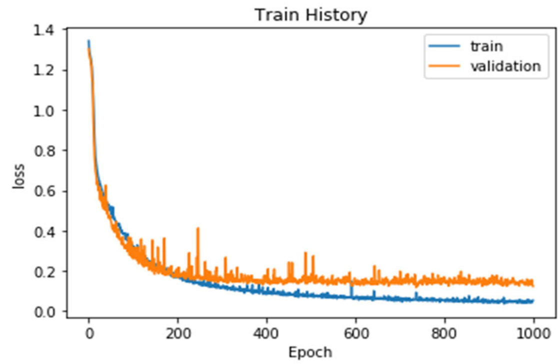

FIGURE 12. Loss for LSTM model training to 1000 epochs.

3) COMPARISON OF LEARNING MODEL

Table 6 indicates that the GRU model has a satisfactory Kappa score, but there are notable discrepancies between precision and recall for the Safe category. Consequently, the LSTM model demonstrates superior classification performance compared to the other models.

C. EXPERIMENTAL RESULTS OF LSTM AND GRU (1000 EPOCH)

1) LSTM MODEL

The stability of LSTM is maintained beyond 500 epochs up to a minimum of 1000 epochs, as depicted in Figs. 11 and 12 [34].

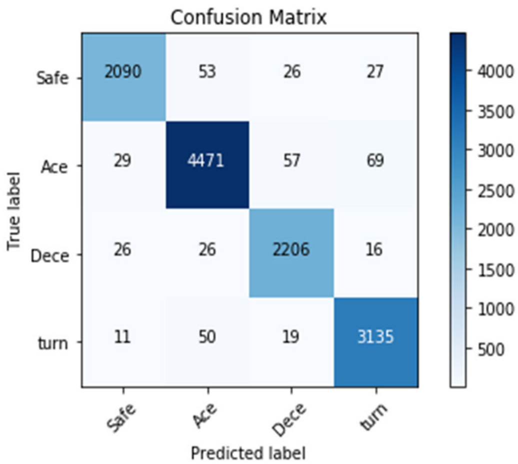

FIGURE 13. Confusion matrix for LSTM training to 1000 epochs.

TABLE 7. LSTM training 1000 epochs classification performance.

	Precision	Recall	F1-score	Support
Safe	0.945	0.945	0.945	2196
Ace	0.958	0.962	0.954	4626
Dece	0.950	0.953	0.947	2274
Turn	0.963	0.956	0.970	3215
Accuracy	0.955	0.955	0.955	0.955
Kappa score	0.938			

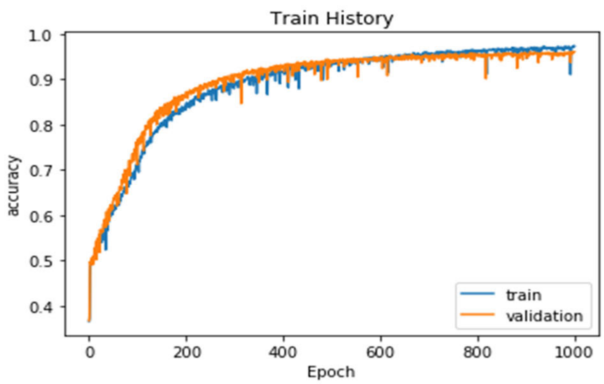

FIGURE 14. Accuracy for GRU model training to 1000 epochs.

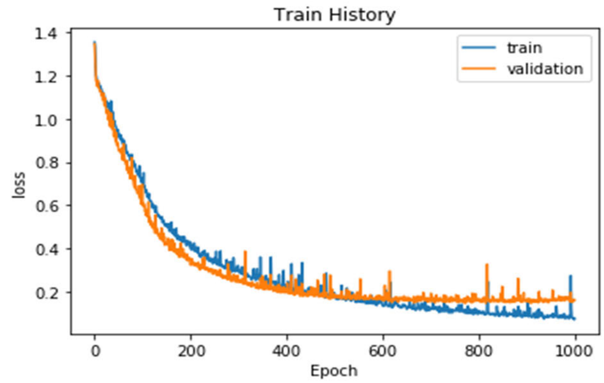

FIGURE 15. Loss for GRU model training to 1000 epochs.

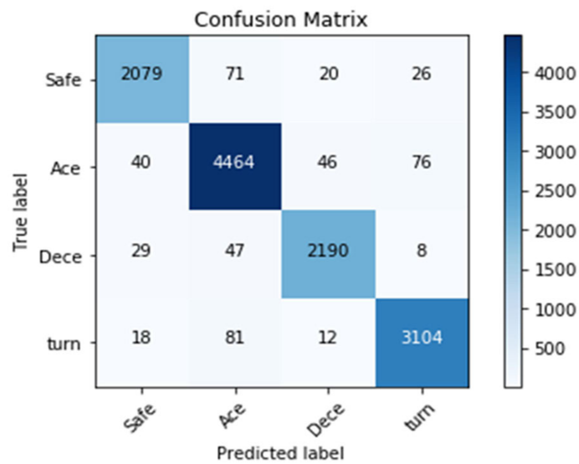

FIGURE 16. Confusion matrix for GRU training 1000 epochs.

TABLE 8. GRU training 1000 epochs classification performance.

	Precision	Recall	F1-score	Support
Safe	0.953	0.960	0.946	2196
Ace	0.961	0.957	0.964	4626
Dece	0.964	0.966	0.963	2274
Turn	0.966	0.966	0.965	3215
Accuracy	0.961	0.961	0.961	0.961
Kappa score	0.947			

Fig. 13 shows comparable results to the shorter training duration of 500 epochs, where Ace exhibits the highest accuracy (4471 records) and is the least susceptible to confusion [34]. Although the accuracy of other categories is slightly lower, their predictability remains high with minimal confusion.

Table 7 illustrates that the LTSM model achieved an accuracy of 0.955 and a kappa score of 0.938 after 1000 epochs, exhibiting excellent agreement between precision and recall. Hence, the model demonstrates exceptional classification performance.

2) GRU MODEL

Figs 14 and 15 show that the GRU curves tend to become more stable as epochs tend toward 1000 [34].

Fig. 16 is similar to Figs. 10 and 13. Ace is the most accurately predicted (4464 records), but all categories have good predictions with some confusion [34].

Table 8 illustrates that the GRU model trained for 1000 epochs achieved an accuracy of 0.961 and a kappa score of 0.947, with minimal variations between precision and recall for all categories. Overall, the extended GRU model outperformed all other models examined.

3) COMPARISON OF LEARNING MODEL

Table 9 indicates that the GRU model achieves a Kappa score of 0.946, which is equivalent to the Kappa score of the LSTM model. Therefore, by increasing the number of epochs to 1000, the GRU model surpasses all other models and delivers superior performance.

TABLE 9. Evaluation and classification performance for the considered models, 1000 epochs.

Learning Model	Class	Precision	Recall	F1-Score	Kappa Score
LSTM	Safe	0.945	0.944	0.945	0.938
	Ace	0.957	0.961	0.953	
	Dece	0.949	0.952	0.947	
	Turn	0.962	0.955	0.970	
GRU	Safe	0.953	0.959	0.946	**0.946**
	Ace	0.961	0.957	0.964	
	Dece	0.964	0.965	0.963	
	Turn	0.965	0.965	0.965	

TABLE 10. Evaluation of deep learning models in different epochs.

Learning Model	Epochs	Accuracy	Loss	Kappa Score
LSTM	500	0.962	0.142	0.947
GRU	500	0.935	0.188	0.910
BiLSTM	500	0.923	0.260	0.893
BiGRU	500	0.963	0.129	0.949
LSTM	1000	0.955	0.181	0.938
GRU	1000	0.962	0.156	0.946
BiLSTM	1000	0.961	0.116	0.945
BiGRU	1000	**0.975**	**0.081**	**0.965**

D. DISCUSSION

In this study, we observed that accurately classifying specific abnormal driving patterns requires the inclusion of a substantial number of characteristic variables that exhibit correlation changes. The choice of classification model significantly influences the classification performance, and therefore, we applied the same network parameters to the learning models.

Based on the results presented in Table 10, it is evident that among the four evaluated models, the GRU model with bidirectional features, training for 500 and 1000 epochs, respectively, demonstrated superior performance in terms of accuracy, loss, and kappa score. The 500-epoch GRU model achieved an accuracy of 0.963, a loss of 0.129, and a kappa score of 0.949, while the 1000-epoch model achieved an accuracy of 0.975, a loss of 0.081, and a kappa score of 0.965. These results indicate that the GRU model with bidirectional features is the most effective model for predicting driving behaviors, including safe and dangerous behaviors.

The incorporation of kinematic data related to vehicular motion is vital for the analysis of driving behavior [35], [36], [37], [38]. In this regard, our proposed model exhibits superior performance compared to other current state-of-the-art models when it comes to detecting driver behavior while ensuring privacy preservation through the utilization of kinematic datasets. The BiGRU model outperforms the multi-classifier fusion approach in accurately identifying safe and aggressive driving events, resulting in a noteworthy 0.75% increase in accuracy [8]. Additionally, the model surpasses the general LSTM model, even when combined with a Regression algorithm [9]. These findings highlight the effectiveness and superiority of our proposed model in the field of intelligent transportation systems.

V. CONCLUSION

In this study, we collected data from a vehicle's ECU using OBD interface devices installed in automobiles. The data was then sent to an onboard device for processing and analysis. The novel methodology of this investigation involves using deep learning models to analyze driving behaviors and patterns gathered from real vehicles. This method offers several advantages. For instance, it enables us to predict driving behavior based on various macroscopic traits, leading to more accurate and comprehensive results. The model can also determine the current driving mode and identify risky driving behaviors without requiring any private driver information. Our proposed deep learning model can match the most advanced models in this field. Moreover, it is reliable enough to directly assign certain tasks to the driver, thus enhancing the safety system.

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