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RESEARCH ARTICLE

Vehicle Driving State Recognition and Test Analysis Using Vehicle Body Attitude Measurement and One-Dimensional Convolutional Neural Network

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ABSTRACT – The increase in the number of cars on the road has led to frequent traffic accidents, some of which may be due to human factors such as poor driving habits. In order to reduce the number of accidents, there is a need to accurately analyze the driver's driving behavior and accurately identify the actual state of motion of the car. A method based on a one-dimensional convolutional neural network to determine the condition of a vehicle is proposed. Vibration acceleration indications for four different fuel-powered vehicle traveling states (constant speed, acceleration, deceleration, acceleration and deceleration) and six electric vehicle driving states (constant driving, acceleration, deceleration, acceleration and deceleration, left-turn driving, and right-turn driving) were measured using GPS inertial navigation sensors. New data samples are then extracted and evaluated to cover the full range of each operational situation. Access to the "keras" package via Python allows the creation of a one-dimensional Convolutional Neural Network (1D-CNN) model. The model receives one-dimensional vibration acceleration signals as input for parameter tuning. The experimental results show that the application of multimodal data fusion in automotive driving state recognition is achieved by combining vehicle attitude signals with the 1D-CNN method and GPS navigation data. This approach features high recognition accuracy, strong generalization ability, short model training time, and high reliability, with the model achieving a training accuracy of 90%. It is aimed at monitoring driver behavior and optimizing driver assistance systems, while also providing new ideas and methods for improving the performance and safety of automatic navigation and autonomous driving systems.

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1. INTRODUCTION

The automobile manufacturing industry is one of the largest and most important industries in the world in terms of production value. However, with the increase in automobile ownership and the emergence of man-made problems such as bad driving habits, which bring major threats to people's lives and property safety, safe automobile driving has increasingly become a key issue in people's discussions [1]. Analysis of driving behaviors has recently been the subject of extensive research by scholars from around the world. [2]. Miyajima was of the opinion that everyone has their own driving style. His statistical approach of combining the non-linear approximation of the optimal speed model with the Gaussian mixture model to collect the pedal strokes of different drivers and analyze their signal frequency characteristics could effectively reflect the unique driving situations of each driver. In 2011 and 2012, the researchers Tran, Doshi, and Triveda [4-5] analyzed the pedal pressure circumstance of automobile drivers. With an accuracy rate of 94%, they proposed a framework for analyzing driver behavior based on visual analysis. He Changwei [6] constructed a distributed in-vehicle network to achieve the digitalization and informatization of the in-vehicle state and to provide a database for the recognition of automotive driving behavior. Haina Song [7] created an accelerometer-based driving behavior analysis system equipped with a Beidou system, which accurately identifies a car's driving state in real time; Guo Wenting [8] used a complex virtual simulation test platform to generate different behavioral characteristics of drivers, established a driving behavior assessment model, conducted hazard assessment and risk prediction of different driving behaviors of drivers and reminded drivers so that drivers can be aware of the wrong driving behaviors in time.

Other researchers have used dedicated standalone sensors combined with statistical machine learning methods such as SVM (Support Vector Machine) [9], KNN (k-Nearest Neighbor) [10], and HMM (Hidden Markov Model) [11] algorithms for classification and recognition, but very few researchers have used deep learning schemes to solve this problem. In order to more scientifically and objectively reflect the real running state of the car, especially for the safety assessment of the car's driving speed, it is necessary to study the new effective assessment method to achieve the driving state safety characteristics, discriminative diagnosis. Compared with statistical machine learning algorithms, methods based on deep learning neural networks can effectively improve recognition accuracy. However, the data collected by

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motion sensors have special correlation characteristics, and how to improve the recognition accuracy of deep learning neural networks on this type of data is an urgent problem to be solved. Yang Xing et al. [12] proposed an energy-aware personalized joint time series modeling (PJTSM) method based on deep recurrent neural networks (RNN) and long and short-term memory units (LSTM) for accurately predicting the trajectory and speed of the vehicle ahead. Hongwei Yang [13] proposed an automatic driving behavior recognition algorithm based on computer vision and deep learning techniques to achieve target detection and driving behavior analysis. Le Yue [14] proposed a deep learning-based method to intelligently and efficiently detect and identify various behaviors of vehicles in the long videos captured by the vehicle recorder or other devices that ingest the environment in front of the vehicle by means of convolutional neural networks and long and short-term memory networks, respectively, to achieve the research on the classification and detection of vehicle dynamic behaviors based on deep learning; Guo Yaohua [15] proposed Multi-View Convolutional Neural Networks (MV-CNN) based on Multi-View Convolutional Neural Networks (MV-CNN) to achieve multi-dimensional feature extraction of the input tensor, and from the experimental results, it can be seen that the MV-CNN has the ability to mine the potential features of the data, and the prediction accuracy can be up to 95.29%; Nana Zhou [16] applied convolutional neural network to the state recognition field of fatigue driving and proposed an Eye and Mouth multi-state recognition network based on Eye and Mouth-CNN (EM-CNN) using a multi-task cascade framework, with an average accuracy of 93.62% and sensitivity of 93.64%, which is higher than that of traditional machine learning detection methods. Nana Zhou [16] applied a convolutional neural network to the state recognition field of fatigue driving and proposed an Eye and Mouth multi-state recognition network based on Eye and Mouth-CNN (EM-CNN) using a multi-task cascade framework, with an average accuracy of 93.62% and sensitivity of 93.64%, which is higher than that of traditional machine learning detection methods.

As mentioned above, vehicle driving state recognition using deep learning methods is more accurate and reliable than traditional recognition methods. After screening the literature, it is found that there are fewer studies on vehicle driving state recognition based on vehicle attitude acceleration signals and one-dimensional convolutional neural network methods. In order to further construct a neural network framework for vehicle driving state recognition and obtain more accurate vehicle state information, vehicle driving state recognition based on vehicle attitude measurement and neural network is proposed. The data acquired by the GPS inertial navigation sensor is processed, and then a one-dimensional convolutional neural network is constructed for training to make recognition judgments.

1.1 1D-CNN Model for Automobile Driving State Recognition

1.1.1 Classification of car driving status

Driving behavior recognition is a cross-disciplinary field, and many scholars have already conducted a lot of research on it, either based on the driver's driving behavior analysis or the vehicle's driving behavior analysis. For the one-dimensional time series obtained from GPS inertial navigation sensors, a one-dimensional Convolutional Neural Network (1D-CNN) matches its input better [17-18], and can learn features directly from the original vibration signals and complete the recognition of automobile driving state [19]. The study designed a driving behavior recognition test scheme, classified the driving behavior into four working conditions: constant speed driving, accelerating driving, decelerating driving, accelerating and decelerating driving, and collected the three-axis vibration acceleration corresponding to the working conditions with GPS inertial navigation sensors, processed the data, constructed a 1D-CNN model to recognize the driving state of the fuel vehicle, and added six kinds of driving conditions of driving under a left-turning driving and a right-turning driving on the basis of the same steps. In addition to the same procedure, we add six driving conditions, including left-turn driving and right-turn driving, to identify the driving state of electric vehicles.

1D-CNN has certain advantages in feature extraction and classification and can better capture the features in time series data. By combining vehicle attitude signals and 1D-CNN algorithms, accurate classification of driving states can be achieved, providing more reliable decision support for automatic navigation and autonomous driving systems.

1.1.2 Construction of coordinate axes

Through the acceleration module of the GPS inertial navigation sensor, the data related to the three-axis acceleration and gyroscope can be obtained. In this paper, only the acceleration information of the X, Y and Z axes is selected for vehicle driving behavior recognition [20]. In order to accurately represent the working condition of the vehicle, the positive direction of the Y-axis will be consistent with the forward direction of the vehicle, while the positive direction of the X-axis will be the same as the right side of the vehicle and the positive direction of the Z-axis will be perpendicular to the ground upwards, as shown in Figure 1. The acceleration information thus obtained can effectively and accurately reflect the motion of the vehicle in the three directions during driving [21].

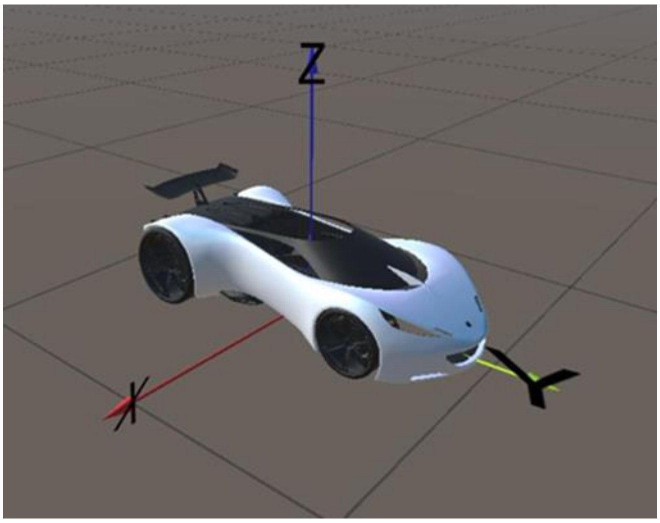

Figure 1. The Vehicle Coordinate System

1.2 Vehicle Driving Status Recognition Flowchart

The process of vehicle driving status recognition based on 1D-CNN is shown in Figure 2. First, GPS inertial navigation sensors capture the Y-axis acceleration signals of the vehicle during various driving processes, which are then divided into training sets, validation sets, and testing sets. Second, the 1D-CNN model is established, the hyperparameters are configured, and the training set is imported into the 1D-CNN model that has been established. The training set then trains the 1D-CNN model via forward propagation and error-minimizing backpropagation. Training error is gradient-reduced for learning during the training procedure. Simultaneously with training, the validation set is used to modify the model's hyperparameters and evaluate the model's ability to evaluate the generalization ability of the 1D-CNN model. Finally, once the model training is complete, the test set will be used to evaluate the 1D-CNN model's final generalization ability and recognition performance.

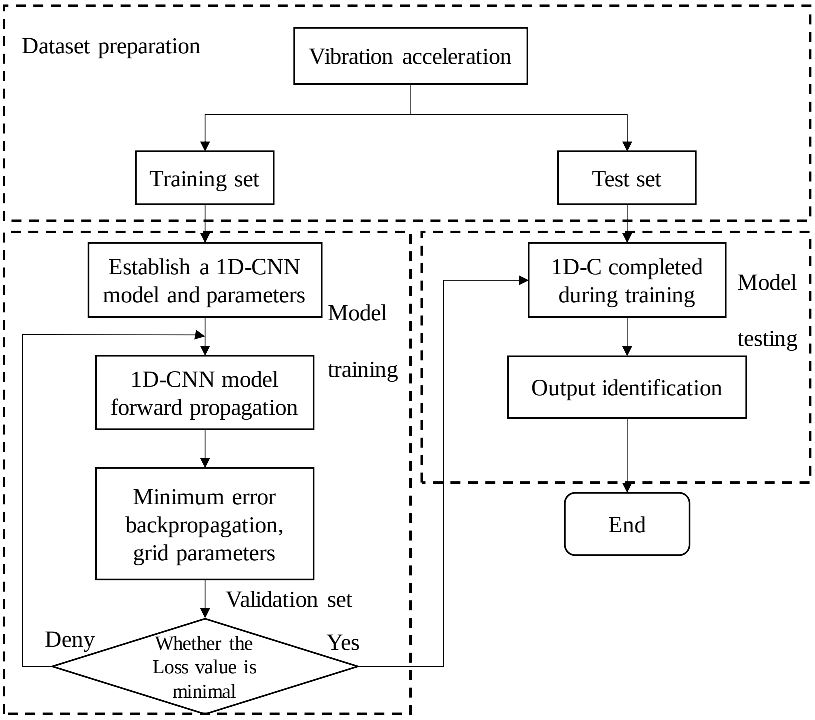

Figure 2. Flowchart for vehicle driving state identification

2. METHODS AND MATERIAL

2.1 Basic Principles of Testing

This experiment employs both fuel-powered and electric vehicles as test subjects. Using GPS inertial navigation sensors, the original acceleration data generated by vibrations is obtained and processed. Then, a 1D-CNN training model is constructed, and the initial vibration acceleration signal is directly learned. Finally, four distinct driving states for fuel-powered vehicles and six distinct driving states for electric vehicles are identified.

2.1.1 Test system composition

The test mainly consists of test objects and test equipment. The vehicles used for the test object are the fuel vehicle GAC GS4, and the electric vehicle GAC GE3 (Figure 3), and the 202 model of GAC GE3 is a 5-door, 5-seat SUV electric vehicle, with the specific parameters shown in Table 1. The test equipment has a GPS inertial navigation sensor using the Kalman filtering method. This use of linear system state equations can be fully integrated with detection data from multiple sensors, enabling dynamic estimation of the system state. It incorporates high-precision satellite positioning from China's BeiDou and the United States' Global Positioning System (GPS), ensuring improved navigation accuracy and stability. The test was conducted under good weather conditions, providing a more stable signal. This approach minimizes the impact of GPS sensor uncertainty and reduces errors to the greatest extent possible. Its basic parameters are shown in Table 2. The position of the sensor installation is shown in Figure 4. When installed, it is necessary to ensure that the fixed surface of the sensor is parallel to the surface of the object to be measured, carry out several measurements to verify the consistency of the results, find deviations to adjust the sensor position in a timely manner, and observe the output of the sensor through the analysis of the data to ensure that it is in line with the expected direction of the axis. Subsequent measurements of acceleration, acceleration sensors and inertial navigation sensors can also measure the acceleration, angular velocity and angle of the car in the X, Y and Z axes in a total of nine sets of data, which can characterize the car's attitude; the test road is an asphalt road with speed bumps in the middle as well as a drainage manhole cover, which is not completely flat and has a good representation. The specific descriptions of the six driving states of the EV collected in this test are shown in Table 3.

Table 1. Vehicle parameters

Maximum power	Maximum torque	Top speeds	Transmission	Energy type	Drive type
132 kW	290 N.m	165 km/h	Single speed transmission	Electric	Front drive

Table 2. Sensor basic parameters

Operating voltage	Operating current	Operating Principle	Serial baud rate	Output frequency	Environment
5 V	40 mA	vibration sensor	2400~921600 bit/s	0.1~200 Hz	dynamic/static

Figure 3. Test vehicle


Figure 4. Sensor position

Table 3. Driving status specifics

Driving status	Driving speed (km/h)	Duration (s)
Constant speed	40	-
Acceleration	0 to 40	40
Deceleration	40 to 0	40
Acceleration and deceleration	0 to 40, then 40 to 0	60
Left-turn	40	25
Right-turn	40	25

2.1.2 Data resampling processing method

Data processing strategy for recognizing the driving status of an automobile: This experiment employs interval resampling to generate a dataset that includes the acceleration signal for the duration of the driving process. Let L be the entire length of the raw data collected for each state, divided on average into i segments, segment i representing Li and segment 1 representing L1. Each segment consists of j data elements (each represented as Lm,n(m ≤ i,n ≤ j). In this experiment, 12 comprehensive data sets for each state were collected. The total length of each data set was set to L, divided into X /200 segments, and one sample data point was collected every X /200 segment to generate a sample data set of 200 points representing the entire driving process. The first point of the first set of sample data is the first point in the first paragraph, with an interval of X /200 points taken as one point. If 200 points are taken, it will stop. Using an interval of X/200 points as one point, the first point of the second set of sample data corresponds to the second point in the first paragraph. If 200 points are collected, it will stop, and so on; the exact sampling procedure is depicted in Figure 5.

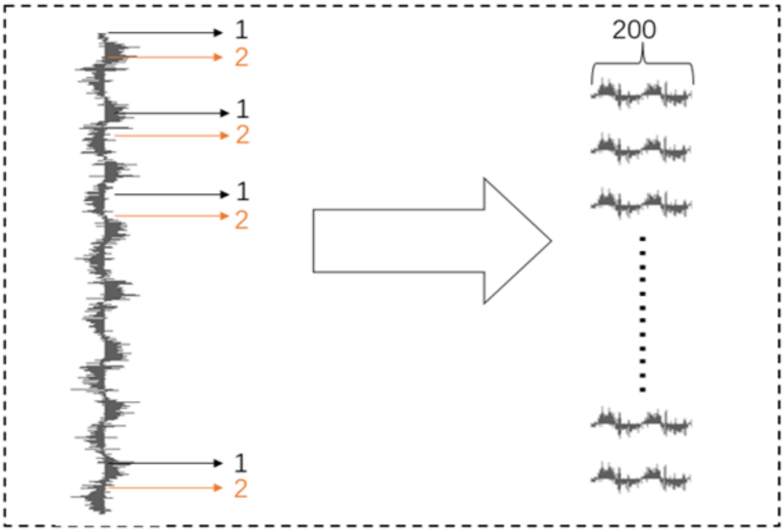

Figure 5. Data resampling

2.1.3 Dataset partitioning

For the electric car driving state signal, each state sampling points for 60000, according to the above processing way to produce training set and validation set that each driving state can get 300 groups of sample data, each group of sample data length of 200, six kinds of working conditions a total of 1800 groups. This experiment also randomly produced 267 groups of data samples of different driving states as a test set. For the vibration signal of the fuel car driving state, the number of sampling points of each state is 19200, and the data set is made according to the same processing method as above, i.e., 96 groups of sample data can be obtained for each driving state, and the length of each group of sample data is 200, which is used as the model training set and validation set, and 79 groups of data samples of different automobile driving states are made as the test set. The above training set, validation set and test set should obey the same data distribution to have practical significance. The training set uses the data information samples fitted by the model to achieve gradient reduction learning in the training process through the training error and changes the built-in weight parameters in the neurons; the validation set is a separate sample set from the simulation training process, which can be used to adjust the hyper-parameters of the model or will be used to make an initial assessment of the model recognition ability, using the validation set to find out the optimal network parameters, the termination nodes calculated by the backpropagation and the number of hidden layer neurons in the network and other hyper-parameters; and the test set is mainly used to evaluate the generalization ability of the model results, only for evaluation of the model effect, not for tuning, feature selection and other algorithms. The validation set can be used to find out the optimal network parameters, the termination nodes calculated by back-propagation, and the number of neurons in the hidden layer of the network and other hyper-parameters, while the test set is mainly used to evaluate the generalization ability of the model results, and is only used for evaluating the model results, and is not used as a basis for the choice of algorithms related to the tuning parameter and the feature selection. The specific division of the automobile vibration signal dataset for this test is shown in Table 4.

Table 4. Dataset segmentation

Driving status	Data set	Training sets	Verification set	Test set	Data length
Constant speed	339	210	90	39	200
Acceleration	321	210	90	21	200
Deceleration	323	210	90	23	200
Acceleration and deceleration	426	210	90	126	200
Left-turn	338	210	90	38	200
Right-turn	320	210	90	20	200
Total	2067	1260	540	267	-

3. RESULTS AND DISCUSSION

Apply the aforementioned procedures to experiments with fuel-powered and electric vehicles, respectively. Experiments with electric vehicles serve as an illustration throughout the subsequent text. The following frequencies were selected for signal acquisition for each operating condition (sampling frequency: 200 Hz).

3.1 Acceleration Signal Selection

This experiment determined the accelerations of all three axes for each working condition; the accelerations of each axis are now being analyzed. Using the aforementioned collection system, acceleration signals on the X, Y, and Z axes can be collected accurately, and these three signals can effectively represent the vehicle's movement in the forward, left or right, and vertical directions, as well as the driver's action signals when stepping on the accelerator pedal, brake pedal, and rotating the steering wheel. For these six conditions, the Z-axis vibration acceleration signal does not change significantly throughout the uniform driving motion, except for the obvious oscillations due to over-deceleration, so the Z-axis signal is not used. Because acceleration, deceleration, and acceleration/deceleration driving conditions are only in opposite directions and left and right turns are also in opposite directions, only accelerated driving, constant speed driving, and left turn driving are displayed here. The waveforms of acceleration signals collected under various driving conditions are depicted in Figures 6, 7, and 8 below, where the acceleration unit is g.

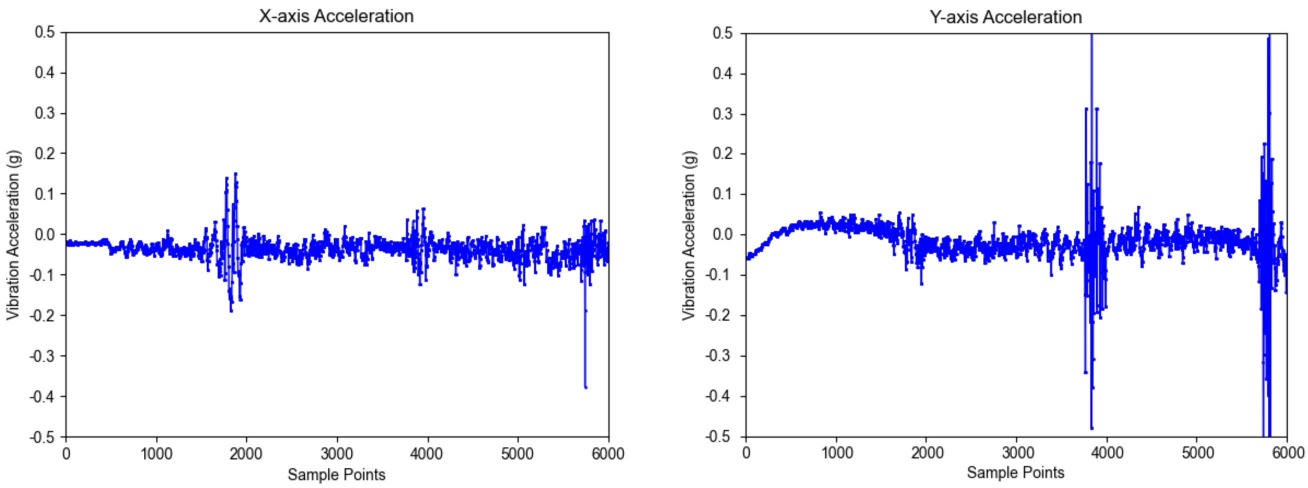

Figure 6. Acceleration signal waveform during acceleration driving

There is a clear upward trend in the acceleration of the Y-axis, which is the direction of forward movement when the car accelerates from a stop by pressing the accelerator pedal; however, the amplitude of the X-axis acceleration does not change significantly, so the Y-axis signal can be used as a one-dimensional data sample. The waveforms of the X and Y axes are comparatively regular when the car is traveling at a constant speed, as depicted in Figure 7. The absolute values of the acceleration signal amplitude along the X axis are typically less than 0.2g, while the absolute values along the Y axis are frequently greater than 0.2g, indicating a high signal-to-noise ratio. The Y-axis signal can be utilized as a one-dimensional data sample. The X-axis acceleration signal has an opposite waveform when the car is making a left turn, which is consistent with our actual driving conditions. The change in acceleration signal indicates that the driver did not apply the brakes and turned the steering wheel to the left before returning to normal. Therefore, the X-axis signal can be used as a one-dimensional data sample for turning driving conditions.

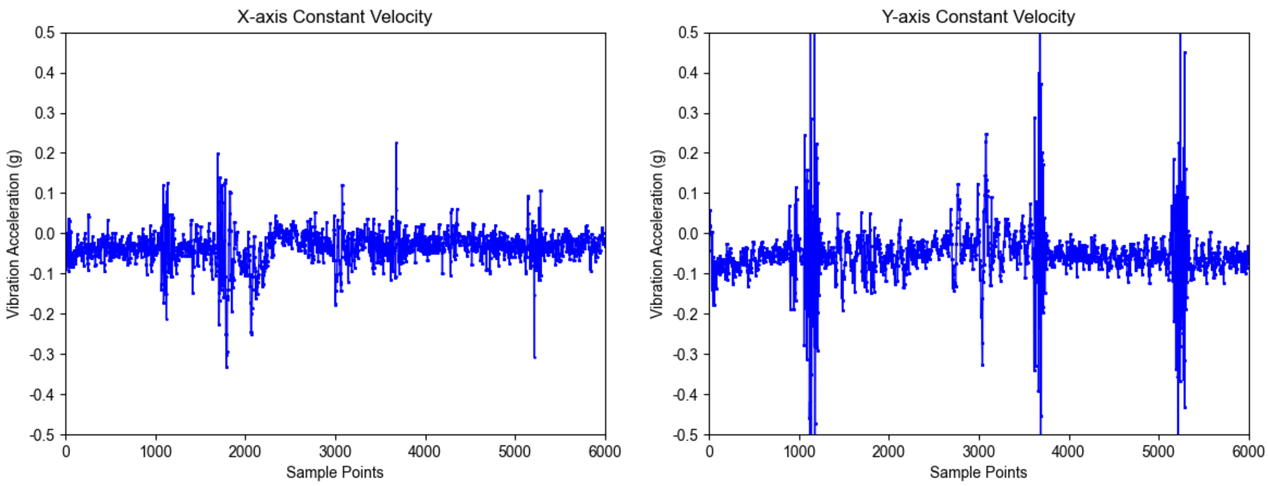

Figure 7. Acceleration signal waveform during constant speed driving

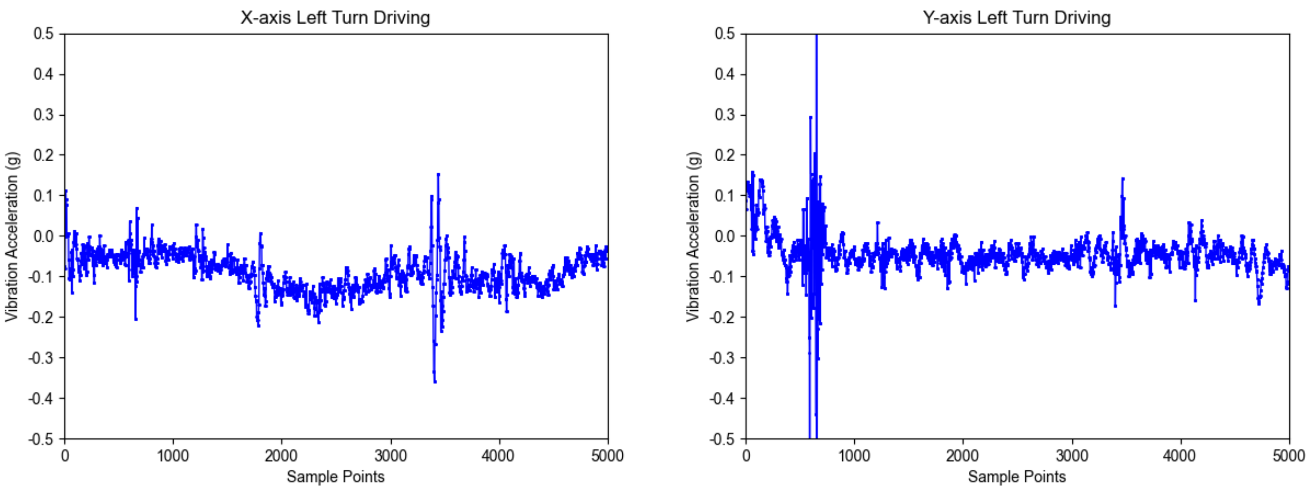

Figure 8. Acceleration waveform during left turn driving

3.2 1D-CNN-Based Electric Vehicle Driving State Recognition Network Architecture

In order to fully extract the characteristics of the vibration acceleration signals while driving, the tanh function in Python is used as the activation function, and three convolutional layers and two pooling layers are used to construct a convolutional neural network architecture, as shown in Figure 9. In this experiment, the maximum pooling layer is adopted: the information extracted from the convolutional layer is further downscaled, and the robustness to offset and translation is enhanced. With the Keras toolkit for Python, weight matrix initialization, dropout function and batch normalization are used to prevent overfitting of the training model.

Input layer: The input signal is the 200×1 vibration acceleration signal of the car, which contains rich information on different driving states of the car and can reflect the six different working conditions of the electric car, namely driving at a constant speed, accelerating, decelerating, accelerating and decelerating, driving in a left turn, and driving in a right turn, and the vibration information received by the sensor is usually cyclic and uniform. When the vehicle is driving normally, the vibration signal received by the sensor is usually periodic and uniform.

One-dimensional convolutional layers: 16 convolutional kernels of length 8 in the first layer, 32 convolutional kernels of length 4 in the second layer, and 32 convolutional layers of length 2 in the third layer. The third convolutional layer is 32 convolutional layers of length 2, where the number of sliding steps of the convolutional layers is 2. The number of sliding steps in the convolutional layers is 2.

One-dimensional pooling layer: the first convolutional layer is followed by the maximum value pooling layer with length 2; the third convolutional layer is followed by the maximum pooling layer, where the sliding step of the convolutional layer is 2.

Fully Connected Layer: Combined with the Softmax regression classifier to complete the 1D-CNN-based car driving state recognition model.

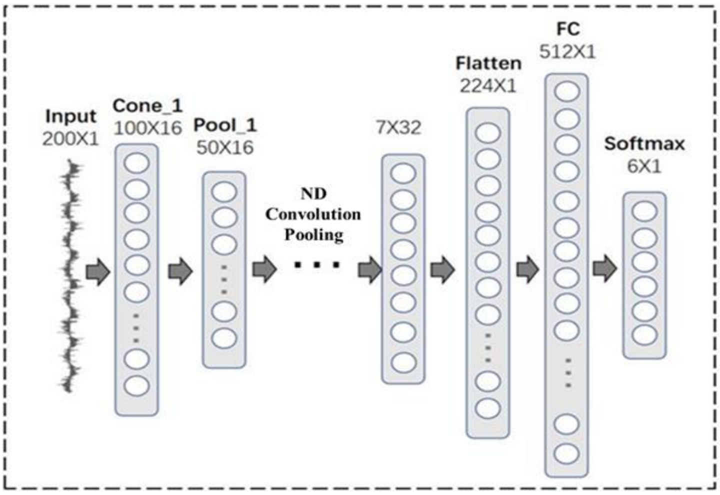

Figure 9. Acceleration waveform during left turn driving

3.3 Selection of CNN Layers

Model 1: 200 training iterations should be conducted using a convolutional neural network with five convolutional layers and two pooling layers, two slip steps, and a learning rate of 0.0001. Figure 10 depicts the loss value and accuracy of training. The confusion matrix of the sample data from the test set is depicted in Figure 11 (DD represents deceleration, ADD represents acceleration, AD represents acceleration, CSD represents uniform motion, RTD represents right turn motion, and LTD represents left turn motion), and the test network is depicted in Table 5.

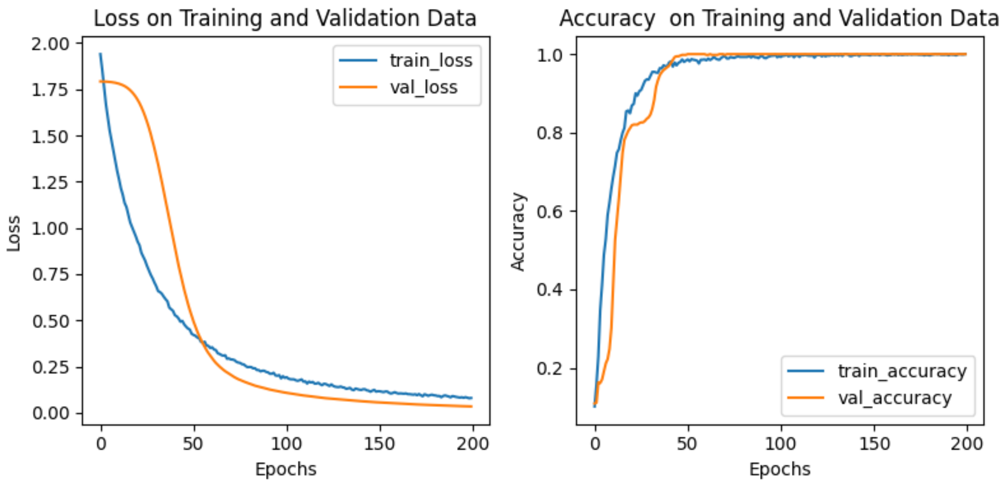

Figure 10. Loss value and accuracy

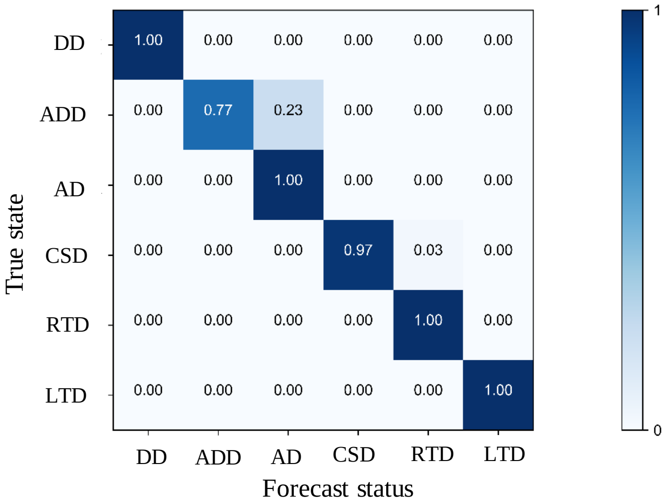

Figure 11. Confusion matrix

Table 5. Test network

Driving status	Precision	Recall	F1-score	Support
Deceleration driving	1.00	1.00	1.00	23
Deceleration and deceleration driving	1.00	0.77	0.87	126
Accelerated driving	0.42	1.00	0.59	21
Constant speed driving	1.00	0.97	0.99	39
Right turn driving	0.95	1.00	0.98	20
Left turn driving	1.00	1.00	1.00	38
Accuracy	—	—	0.89	267
Macro avg	0.90	0.96	0.90	267
Weighted avg	0.95	0.89	0.90	267

Model 2: 200 training iterations should be performed using a convolutional neural network with three convolutional layers and two pooling layers, two slip steps, and a learning rate of 0.0001. The loss value and training precision are depicted in Figure 12. Figure 13 depicts the confusion matrix of the sample data from the test set, while Table 6 depicts the test network.

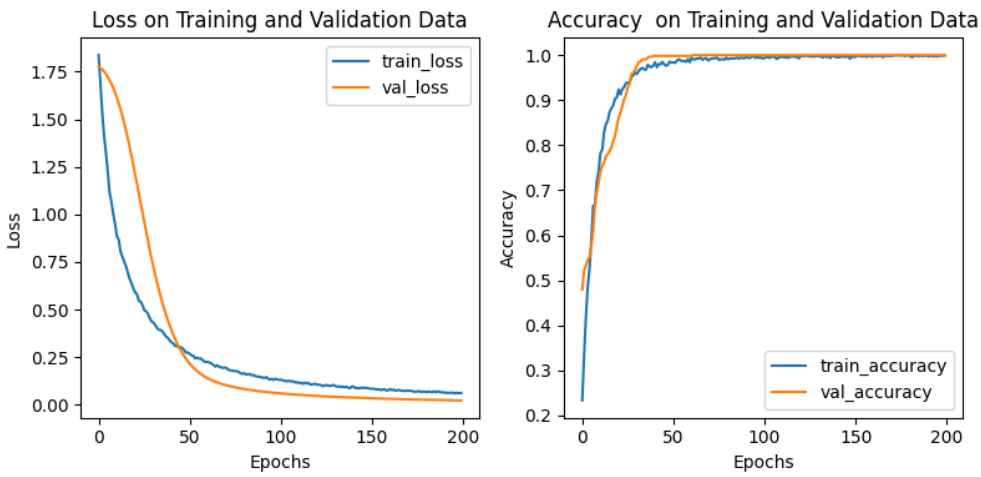

Figure 12. Loss value and accuracy

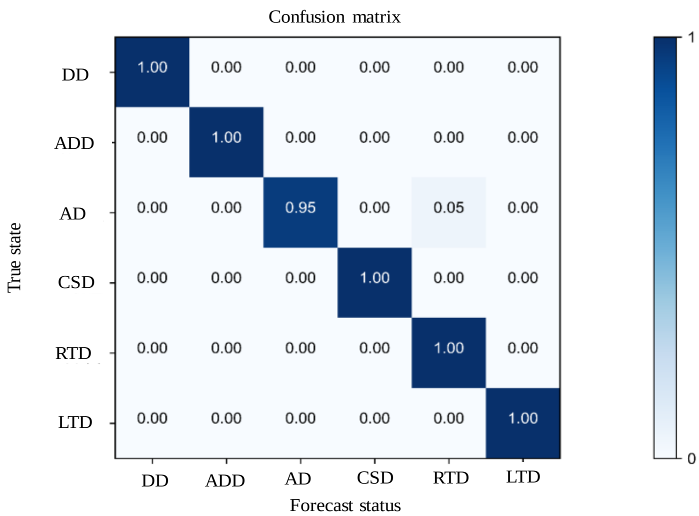

Figure 13. Confusion matrix

Table 6. Test network

Driving status	Precision	Recall	F1-score	Support
Deceleration driving	1.00	1.00	1.00	23
Deceleration and deceleration driving	1.00	1.00	1.00	126
Accelerated driving	1.00	0.95	0.98	21
Constant speed driving	1.00	1.00	1.00	39
Right turn driving	0.95	1.00	0.98	20
Left turn driving	1.00	1.00	1.00	38
Accuracy	—	—	1.00	267
Macro avg	0.99	0.99	0.99	267
Weighted avg	1.00	1.00	1.00	267

Model 3: 200 training iterations should be performed using a convolutional neural network with three convolutional layers and two pooling layers, one slip step, and a learning rate of 0.0001. The loss value and training precision are depicted in Figure 14. Figure 15 depicts the confusion matrix of the sample data from the test set, while Table 7 depicts the test network.

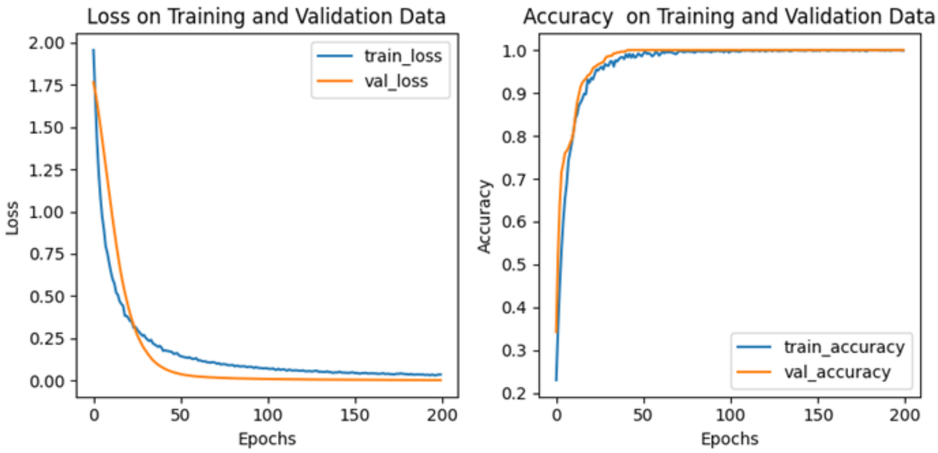

Figure 14. Loss value and accuracy

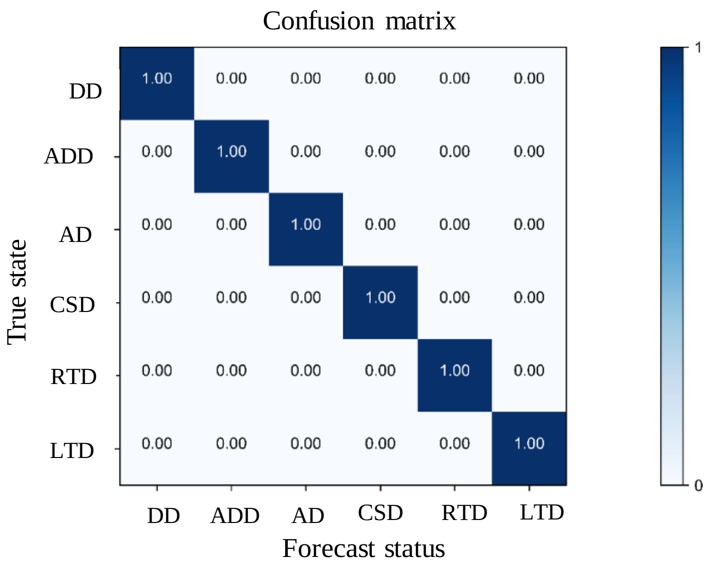

Figure 15. Confusion matrix

From the training result plots, confusion matrices and test networks of the previous three models, it can be seen that a learning rate of 0.0001 and 3 convolutional layers are the best choices for recognizing the six different driving states of an electric vehicle without over-learning the data features and achieving model optimization. The data features can be accurately derived when the number of sliding steps is 1. 88.764%, 99.625% and 100% are the accuracies of the three models tested using the test set, respectively. The test set contains a total of 267 data sets, including 30 misidentifications for Model 1, 1 misidentification for Model 2, and all pairs for Model 3.

Table 7. Test network

Driving status	Precision	Recall	F1-score	Support
Deceleration driving	1.00	1.00	1.00	23
Deceleration and deceleration driving	1.00	1.00	1.00	126
Accelerated driving	1.00	1.00	1.00	21
Constant speed driving	1.00	1.00	1.00	39
Right turn driving	1.00	1.00	1.00	20
Left turn driving	1.00	1.00	1.00	38
Accuracy	—	—	1.00	267
Macro avg	1.00	1.00	1.00	267
Weighted avg	1.00	1.00	1.00	267

The number of convolutional layers and the number of pooling layers have different effects on the training of the convolutional neural network for different datasets. The more layers the network has, the greater the risk of gradient vanishing, gradient inflation, or even overfitting, leading to the inability to find a local optimum. For the experimental data in this experiment, the network with an increased number of layers learned data features out of proportion, preventing it from obtaining optimal results.

3.4 Hyperparameter Selection

Adjustment of hyperparameters can perpetually optimize the network in accordance with the curve's distinct characteristics. The validation set curve oscillates, as displayed in Figure 16. Analyze motive: It is possible that the training group size is too small or the learning rate is too fast. The oscillation progressively disappears as the batch size increases, and the validation set's precision also improves. When the batch size is 128, the accuracy of the training set is lower than that of the test set, and the model is underfitting, necessitating an increase in the epoch. The learning rate dictates the rate at which weight values are updated. Setting it too high can lead to inaccurate results, while setting it too low can delay the convergence speed.

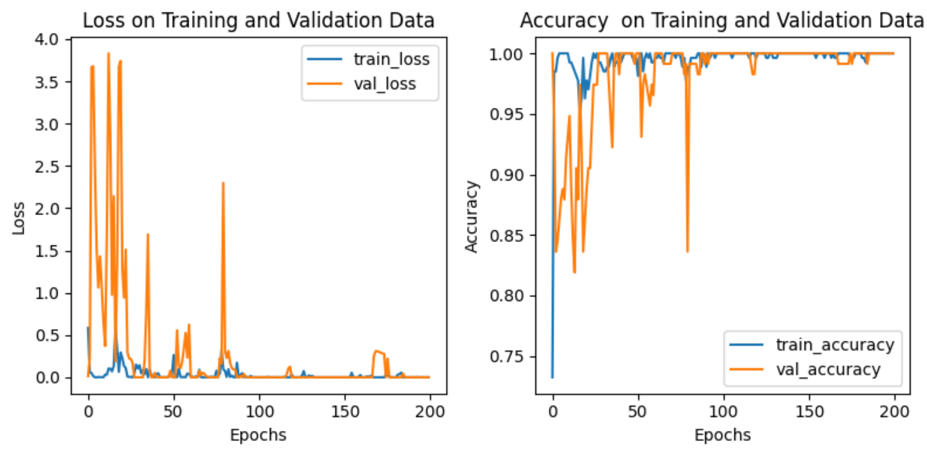

Figure 16. Loss value and accuracy

With a learning rate of 0.001, we are endeavoring to construct models 4, 5, and 6 for analysis.

Model 4: 200 training iterations should be conducted using a convolutional neural network with five convolutional layers and two pooling layers, two slip steps, and a learning rate of 0.001.

Model 5: 200 training iterations should be conducted using a convolutional neural network with three convolutional layers and two pooling layers, two slip steps, and a learning rate of 0.001.

Model 6: 200 training iterations should be conducted using a convolutional neural network with three layers of convolutional layers and two layers of pooling layers, one slip step, and a learning rate of 0.001.

The above-mentioned models were evaluated using 267 sets of test sets, with respective accuracy rates of 93.633%, 100%, and 99.6255%. The identification outcomes of both model 3 and model 5 test sets are capable of reaching 100 percent. Considering the effectiveness of training time, Table 8 displays the final model hyperparameter settings.

Table 8. Hyperparameter setting

Learning rate	Batch size	Iterations	Carburetor	Optimizer
0.001	128	200	SGD Optimizer	Loss Calculation

3.5 Analysis of Test Results

Table 9 outlines the results of tests conducted on electric vehicles. When the learning rate is 0.0001, the number of convolutional layers has the greatest impact on the training outcomes. Three convolutional layers are superior to five in terms of learning efficacy. When three convolutional layers are configured, the accuracy exceeds 90%, and when the number of steps is 1, the accuracy reaches 100%; when the learning rate is 0.001, the accuracy of 5-layer convolutional layers can also reach over 90%. The accuracy of 3-layer convolutional layers is greater than 90%, and when the number of stages is reduced to 2, the accuracy reaches 100%.

Table 9. Electric vehicle test results

Model	Learning rate	CNN layers	Step	Data preprocessing	Accuracy
Model 1	0.0001	5	2	Standardization	88.7640%
Model 2	0.0001	3	2	Standardization	99.6255%
Model 3	0.0001	3	1	Standardization	100.0000%
Model 4	0.0010	5	2	Standardization	93.6330%
Model 5	0.0010	3	2	Standardization	100.0000%
Model 6	0.0010	3	1	Standardization	99.6255%

The results of the same program's experimental analysis of the fuel-powered vehicle are displayed in Table 10. Different datasets necessitate distinct preprocessing techniques. Model 1's normalization method determines the range of variables based solely on the extreme value problem, resulting in weak learning performance and an accuracy rate below 50%. Choosing an appropriate data preprocessing method has a substantial effect on the model's training outcomes. More convolutional layers are not inherently preferable when building a model. When the model identifies the optimal solution, the deep convolutional layer will overlearn and learn noise. For instance, Model 2's accuracy is 88%, which is significantly lower than Model 3's 97%. Step size and learning rate also influence learning outcomes, and each model has optimal parameters for distinct datasets. On the test set, both Model 4 and Model 5 are capable of achieving 100 percent accuracy. To increase the model's training speed, the learning rate is adjusted to 0.001. Table 11 displays the adjusted model's final hyperparameter settings. The number of iterations for training on the electric vehicle model is 200, while the number of iterations for training on the fuel vehicle model must increase to 500 for optimal learning effect. A possible cause is that the sensor signal is affected by engine vibration due to the engine's intense excitation effect.

Table 10. Fuel vehicle test results

Model	Learning rate	CNN layers	Step	Data preprocessing	Accuracy
Model 1	0.0001	3	2	Normalization	49.3671%
Model 2	0.0001	5	2	Standardization	88.6076%
Model 3	0.0001	3	2	Standardization	97.4684%
Model 4	0.0001	3	1	Standardization	100.0000%
Model 5	0.0010	3	1	Standardization	100.0000%

Table 11. Hyperparameter setting

Learning rate	Batch size	Iterations	Carburetor	Optimizer
0.001	128	500	SGD Optimizer	Loss Calculation

In summary, the combination of vehicle attitude data and a one-dimensional convolutional neural network has yielded excellent results in identifying the driving status of a vehicle.

4. CONCLUSION

This paper focuses on accurately recognizing vehicle driving states for road safety and better driver assistance. With more vehicles and human-factor issues, reliable driving behavior monitoring is crucial. We proposed a 1D - CNN-based method using vibration acceleration from GPS inertial sensors. The data was processed and resampled for training and validating the 1D - CNN model, which extracts features from raw signals for state classification. Experiments show high accuracy: 100% for EVs with three convolutional layers, 0.0001 learning rate, step 1, and for fuel-powered vehicles under optimal settings. The model has good generalization, short training time, and high reliability. In conclusion, our 1D - CNN approach, combined with vehicle attitude data, is effective for driving state recognition, laying a foundation for advanced driver-related technology. Future work may integrate more sensor data and test in complex scenarios.

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CONFLICT OF 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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