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HONGWEI QUAN, Guilin University of Electronic Technology, Guilin, Guangxi, China

CHENCHEN LU

YUFAN ZENG

HUIBING ZHANG, Guilin University of Electronic Technology, Guilin, Guangxi, China

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Hongwei Quan
School of Computer Science and Information Security
Guilin University of Electronic Technology
Guilin, Guangxi, China
hongwei_quan@126.com

Chenchen Lu*
Guangxi Jet Toll Technology CO., LTD
Nanning, Guangxi, China
pscapquan@qq.com

Yufan Zeng
Guangxi Jet Toll Technology CO., LTD
Nanning, Guangxi, China
pscapyun@qq.com

Huibing Zhang
School of Computer Science and Information Security
Guilin University of Electronic Technology
Guilin, Guangxi, China
22032202026@mails.guet.edu.cn

Abstract

Along with the escalating demand for traffic supervision and the swift development of assisted driving, there are heightened requirements for the accuracy and diversity of identifying abnormal driving behaviors. Existing research is predominantly contingent upon trajectory data, resulting in limited types of abnormalities recognized in activities such as lane changes and turns. In response to this limitation, this paper proposes a method for classifying driving behaviors by integrating environmental factors and employing an identification model based on Bidirectional Long Short-Term Memory (BiLSTM) networks and Transformer. By incorporating road environment data to precisely define driving behaviors and expanding the range of abnormalities, the model utilizes BiLSTM to extract bidirectional features of driving behaviors in time series. Furthermore, in tandem with the Transformer, it can capture global information for feature fusion, culminating in the identification of abnormal driving behaviors. Experimental results indicate that the recognition accuracy can reach 98.85%, demonstrating an improvement of 0.4% when juxtaposed with models like ResNet.

CCS Concepts

• **Computing methodologies** → Machine learning; Machine learning approaches; Neural networks.

Keywords

Abnormal driving behaviors, Road environment, Feature fusion, Transformer

*Corresponding author.

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1 INTRODUCTION

Recent years have witnessed an augmentation in the frequency of motor vehicle traffic accidents, with research indicating that majority of traffic accidents are conjured up by drivers' abnormal driving behavior [1]. To ensure driving safety and improve users' commuting experience, it is crucial for vehicle auxiliary driving systems to accurately identify abnormal driving behaviors that detects anomalous driving patterns based on anomaly detection [2]. Given the intensified supervision of abnormal driving behaviors by relevant authorities, the proposed effective method for identifying abnormal driving behaviors holds significant importance.

A part of the research relies only on vehicle kinematics data and uses machine learning algorithms and neural network models for data mining and behavioral feature extraction based on speed, acceleration, angular velocity and other parameters in the vehicle kinematics data to obtain abnormal driving behaviors from vehicle driving states [3, 11]. However, the above studies have not considered in depth the influence of complex driving environments on the occurrence of abnormal driving behaviors, and the research data lacks the relevant parameters of driving environments. Fewer extracted driving types exist, and abnormal driving behaviors cannot be identified accurately. Another part of the studies considered the influence of the driving environment on the incidence of abnormal driving behavior, analyzing the influence of road and weather conditions on the incidence of driving behavior, i.e., the change in data on the number of occurrences of abnormal driving behavior under different driving environment [12, 18]. However, these studies did not analyze the influence of environmental factors on identifying abnormal driving behavior. This paper starts from the environmental factors affecting abnormal driving behaviors, conducts research based on vehicle trajectory data combined with road environment parameters, accurately defines driving behaviors such as abnormal lane changing and abnormal turning, and proposes a BiLSTM-Transformer model to identify abnormal driving behaviors accurately.

The main contributions are as follows: first, considering the road environment factor, the original trajectory data are supplemented with two features, namely, road scene and road class, to accurately define the abnormal driving behaviors such as abnormal lane changing and abnormal turning. Second, proposing the classification method of abnormal driving behaviors by integrating the environmental factors, and extracting eight abnormal driving behaviors to construct the dataset. Third, proposing an abnormal driving behavior recognition model (BiLSTM-Transformer) that combines Bidirectional Long Short-term Memory Network (BiLSTM) and Transformer network. It can achieve two-layer extraction process of feature extraction and feature fusion for driving behaviors, which further improves the recognition accuracy compared with other studies, and is capable of effectively recognizing abnormal driving behaviors.

The rest of the paper is organized as follows: Section 2 describes related research work on abnormal driving behaviors; Section 3 analyzes abnormal driving behavior in the context of road factors; Section 4 proposes a model for identifying abnormal driving behavior and describes the role and workings of each module; Section 5 describes the related experimental work; and Section 6 describes the conclusions of the experiments as well as future work.

2 RELATED WORK

Research on the identification of abnormal driving behaviors mainly focuses on two aspects: the continual enrichment of types of abnormal driving behaviors and the optimization of algorithms and models for identifying such behaviors. Regarding the types of abnormal driving behaviors studied, Research [3, 11] lucks road-related factors, cannot distinguish between abnormal turning and abnormal lane changing behaviors solely reliant on trajectory data. These studies included speeding, rapid acceleration, deceleration, etc.; the number is up to six. Hence, supplementing road-related data is crucial for studying abnormal driving behaviors. Our study based on trajectory data integrated with road parameters, extracts more types of abnormalities than other research efforts.

Most of the previous analyses were conducted using mathematical statistics and machine learning related algorithms for the research on driving behavior recognition algorithms. Liu et al. designed a recognition algorithm based on threshold judgment and constructed a driving behavior scoring model [3]. The above study used mathematical statistics and a priori threshold methods, lack of deep analysis of data and information mining. There is a great deal of subjectivity, and do not fully extract the behavioral characteristics. With the deepening of machine learning research, Zhou et al. used an online analysis algorithm based on support vector machine (SVM) to identify in real-time [4]. Yang et al. used a Hidden Markov Model (HMM) to achieve the recognition of behaviors such as driving out and driving back [5]. Pang et al. used Clustering to determine the data thresholds to identify and classify vehicle behaviors [6]. The researchers mainly used machine learning to identify and classify vehicle behaviors. These studies mainly use SVM, HMM and Clustering to isolate driving behaviors from massive trajectory data. However, these methods do not consider the time-series characteristics of vehicle movement, making it difficult to accurately analyze and identify driving behaviors.

The study of abnormal driving behavior recognition using deep learning has developed rapidly, and the algorithmic models have been continuously optimized. Neural networks can preserve the time series features of trajectory data. This approach can fully extract the features of driving behaviors and address the limitations of previous studies that relied on prior thresholds and traditional machine learning algorithms. The following studies have proposed various neural network models for abnormal driving behavior recognition. Hui et al. proposed a combined model based on BiLSTM and Full Connect Neural Network (FCNN) for recognition [7]. Jia et al. proposed a combination model of Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) for anomaly recognition [8]. Du et al. introduced an LSTM-Att model, which integrates a LSTM architecture with an attention mechanism [9]. Zhao et al. proposed a time series symbolization algorithm and multi-scale convolutional neural network model (TSA-MCNN) [10]. Jia proposed a Deep Residual Network model with a self-attention mechanism (AM-DRN) [11]. The optimization of models in a forementioned study has notably enhanced the accuracy of abnormality detection, facilitating a more profound comprehension of abnormal driving behaviors. Nonetheless, prevailing research predominantly relies on CNN, LSTM, and their derivatives. This approach overlooks crucial road environment factors, resulting in inadequately extracted features of driving behaviors and ineffective identification of abnormal lane changes and turning behaviors.

In actual driving scenarios, vehicles are affected by various environmental factors such as road and weather conditions, which may threaten driving safety [12, 13]. Zhang developed a model on prevalence of such behaviors under typical weather, meticulously examining the impact of weather and road conditions [14]. Wang et al. proposed a model of the spatial distribution of abnormal driving behavior based on vehicle onboard diagnostic data (OBD) in mountainous cities [15]. Zhang et al. proposed the NaSch model in Cellular Automata to study the highway deceleration and speed limit strategies in rainy environments [16, 17]. Although previous studies integrate driving environments to investigate vehicle driving behavior safety, they primarily focus on the environment's influence on the occurrence rate of abnormal driving behaviors, neglecting the detection and identification of such behaviors.

3 ANALYSISOF ABNORMAL DRIVING BEHAVIORS

During normal driving, vehicles maintain relatively stable states. However, when drivers deviate from normal driving behaviors while the vehicle is in motion, the vehicle undergoes unstable changes, manifested in the trajectory data of the vehicle's operation. Based on this consideration, this paper capitalizes on abnormal points in the data to reflect abnormal driving behaviors. Since driving behaviors typically persist for some time, data segments composed of a certain continuous time of abnormal points represent abnormal driving behaviors. This section primarily relies on trajectory data that integrates road environmental factors, along with feature data, to accurately define each type of abnormal driving behavior. The feature parameters are symbolically represented as follows: time *t*, velocity *V*, longitudinal acceleration *Accx*, lateral acceleration *Accy*, yaw rate *Yawr*, time window *ws*, and road scene *Dr*.

In previous studies, three types of abnormal driving behaviors, namely speeding (DS), rapid acceleration (DRA), and rapid deceleration (DRD), have been accurately defined.

3.1 Serpentine driving (DSD)

Serpentine driving (DSD) refers to a driving behavior where *Accy* alternates between positive and negative values during the driving process, and the average acceleration over a certain period approaches zero, as given by Equations (1)-(3). In reality, the vehicle undergoes multiple abnormal lateral movements, frequently changing lanes, thereby exhibiting DSD behavior.

$$DSD : Accy_i > 0, Accy_j < 0, Accy_k > 0 (t \le i < j < k \le t + ws); \tag{1}$$

$$or : Accy_i < 0, Accy_j > 0, Accy_k < 0 (t \le i < j < k \le t + ws); \tag{2}$$

$$\mathrm{Accy}_t + \mathrm{Accy}_{t+1} + \cdots + \mathrm{Accy}_{t+ws} \approx 0 \tag{3}$$

3.2 Abnormal left lane change (DLL)

Abnormal lane change signifies a sudden lateral lane change behavior that occurs during driving in the scenario as a non-curved road (Dr=0), including abnormal left lane change (DLL) and abnormal right lane change (DRL). When DLL behavior occurs, *Yawr* and *Accy* in the trajectory data will undergo abnormal changes, revealing that all *Yawr* within the time window are abnormal points, and if changing lanes to the left, both *Yawr* and *Accy* should be negative values, as represented in Equation (4).

$$DLL : Dr = 0; Abnormal : Yawr_i; Yawr_i < 0, Accy_i < 0 (t \le i \le t+ws) \tag{4}$$

3.3 Abnormal right lane change (DRL)

In the event of DRL behavior, *Yawr* parameters within the time window exhibit abnormalities, both *Yawr* and *Accy* should be positive values. Additionally, the corresponding road feature is not a curve segment indicating the occurrence of DRL behavior, as described in Equation (5).

$$DRL : Dr = 0, Abnormal : Yawr_i; Yawr_i > 0, Accy_i > 0 (t \le i \le t+ws) \tag{5}$$

3.4 Left sharp turn (DLT)

The sharp turn represents the abrupt turning behavior that occurs on curved road segments (Dr=1), including left sharp turn (DLT) and right sharp turn (DRT). When the DLT behavior occurs, *Yawr* parameters within the time window exhibit abnormalities, both *Yawr* and *Accy* should be negative values, as illustrated in Equation (6).

$$DLT : Dr = 1; Abnormal : Yawr_i; Yawr_i < 0, Accy_i < 0 (t \le i \le t+ws) \tag{6}$$

3.5 Right sharp turn (DRT)

When DRT behavior occurs, *Yawr* parameters within the time window become abnormal points, both *Yawr* and *Accy* should be positive values, and corresponding to a road feature being a curve, as per Equation (7). Extracting trajectory data within the time window that meets these characteristics represents a DRT behavior.

$$DRT : Dr = 1; Abnormal : Yawr_i; Yawr_i > 0, Accy_i > 0 (t \le i \le t+ws) \tag{7}$$

4 ABNORMAL DRIVING BEHAVIOR RECOGNITION

The proposed model for abnormal driving behavior recognition based on Bidirectional Long Short-Term Memory (BiLSTM)-Transformer is illustrated in Figure 1. The entire recognition model consists of four parts: anomaly detection, feature extraction, feature fusion, and anomaly classification. Trajectory data based on fused road parameters are input into the model in the form of a 30×17 matrix. The BiLSTM layer correlates the trajectory information before and after each time point, capturing the bidirectional dependencies of driving behavior in the time series and extracting features before and after the occurrence of driving behavior. The Transformer layer globally models the hidden state sequence output by the BiLSTM layer, yielding sufficient global information on driving behavior and achieving the fusion of sequence features. Finally, a fully connected neural network is utilized to classify the output features of the Transformer after normalization, enabling the recognition and classification of eight types of abnormal driving behaviors.

In this study, we employ the Isolation Forest algorithm based on the LSTM autoencoder (LAIF model) [18] for anomaly detection in vehicle driving data. The LAIF model leverages an autoencoder built on LSTM networks to reconstruct the data, facilitating the identification of data anomalies. Subsequently, we utilize the Isolation Forest (iForest) algorithm to detect anomalies by assigning anomaly scores to each type of data value and determining anomalies based on these scores.

4.1 Feature extraction

The feature extraction module is comprised of BiLSTM networks that integrate both forward and backward LSTMs by linking the hidden layers of the two networks. It processes input sequences in both directions, capturing data information in the forward and backward time directions before and after the occurrence of driving behavior. This approach preserves trajectory information not only at time *t* but also at the preceding time *t-1* and succeeding time *t+1*, maximizing the exploration of temporal correlations in the data. By integrating the features of sequential data at continuous time points, it extracts comprehensive features of driving behavior. The structure of the BiLSTM network is depicted in Figure 2.

As witnessed by this figure, x_{t-1}, x_t, x_{t+1} denote input data from neighboring time steps, while $\{x_1, \cdots, x_{ws}\}$ represent driving behavior data over *ws* consecutive time steps. Each operation within the network corresponds to a specific weight, designated as follows: weight w_1 signifies the connection from the input layer to the forward hidden layer; weight w_3 denotes the connection from

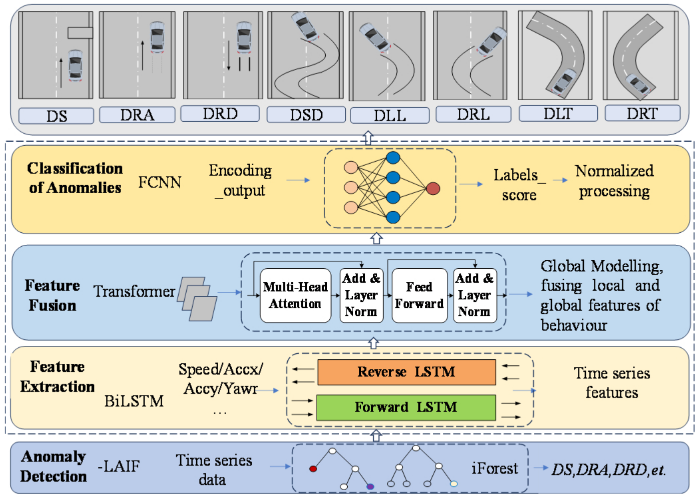

Figure 1: BiLSTM-Transformer structure

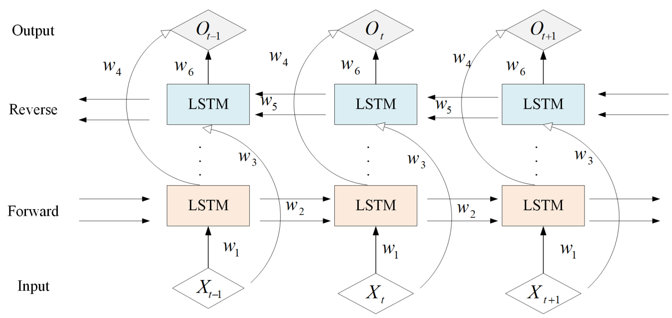

Figure 2: BiLSTM structure

the input layer to the backward hidden layer; weight w_2 represents transitions between hidden states within the forward hidden layer; weight w_5 signifies transitions between hidden states within the backward hidden layer; weight w_4 symbolizes the connection from the forward hidden layer to the output layer; and weight w_6 represents the connection from the backward hidden layer to the output layer. The precise computational procedure is elucidated by Equations (8)-(10):

$$h_t = f(w_1 * x_t + w_2 * h_{t-1}) \tag{8}$$

$$h_t^{'} = f(w_3 * x_t + w_5 * h_{t-1}^{'}) \tag{9}$$

$$O_t = g(w_4 * h_t + w_6 * h_t^{'}) \in \mathbb{R}^{batch\_size \times hidden\_size \times 2} \tag{10}$$

4.2 Feature fusion

The feature fusion module consists of Transformer. The hidden state sequence output from the BiLSTM layer is used as input. The driving behavior sequence is encoded using the self-attention mechanism to capture the global information and long-term dependencies in the sequence, which enhances the feature expression ability; in this way, the Transformer can fuse the local features with the global features, better understand the semantic and structural features of the input sequence, and further extract the abnormal driving behavior features, which effectively improves the recognition effect of abnormal driving behavior.

The special feature is that the model replaces the most commonly used recurrent layer in the encoder-decoder architecture with a multi-head self-attention. This mechanism allows it to focus on different parts of the input sequence during processing, not only processing each part sequentially, modeling the dependencies between all the parts of the input sequence of the trajectory data, taking into account the holistic and global nature of the characteristics of the driving behavior, and fusing the parts of the features between the dependencies.

The output sequence of BiLSTM is denoted as $Out = \{x_1, x_2, \cdots, x_{ws}\}$, where ws is the size of the time window. Before performing attention calculation, the data at each time step t_j will undergo three linear transformations to obtain Query (Q), Key (K), and Value (V), shaped by (ws, d), where d represents the dimensions of Q and V. Then, attention scores ($score$) are computed, with a shape of (ws, ws) to indicate the relevance of features at different positions in the sequence Out, as shown in Equation (11). Subsequently, the $score$ is scaled to alleviate the vanishing gradient problem, as depicted in Equation (12). Finally, the $Softmax$ function is applied to compute the attention weights for each Q and K, and the weighted sum of V is obtained to yield the output of the entire attention calculation, as illustrated in Equation (13), where A and S represent self-attention operation and the $Softmax$ function, respectively.

$$score = QK^T \tag{11}$$

$$Score = \frac{score}{\sqrt{d}} \tag{12}$$

$$A(Q, K, V) = S(\frac{score}{\sqrt{d}})V \tag{13}$$

Multi-head attention concatenates multiple self-attention mechanisms, enabling the model to focus on information from different positions and representation subspaces, thus effectively extracting internal relationships.

4.3 Classification of anomalies

The anomaly classification module mainly consists of FCNN. The fully connected layer maps the output of the Transformer encoder to the final label categories. This process transforms the high-level feature representation into a suitable format for classification, generating scores representing each category. Subsequently, the *Softmax* function is applied to normalize these scores, converting the output of the fully connected layer into a probability distribution over the categories. This allows the model to perform multi-class classification tasks, resulting in an output dimension of 8.

The output of the feature fusion module, denoted as $M(Q, K, V)$, undergoes further processing, including linear transformations, to prepare it for classification. The computation process is illustrated in Equations (14) and (15), where W represents the weight matrix used for linear transformation, and b is the bias vector. The cross-entropy loss function, as shown in Equation (16), is employed during the classification process.

$$FC\_output = M(Q, K, V) \bullet W + b \tag{14}$$

$$soft\max\_output = soft\max(FC\_output) \tag{15}$$

$$Loss = -(y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})) \tag{16}$$

5 EXPERIMENTS

The model algorithms used in this paper were trained in this experimental environment: the operating system is Ubuntu 22.04, the CPU is AMD EPYC 7742, the GPU is RTX 3090 (24GB), the PyTorch framework version is 2.1.0, and the Python version is 3.10.

5.1 Experimental data and processing

The experimental data used in this study was sourced from the Basic Safety Message Part 1 (BSMP1) data set, released in October 2014 by the US Department of Transportation as part of the Safety Pilot Model Deployment (SPMD) program. The data were collected from 26 vehicles equipped with onboard Wireless Safety Units (WSUs) that transmitted frequently changing BSM measurements. The data collection frequency was approximately 10 Hz, meaning that measurements were taken every 0.1 seconds. The dataset primarily includes parameters related to vehicle motion characteristics and positional features. Motion-related parameters include speed, longitudinal acceleration, lateral acceleration, and yaw rate. Positional features encompass longitude, latitude, and altitude [19].

Due to external factors affecting data transmission via the WSU, issues such as missing or duplicated data, particularly with latitude and longitude parameters, can emerge. Therefore, initial processing of the raw vehicle trajectory data is necessary. This preprocessing includes map matching, data classification (trip segmentation), deletion of invalid data, imputation of missing data, and data standardization. Data standardization proceeds with the Z-score normalization method, which preserves the distribution information of the original data. This standardized data retains useful information from abnormal values, making it more suitable for anomaly detection tasks.

After the initial processing of the raw vehicle trajectory data, additional road-related parameters were incorporated. Two new fields, "division_scene" and "division_road" were added to describe the conditions of the roads on which the vehicles traveled. The "division_scene" differentiates between curves and straight segments, represented by 0 and 1, respectively. According to the "division_road" by research [16], road grades 1-4 correspond to interstate highways (I), national highways (US), state-numbered highways (M), and local roads and streets (Rd), etc. Based on existing studies, speed limits are assigned according to the road grade. Table 1 lists the road segments included in this study, along with their corresponding speed limits.

Table 1: Road Grades and Their Speed Limits

Number	Division_road	Speeding Limits(mph)
1	I-94, I-96, I-75, I-696, I-275, I-475	70
2	US-23, US-12, US-24	70
3	M-14, M-52, M-153, M-17, M-8	70
4	Rd, St, Way, Ave, Dr, Pkwy	45
5	School, et	25

After the initial data processing and addition of road parameters, the trajectory data, now integrated with road parameters, underwent anomaly detection. Using a sliding window technique, segments of data containing anomalies were extracted. Based on the characteristics of each type of abnormal driving behavior, data segments in alignment with these features were selected to represent the respective behaviors, forming an abnormal driving behavior dataset. The specific data are detailed in Table 2.

Table 2: Abnormal Driving Behavior Dataset

Number	Types of Driving Behavior	Dataset	Sample set
0	Normal driving	12466	3400
1	DS	25055	3400
2	DRA	3482	3400
3	DRD	6091	3400
4	DSD	604	604
5	DLL	4497	3400
6	DRL	3722	3400
7	DLT	4638	3400
8	DRT	5628	3400

This dataset includes nine types of driving behaviors. For model training, the dataset was divided into a training set and a testing set in a 7:3 ratio, with 70% of the samples used for training and 30% for validation.

5.2 Experimental results and analysis

During the training process, recognition accuracy (Accuracy) value (Loss) are used as key metrics to evaluate model performance. Higher Accuracy and lower Loss indicate better model performance in detecting anomalies. This study proposes an abnormal driving behavior detection model based on BiLSTM-Transformer. Through

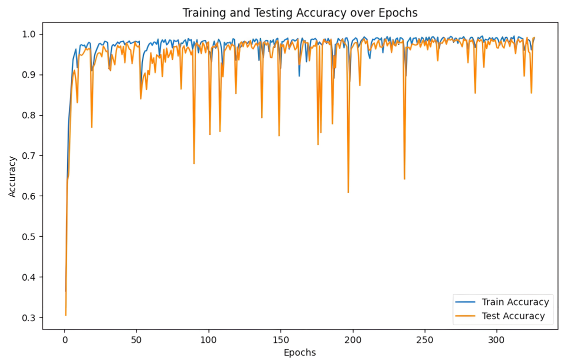

Figure 3: Recognition accuracy value of BiLSTM-Transformer

Figure 4: Recognition accuracy value of BiLSTM

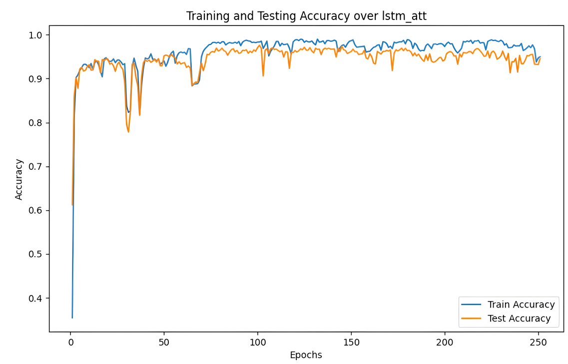

Figure 5: Recognition accuracy value of LSTM-Att

Figure 6: Recognition accuracy value of AM-DRN

multiple training sessions and parameter adjustments, the experimental results of the algorithm are illustrated in Figure 3.

Figure 3 elucidates the variations in Accuracy during the training of the BiLSTM-Transformer model. The orange curve represents the Accuracy of the testing set, while the blue curve represents the training set results. After approximately 300 iterations, the Accuracy reaches 98.8%, with occasional minor fluctuations but generally staying above 98.5%.

To provide a comparative analysis of the proposed algorithm model's recognition performance, we reproduced the BiLSTM model [7], the LSTM-Att model [9], and the AM-DRN model [11] (i.e., ResNet-Attention model) as baseline models for comparison. These models were trained and validated using our dataset to demonstrate the higher accuracy value of our proposed model. The details are as follows:

In the first comparative experiment, the parameter variations during the training of the BiLSTM model are depicted in Figure 4. Figure 4 indicates that after 500 iterations, the BiLSTM model converges with an Accuracy of 98.21%. In the second comparative experiment, Figure 5 shows that the LSTM-Att model stabilizes after 150 iterations, achieving an Accuracy of 97.61%. In the third comparative experiment, Figure 6 demonstrates that the ResNet-Attention(AM-DRN) model converges after 150 iterations with an Accuracy of 96.17%. In contrast, our proposed BiLSTM-Transformer model achieves an impressive Accuracy of 98.85%, as shown in the experimental results. This demonstrates that the BiLSTM-Transformer model performs better, highlighting its advantages over the baseline models.

To validate the performance of machine learning algorithms in the task of abnormal driving behavior detection, we implemented a Support Vector Machine (SVM) algorithm [4] for anomaly classification as the first supplementary experiment. As evidenced by Table III, the Accuracy of SVM is significantly lower than that of the other experimental models, indicating that deep learning models outperform machine learning algorithms in this task. For further validation of the superiority of our proposed model, we implemented a Transformer algorithm as the second supplementary experiment. Figure 7 illustrates the parameter variations during the training process of the Transformer model. It can be observed that after 100 iterations, the Transformer model converges quickly, with both Accuracy and Loss stabilizing. The Transformer model achieves an Accuracy of 98.45%. Compared to our proposed model, the Transformer model performs worse, which underscores the effectiveness and advancement of our BiLSTM-Transformer model.

Through the three comparative experiments and two supplementary experiments mentioned above, it is demonstrated that our proposed model outperforms other models in detecting abnormal driving behaviors. The Accuracy and Loss data for all experiments are presented in Table 3.

Figure 7: Recognition accuracy value of Transformer

Table 3: Recognition Accuracy and Loss Values for All Experiments

Models	Accuracy	Loss
SVM [4]	90.85%	-
AM-DRN [11]	96.17%	0.2519
LSTM-att [9]	97.61%	0.1981
BiLSTM [7]	98.21%	0.1646
Transformer	98.45%	0.1364
BiLSM-Transformer	98.85%	0.1092

6 CONCLUSION

The identification of abnormal driving behaviors bears considerable practical significance. Precisely discerning such behaviors can empower relevant authorities to oversee vehicle operations, aid drivers in adhering to appropriate driving norms, and elevate the passenger experience. This study harnesses trajectory data integrating environmental parameters to precisely delineate abnormal driving behaviors, such as abnormal lane changes and sharp turns, thereby augmenting the dataset for abnormal driving behaviors. Furthermore, the proposed BiLSTM-Transformer model employs a dual-layer approach of "feature extraction + feature fusion" resulting in more comprehensive feature extraction and superior recognition performance when juxtaposed with prior investigations.

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References

[1] Jia, Y., Zhang, L., Duan, Y., *et al.* 2016. Associations of anger while driving and driving style with aggressive behaviors in drivers. J. China J Public Health., 32(10):1373-1377. DOI: 10.11847/zgggws2016-32-10-20.
[2] Matousek M, Yassin M, van der Heijden R, *et al.* 2018. Robust detection of anomalous driving behavior. C. 2018 IEEE 87th Vehicular Technology Conference (VTC Spring). IEEE, 2018: 1-5. DOI: 10.1109/VTCSpring.2018.8417777.
[3] Liu, T., Yang, G., Shi, D., *et al.* 2020. Construction of Driving Behavior Scoring Model based on OBD Terminal Data Analysis. C. 2020 5th International Conference on Information Science, Computer Technology and Transportation (ISCTT). Shenyang, China. 24-27. DOI: 10.1109/ISCTT51595.2020.00012.
[4] Zhou, H., Liu, H., Shi H., *et al.* 2016. Abnormal driving behavior based on the smart phone. J. CAAI Transactions on Intelligent Systems, 11(03):410-417. DOI: 10.11992/tis.201504022.
[5] Yang, L., Luo, Y., Xu, H. 2017. Analysis and recognition of highway lane-changing behavior characteristics based on GPS location data. J. Journal of Beijing Jiaotong University, 41(03):39-46. DOI: CNKI:SUN:BFJT.0.2017-03-007.
[6] Hui, F., Peng, N., Jing, S., *et al.* 2018. Driving behavior clustering and abnormal detection method based on agglomerative hierarchy. J. Computer Engineering., 44(12):196-201. DOI: 10.19678/j.issn.1000-3428.0050708.
[7] Hui, F., Guo, J., Jia, S., *et al.* 2020. Detection of abnormal driving behavior based on BiLSTM. J. Computer Engineering and Applications., 56(24):116-122. DOI: 10.3778/j.issn.1002-8331.2006-0079.
[8] Jia, S., Hui, F., Li, S., *et al.* 2020. Long short-term memory and convolutional neural network for abnormal driving behavior recognition. J. IET Intelligent Transport Systems., 14(5): 306-312. DOI: 10.1049/iet-its.2019.0200.
[9] Du, Y., Ma, Y., Wu, J., *et al.* 2022. Recognition of vehicle abnormal driving behaviors based on LSTM-att. J. Computer Systems & Applications., 31(05):165-173. DOI: 10.15888/j.cnki.csa.008478.
[10] Zhao, J., Chen, Q., Jiao, Y., *et al.* 2022. Recognition of abnormal driving behavior of key commercial vehicles. J. Journal of Transportation Systems Engineering and Information Technology., 22(01):282-291. DOI: 10.16097/j.cnki.1009-6744.2022.01.030.
[11] Jia, S. 2022. Research on driving behavior recognition and prediction and early warning methods for intelligent connected environment. D. Chang'an University. DOI: 10.26976/d.cnki.gchau.2022.000796.
[12] Al-Sultan S, Al-Bayatti A H, Zedan H. 2013. Context-aware driver behavior detection system in intelligent transportation systems. J. IEEE transactions on vehicular technology, 2013, 62(9): 4264-4275.
[13] Das S, Geedipally S R, Fitzpatrick K. 2021. Inclusion of speed and weather measures in safety performance functions for rural roadways. J. IATSS research, 2021, 45(1): 60-69.
[14] Zhang, L. 2021. Research on abnormal driving behavior of mountain city road under typical weather conditions. D. Chongqing Jiaotong University. DOI: 10.27671/d.cnki.gcjtc.2021.000527.
[15] Wang Y., Zhang, M., *et al.* 2022. Spatial distribution characteristics of abnormal driving behavior on mountain roads based on vehicle on-board diagnostic data. J. Science Technology and Engineering., 22(13):5472-5480. DOI: 10.3969/j.issn.1671-1815.2022.13.048.
[16] Zhang, J., Jiang, F., Peng, D., *et al.* 2023. Research on impact of traffic flow in rainy day environments. J. China Safety Science Journal., 33(05):134-143. DOI:10.16265/j.cnki.issn1003-3033.2023.05.0400.
[17] Ali E M, Ahmed M M, Yang G. 2021. Normal and risky driving patterns identification in clear and rainy weather on freeway segments using vehicle kinematics trajectories and time series cluster analysis. J. IATSS research, 2021, 45(1): 137-152.
[18] Heng, H., Liu, J. 2020. Driving outlier detection using multidimensional time series based on hybrid methods. J. Computer Engineering., 46(03):99-104. DOI:10.19678/j.issn.1000-3428.0055186.
[19] U.S Department of Transportation. 2023. Highway Functional Classification Concepts, Criteria and Procedures 2023 Edition. https://www.fhwa.dot.gov/planning/processes/statewide/related/hwy-functional-classification-2023.pdf.