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An Expressway Driving Stress Prediction Model Based on Vehicle, Road and Environment Features

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ABSTRACT Driving stress is the demand for reserved cognitive space after a driver perceives changes in vehicle, road and environmental factors during driving, which has been proven to affect driving behaviour, interfering with driving safety. Traditional stress prediction relies extensively on psychological data and is limited by the unpopularity of psychological data collection technology, which cannot be applied in daily life on a large scale. In recent years, advances in high-precision visual analysis technology represented by deep learning have laid the foundation for automated and large-scale visual environment analysis. This study proposes a framework for the quantitative analysis of highway driving stress based on multiple vehicle, road, and environmental factors. A dilated residual network model and other methods were used to extract visual environmental indexes. Combined with multisource data such as traffic volume and road design parameters, the LightGBM method was used to construct an expressway driving stress prediction model with high accuracy. The MAE, RMSE and R^2 values of the proposed model are 0.042, 0.004 and 0.881, respectively, demonstrating the usefulness for scaled and efficient assessment of expressway stress loads. The SHAP method was used to explore the relationship between different influencing factors and driving stress to quantify the mechanism of vehicle, road and environment influences on stress load, and to propose recommendations for highway design and planning from the perspective of reducing stress load. This study provides a new way of thinking to quantitatively investigate the link between multiple road traffic factors and driving stress, providing efficient and large-scale assessment of expressway driving stress, as well as proposing some suggestions for highway design and planning to enhance stress reduction.

INDEX TERMS Expressway, prediction model, driving stress, LightGBM method, SHAP method.

I. INTRODUCTION

This Mental workload is the interaction of task demands and human characteristics, which affects people's performance on a task [1], [2]. Driving stress refers to the demand index of reserved cognitive space after a driver perceives changes in the vehicle, road and environmental factors during driving. An abnormal increase in driving stress will lead to the failure of driving behaviour for completing an expected operation, which will eventually affect the operation of the vehicle and cause traffic accidents [3]. Excessive mental workload has been confirmed to increase the probability of dangerous driving [4] and distracted driving [5], thus causing traffic safety problems. Effectively predicting and controlling the psychological load of drivers to improve driving tasks has been a concern within the industry [6]. Driving tasks include psychological tasks, physical tasks and visual tasks. The comfort and stability of a driver's driving psychology ensure the safety and control of driving behaviour; therefore, a fundamental way to improve traffic safety is to ensure stable and appropriate psychological expectations for drivers. However, the quantification of driving stress load is overly dependent on physiological data, and the daily collection of physiological data is difficult; as a result, stress monitoring and assessment methods remain difficult to apply in daily life.

Thanks to the widespread application of deep learning algorithms in the field of computer vision and the rapid

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development of image processing devices, image segmentation algorithms help us better understand the semantic information of images and provide a means to better understand highway scene information and quantify the relationship between driver perception and the traffic environment. Efficient image segmentation methods offer the possibility for large-scale and efficient assessment of the mental workload of expressway drivers.

Based on real driving data (Electrocardiography and Electrodermal activity) and Driver Stress Inventory (DSI) data from a total of 21 participants, this study used K-means three-dimensional cluster analysis to construct a ranking criterion for driver psychological load and proposes a driving stress prediction model based on a machine learning algorithm from the perspective of the combined influence of the vehicle, road and environment. In the proposed model, Annual Average Daily Traffic (AADT) was used to describe the vehicle influencing factors, road design indexes were used to quantify the road influencing factors, a dilated residual network (DRN) model was used to segment the traffic environment to describe environmental influencing factors, the LightGBM model was used to construct a prediction model of driving stress, and the SHapley Additive exPlanations(SHAP) algorithm was used to analyse the importance and correlation of features to explore the impact of different influencing factors on driving stress(A reliable intelligent diagnostic assistant for nuclear power plants using explainable artificial intelligence of GRU-AE, LightGBM and SHAP) [32].

In this article, Section 1 reviews related work related to this study. Section 2 presents the experimental design and feature extraction. Section 3 introduces the process of establishing the driving stress monitoring model based on the LightGBM model. Section 4 gives the conclusion of the study, the performance of the model and a comparison with other related methods, and the importance of different eigenvalues to the model is explored. In Sections 5 and 6, we discuss the conclusions and significance of this study and present insufficiencies.

II. RELATED WORK

A cognitive load is the multidimensional structure of a load imposed on a learner's cognitive system when a specific task is processed and is often used to describe the mental resources that a person requires to complete or solve a problem in a given amount of time [7]. The mental load is the aspect of a cognitive load that originates from the interaction of the task and subject characteristics and is the demand for cognitive space that is reserved after perception of the task. It can also be seen as an a priori estimate of cognitive load. A survey has shown that mental load affects, to some extent, people's performance on tasks and health problems [8]. Driving is a complex task that requires continuous dynamic attention to the task and resilience to complex environmental changes. Many studies have demonstrated that psychological load can affect driver performance on driving tasks and create driving risks [9]. As the impact of psychological load on traffic safety has been confirmed by a growing number of studies, researchers are attempting to assess and control the psychological load of drivers [10].

The measurement of stress is the basis of stress research. Stress is usually caused by unpleasant external disturbing events and influenced by the experimenter and the environment, so stress measurement studies are generally divided into four categories: psychological assessment, internal physiological responses, external physical responses, and changes in the environment. (1) A psychological assessment is often measured in the form of questionnaires [11]–[13]. A driving skills questionnaire is the most used method to measure the psychological condition of a driver. The Driver Stress Inventory (DSI) evaluates the stress response ability of a driver during driving from five different dimensions, including aggression, dislike of driving, hazard monitoring, fatigue tendency, and stimulation seeking, and has achieved good results. At the same time, the DSI has been translated into multiple languages based on language, traffic rules, and driving habits in different countries [14]. (2) Internal physiological responses. The essence of stress regulation is the modulation of the physiological stress response by the autonomic nervous system through the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS), so adrenaline and cortisol levels can be used as two major physiological indicators of stress detection [15]. Other physiological data are also commonly used in stress measurement, such as electrocardiogram [16], [17], electrodermal activity [18], respiration activity [19], electromyography [20], skin temperature [21] and pupillary dilation [22]. (3) External physical responses. External and voluntary behavioural responses such as facial, verbal, and driving behaviours can also measure a driver's stress status. Some researchers have identified facial reactions of drivers to negative emotions [23] and analysed the sound waveforms of a driver's verbal communication to identify their stress condition. More researchers have chosen to represent a driver's driving behaviour and determine their psychological conditions based on dynamic vehicle data and from more diverse sources, such as vehicle operating speed, acceleration, braking frequency, and steering wheel declination [18], [24]. Regardless of the data source, vehicle dynamics data have been shown to better predict a driver's stress conditions. (4) The external environment, as external stress, also affects a driver's stress condition, such as traffic jams, heavy rain, and night driving [25], [26]. There are four main categories: (a) weather conditions, as measured through automatic driver stress level classification using multimodal deep learning; (b) driver visibility conditions, which evaluates a 'driver's visual attention using a driving simulator to explore the driver's eye movements in day, night and rain driving; (c) road landscape; and (d) driving routes [27]. However, due to the lack of accurate and efficient methods for quantifying the driving environment, the important factor of the external environment has not been widely introduced into research due to its complex statistical and analytical methods [24].

Stress prediction and evaluation models have been a hot topic in industry. Jong-Pil Kim *et al.* used EEG data to explore the effects of mental workload on a driver's brain activity during emergency situations in a driving simulator and eventually achieved an accurate identification of mental workload categories [28]. Sega *et al.* [29] constructed a prediction model of a driver's mental workload during driving using data on a driver's eye movements, braking, acceleration, and steering angle and other data in a framework of qualitative reasoning and validated the performance of the model using datasets of real driving tasks. Mohammad *et al.* constructed a prediction model of a driver's mental load using an LSTM method by considering the data of physiological indicators, operational conditions and driving environment, and the accuracy of the model reached 92.8% [30]. Yue Lu *et al.* attempted to construct a monitoring model of urban drivers' psychological load based only on driving behaviour, driving environment, and route familiarity, and the model achieved a regression accuracy of 93.78% based on unused psychological data, which provides a possibility for large-scale application of psychological load monitoring in daily driving [31].

In summary, most stress studies are based on the analysis of physiological index data, but physiological collection techniques are not yet widespread, leading to the inability to apply stress monitoring on a large scale. At the same time, the impact of environmental factors on driver stress conditions is only analysed from a qualitative perspective due to the lack of quantitative methods for the traffic environment. This study attempts to propose a research framework for expressway stress based on vehicle, road and environmental factors, using multisource data and a DRN model to describe the vehicle, road and environmental characteristics, which provides a new research perspective for the study of expressway driving stress.

III. DATA AND FEATURE EXTRACTION

A. NATURAL DRIVING EXPERIMENTS

1) EXPERIMENTAL LOCATION

Taking an expressway as the experiment scene, the experimental location is set on a section of the Erenhot – Guangzhou Expressway (G55) from Sanshui to Huaiji, starting from the Tangjia Toll Station in the Sanshui District of Foshan City and ending at the Huaiji South Toll Station in Huaiji County of Zhaoqing City, with a total of 112 kilometres. G55 is one of the main lines of China's national expressway network running from north to south, and the section from Sanshui to Huaiji is the middle section of G55 in Guangdong Province. The terrain transitions from plains to microhills, the design speed changes from 100 km/h to 80 km/h, and the road landscape and traffic driving conditions vary greatly. The experimental route has 10 interchanges, 15 tunnels, 2 service areas and 2 large-span bridges. The experiment was designed to classify and number the above 29 control points of the road section in advance so that the fusion of multisource data could be performed later. The driving time of each complete

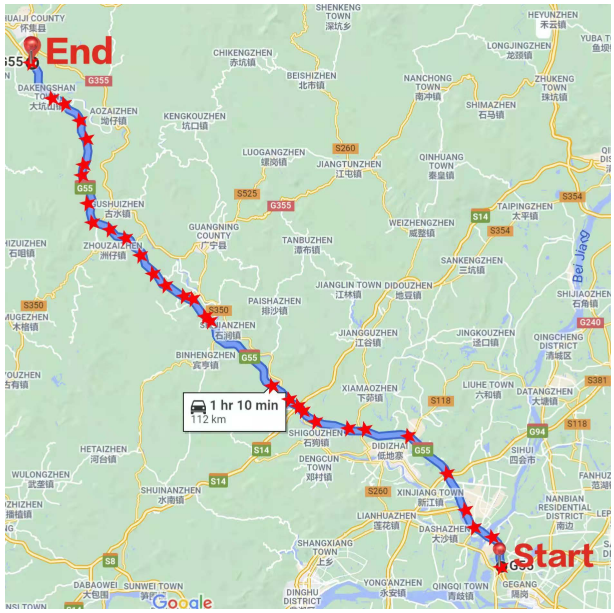

FIGURE 1. Experimental route.

experiment was approximately 1 hour. Before the experiment, only the starting point and ending point were given to the driver, and the driver determined their own experimental route according to the actual situation and road signs. The specific experimental route and control points along the route are shown in Figure 1.

2) EXPERIMENTAL ROUTE SEGMENTATION

To fully explore the mechanism of the influence of the vehicle, road and environment on a driver's psychology and the synergistic effect among them, the experimental route was segmented at abrupt change point of the road design indexes, namely, the change points of the radius of a circular curve and the longitudinal slope. Since the road alignment is designed by projecting the road to the horizontal and longitudinal sections separately, a horizontal alignment mutation point is designated as the point tangent to the spiral, while the longitudinal section alignment mutation point is designated as the slope change point. According to the above segmentation principle, the complete experimental route is divided into 299 segments, among which the radii of the curved sections change in the range of [658,6000] and the absolute value of the longitudinal slope changes in the range of [0,4.5%]. After the experimental sections were divided, the alignment design indexes and pavement testing indexes of each segment were counted according to the design data and detection data.

3) PARTICIPANTS

The experimental participants were 6 female and 15 male college students from the South China University of Technology, with an average age of 25 years old. Recruitment was conducted mainly through email, social media, course internships, and payments. To ensure the validity and safety of the experiment, the recruitment process explicitly required the candidates to hold a Chinese C1 driver's licence, have at least two years of driving experience, maintain continuous driving status in the near future, have naked eye vision or corrected vision of 0.8 and above, and ensure that they had no driving experience on the experimental route. Prior to the start of the experiment, participants were informed of the experimental plan and signed an informed consent form. Upon completion of the experiment, the participants were paid accordingly.

4) EXPERIMENTAL DEVICES

The experimental process required real-time recording of the driving environment, vehicle operating conditions and changes in the driver's raw psychological signals. The following devices were used in this experiment, as shown in Figure 2.

a: DASHCAM

Installed in the middle position above the front windshield of the car, it recorded the forwards running status of the vehicle and changes in the external environment during the experiment through video. To facilitate the subsequent processing of driving videos, the resolution of dashcam was set to 2560×1600 in advance.

b: YOUJIA BOX

The driving computer data of the vehicle was read through the OBD interface of the vehicle, including more than 200 real-time operation parameters, such as speed, acceleration, rotational speed, and driving time. This experiment mainly obtained the real-time operating speed of the vehicle through the Youjia box, which was used for the subsequent alignment and fusion of multisource data.

c: BIOPAC MP160

Sixteen channels of physiological detection equipment from the BIOPAC were used to collect and record the driver's biopsychological signals and the vehicle's operating status in real time during the experiment. In this experiment, the ECG, EDA, EMG and TSD109C2 three-axis acceleration (X/Y/Z) channel data were collected. The EDA sensor was placed on the index finger and middle finger of the nondominant hand, the ECG sensor was fixed in a triangular shape on the chest and the left and right sides of the waist, the EMG sensor was also fixed in a triangular shape on the right leg below the knee joint and above the ankle joint, and the triaxial acceleration sensor was pasted in the middle of the top of the inside of the vehicle to avoid interference from engine vibration. Before the experiment, the sampling frequency of the instrument was set to 500 samples/s, and the acquisition parameters were calibrated.

d: LAPTOP

The biopsychological instrument was connected to a computer and data acquisition was conducted using the self-developed AcqKnowledge software. At the same time, the recorder in the copilot position marked the control points along the route while collecting physiological data to facilitate the subsequent alignment and fusion of multisource data.

e: EXPERIMENTAL VEHICLE

In the actual driving process, different vehicle models and performance may also lead to differences in the driver's psychological condition and driving behaviour. To avoid data noise caused by the performance of the vehicle itself, the same vehicle was used throughout the experiment, and the specific model of the vehicle was a 2017 Volkswagen Lavida.

5) PROCEDURE

The experiment was conducted in March 2021 on the G55 Sanshui-Huaiji section, and to ensure good visual conditions and avoid the effects of bad weather and light, the experiment was conducted on good weather days, and the experiment time was set to 8:30 am-17:30 pm. Twenty-one drivers completed 84 experiments within 28 experimental days. However, one experiment experienced equipment failure, so the number of valid experiments was 83. The specific process of each experiment is as follows:

a: EXPERIMENTAL VEHICLE PREPARATION

To ensure driving safety, the vehicle conditions before the experiment, such as fuel level, tire pressure, brake, etc., were checked and the front glass and mirrors were checked for good clarity to avoid affecting the driving vision.

b: EXPERIMENTAL EQUIPMENT WEARING AND DEBUGGING

Before the driver got into the car, the Youjia box was inserted into the OBD interface of the vehicle and the app was initialized on a cell phone; the dashcam was fixed in the middle of the top of the front glass and a memory card with sufficient capacity after formatting was inserted; after the driver got into the car and adjusted the seat and rearview mirror, the recorder was connected to the laptop and the physiological equipment was connected to an external power supply and turned on; the driver was assisted to fix the EDA, ECG and EMG equipment in the corresponding positions and the equipment was calibrated; the three-axis acceleration sensor was calibrated and fixed in the middle of the top of the car; the connection between the driver, physiological equipment and computer was completed, and the operating status of the equipment was confirmed.

c: RESTING DATA COLLECTION

Since different drivers have different heart rates and skin electric reference values, as well as certain differences in each three-axis acceleration calibration, the driver needed to sit still in the car for five minutes to complete the resting data collection after completing the equipment donning and debugging to standardize the subsequent data processing.

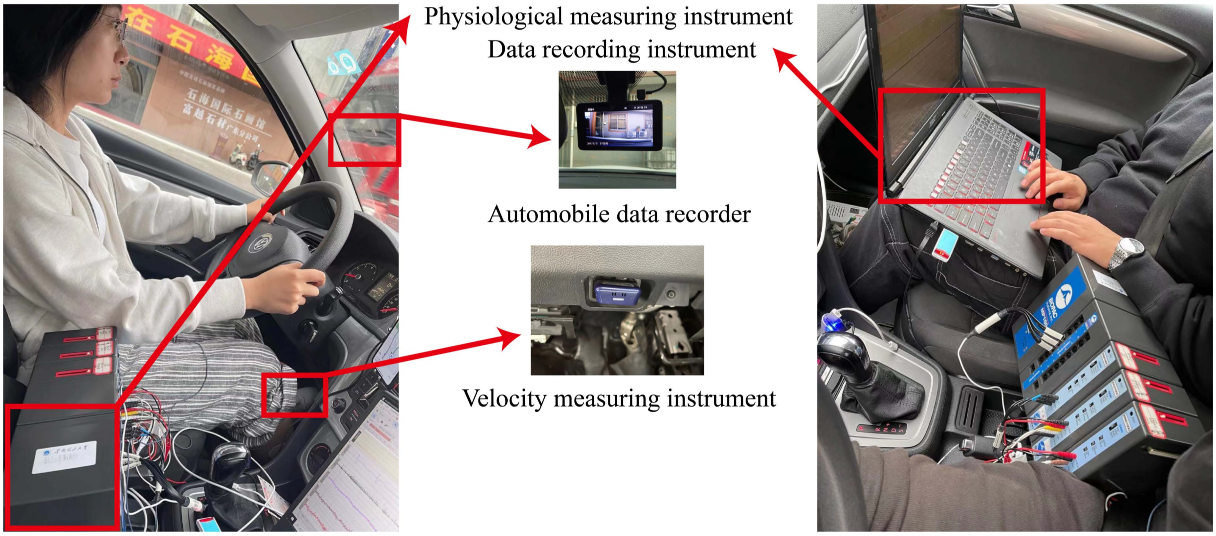

FIGURE 2. **Experimental devices.**

d: EQUIPMENT AND VEHICLE ADAPTATION

Although the wearing of physiological equipment does not affect the safety of vehicle driving, it can still cause some discomfort to a driver, and there may be subtle differences in the driving operation of different models. To reduce the interference of wearing equipment and familiarize the driver with the operation of the vehicle, the driver wore the instrument on other roads for a test drive of 10-15 minutes before the official start of the experiment.

e: DRIVING

Carrying out tasks unrelated to driving may cause driving distractions and other adverse effects on driving safety and influence the research results. Different interior temperatures may also affect a driver's psychological state and data measurement to a certain extent. The following guidelines were followed during the driving process of the experiment: the windows and sunroof were closed; navigation was turned off; operating the radio, music and other audio-visual systems was prohibited; talking and eating between the driver and passengers in the car was prohibited; the car's air conditioner was set to maintain a temperature of 26 degrees Celsius; sunglasses were not worn while driving to ensure normal vision; traffic safety rules were observed and normal driving was ensured.

f: DEVICE REMOVAL AND DATA STORAGE

When the driver drove away from the end of the experiment, the recorder marked the time point on the computer side of the software, stored the data according to a Date-Num-Driver nomenclature, the equipment was turned off, and the computer was disconnected. After the driver parked the vehicle in a safe location, the recorder assisted the driver in removing the physiological equipment from the body and cleaning it up for the next experiment.

g: DRIVING STRESS INVENTORY

At the end of each experiment, drivers were asked to fill out a stress questionnaire to assess their psychological stress while driving based on their driving experience.

B. FEATURE EXTRACTION

1) VEHICLE OPERATION DATA

Studies have shown that there is an interactive relationship between a driver's psychological state and driving behaviour. Therefore, it is necessary to extract data representing driving behaviour to analyse physiological changes during driving. However, under different traffic conditions, the driving behaviour and driving strategy adopted by drivers are different; that is, traffic volume data are an indirect representation of the overall driving behaviour on a road section to a certain extent. In this study, the AADT and the proportion of five types of vehicles on each road segment were obtained by collecting data from toll points throughout the experimental route, and the operating speed data of the vehicle were collected at a frequency of 1 Hz by the Youjia Box.

2) ROAD DATA

Because of the high speed on the expressway, changes in alignment and road surface conditions have a much more significant impact on safety and driver psychology than on urban roads. Small radius curves, longitudinal slopes, poor alignment combinations, potholes and entrance/exit ramp intertwined sections, and other road conditions that do not meet driving expectations may cause significant changes in a driver's mental state. According to the road design data, the experimental route was divided into different road segments according to the mutation point of the alignment design indexes. After road segmentation, 12 characterization factors, such as the segment length, curvature, longitudinal slope, PCI, RQI, SRI, etc., were counted referring to the design data and pavement inspection data for each segment.

3) DRIVING ENVIRONMENT DATA

The driving environment is also one of the most important factors affecting a driver's mental state. A continuous monotonous driving environment may lead to driver fatigue, while a complex and changing driving environment may lead to an increase in driving stress, thus affecting driving safety. Previously, the driving environment was difficult to quantify and analyse due to technical limitations. With the application of deep learning in the field of computer vision, the semantic segmentation effect of images has been greatly developed, which makes it possible to quantify the driving environment. Therefore, this study uses a dilated residual network (DRN) to semantically segment the images of driving videos from the dashcam and obtains 12 influencing factors characterizing the driving environment from the images, such as the average percentage of roads, the average percentage of buildings, and the average percentage of sky.

4) DRIVER DATA

The process of driving on a road is a dynamic and coordinated change between a driver's psychological state and other factors. As the centre of receiving, processing and transmitting information, a driver's psychological state greatly affects the performance of a driving task. To better analyse the correlation and influence mechanism between human factors, the vehicle, road and environment, this study introduces the concept of driving stress to characterize a driver's psychological condition. Numerous studies have shown that driving stress can have a direct impact on driver awareness and performance, leading drivers to engage in aggressive or dangerous driving behaviours on the road. In this study, the psychological condition of the drivers was extracted from both subjective and objective aspects, with the DSI questionnaire data completed by drivers at the end of each experiment as the main source at the subjective level and the ECG and EDA data collected by physiological equipment as the main source at the objective level.

ECG signals are electrical signals that record the heart activity status. A complete cardiac cycle is composed of a series of regular waveforms, that is, P-wave, QRS complex wave and T-wave, and two indicators, the heart rate (HR) and heart rate variability (HRV), are commonly used in studies to quantify mental status. Many experiments have been conducted to demonstrate that changes in HR and HRV are strongly correlated with driving stress levels. General studies usually use the HRV RMSSD index for analysis, but since the extraction interval of the RMSSD index is 10 s, the short operating time of some sections in this study is not applicable. Furthermore, considering the existence of individual differences, the relative heart rate HRrel was used as the characteristic index of the ECG signals, and the calculation formula is as follows:

$$HR_{rel} = HR/HR_{base}, \tag{1}$$

where HR_{base} is the average value of the heart rate collected by the driver sitting quietly for five minutes after wearing and debugging the device before the test started.

The EDA reflects changes in skin resistance and conductance under different stimuli and is one of the most sensitive emotional feedbacks. This response is closely related to human emotion, physiological arousal, cognitive load and attention, i.e., the EDA can be used to understand the psychological state or arousal of a research subject. Since the degree of driver psychological changes caused by external changes in driving tasks is generally low, the transient and faster fluctuations in skin conductance levels characterized by the SCR can visually reflect changes in physiological conditions caused by stimuli. In this study, the SCR was used as a characteristic indicator of the EDA signal.

C. MULTISOURCE DATA INTEGRATION

Physiological data and image data are time series data that were dynamically collected during driving, while traffic operation conditions, road alignment design and road surface detection data are nontime series data. It is difficult for a driver to distinguish alignment change points with the naked eye while driving on an expressway. Therefore, aligning the temporal data with other nontemporal data according to the time axis was the most difficult problem during data processing. To solve this problem, nodes with obvious changes on the road (such as tunnels, interchanges, and service area start and end points) were taken as control points. When vehicles arrived at the control points, corresponding marks were made in the physiological data acquisition software.

Step 1: According to the principle of time axis alignment, the image data of the dashcam correspond to the markers in the physiological data to complete the alignment of the two time series data.

Step 2: Referring to the physical formula t=L/v, the road length was divided by the average speed of the road section to obtain the driving time of the vehicle on the road section. Since the speed of the expressway is fast and the length of each segment was not long, from the starting point of the test, the starting point speed was assumed to be $V_1 = \bar{V_{L1}}'$; hence, $t_{L1}' = L/\bar{V_{L1}}'$. The actual average speed on a road segment was back calculated as $V_{L1} = V_1 + V_2 + \cdots + V_{t_{L1}}'/t_{L1}'$, according to the obtained time t_{L1}'. If $\bar{V_{L1}} = \bar{V_{L1}}'$, t_{L1}' was the actual travel time t_{L1} of the segment. If not, V_{L1}' was substituted into L/V to calculate t_{L1}'', and then t_{L1}'' was used to calculate the average speed, correcting it repeatedly until the data no longer changed.

Step 3: Considering that there is always a certain error in the travel time obtained from the average speed calculation, time correction was made according to the time of the vehicle passing through a control point to obtain the actual travel time of the vehicle on each road segment.

Step 4: According to the calculated travel time interval of each road segment, the physiological data and image data within the interval were statistically processed to complete

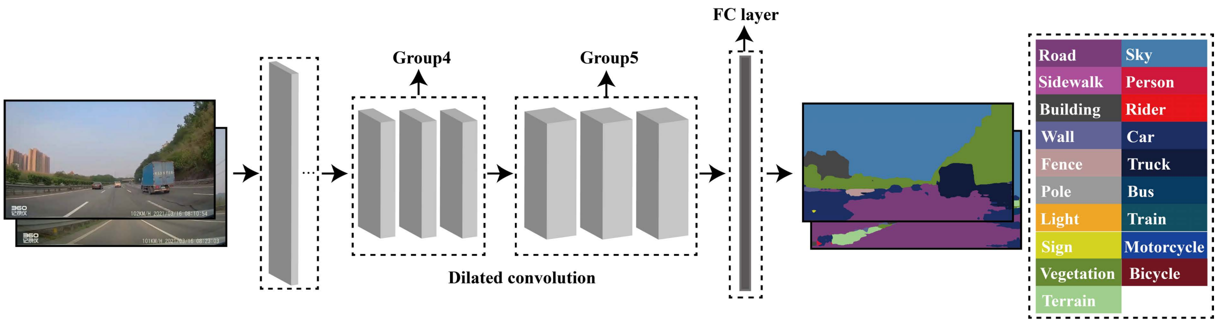

FIGURE 3. Image segmentation procedure based on a DRN.

the alignment and fusion of all heterogeneous data on the time axis.

D. QUANTIFICATION AND CLASSIFICATION OF DRIVING STRESS

The quantitative method to determine driving stress is the premise of stress load research, among which the most commonly used method is a Driver Stress Inventory (DSI), which evaluates the stress response ability of drivers during driving using five different dimensions and has achieved good results. As the similarity of driver stress influences across geographic regions was confirmed [4], [26], Chinese researchers adapted the questionnaire to their own country, and it was eventually proven to be reliable and valid [27]. In this study, the Chinese version of the DSI was used to quantify the stress status of the experimental participants. The participants were required to review their stress status at the end of each experiment by filling out the DSI for stress self-assessment.

Driving stress is a measure that characterizes a driver's perception of road safety while driving on the road. To quantify driving stress, the SCR and HR, which objectively reflect a driver's physiological state, were used in each experiment circle and were combined with the DSI, which objectively reflects a driver's psychological state, and the potential relationship between the DSI and physiological data (SCR and HR) was explored by K-means three-dimensional clustering. A calculation method for the stress load represented by the SCR and HR and the classification threshold were obtained, and the stress was divided into three grades: high, medium and low. Considering the individual differences in the ECG among different drivers and the fluctuation of the SCR signal, the SCR85% and relative heart rate HRrel of each experiment cycle were used as the psychological indicators of the drivers. According to relevant research results and based on the experimental data, the following quantitative formula was obtained:

$$Str_{level} = \begin{cases} High & if \quad SCR_{85\%} + 1.2(HR_{rel} - 1)^2 > 0.43 \\ Medium & if \quad 0.43 \geq SCR_{85\%} + 1.2(HR_{rel} - 1)^2 > 0.25 \\ Low & if \quad 0.25 \geq SCR_{85\%} + 1.2(HR_{rel} - 1)^2 \end{cases} \tag{2}$$

The quantitative classification method of driving stress load described above establishes a potential link between psychological data and driving stress. Based on the above formula, the driving stress can be quantified for each experimental road segment. In the process of multisource data fusion processing, the psychological data within the operating time interval of each road segment have been segmented, and assuming that the operating time of the vehicle on road segment i is t seconds, during which the HR and SCR are sampled at a frequency of 1 Hz, the driving stress of each road segment can be calculated using the following equation:

$$Stress_i = \frac{\sum_{n=1}^{t} [SCR_n + 1.2 \times (HR_{rel_n} - 1)^2]}{t} \tag{3}$$

IV. METHODS

In this study, a Light Gradient Boosting Machine (LightGBM) was used to explore the deep connection between the vehicle, road, environment and driving stress, and an expressway driving stress prediction model based on the vehicle, road and environment factors is proposed.

A. LIGHT GRADIENT BOOSTING MACHINE

The GBDT method is a widely used machine learning algorithm whose core idea is to strengthen weak classifiers (decision trees) into strong classifiers after several iterations of training to obtain the optimal model. The advantage of this algorithm is that it has high accuracy and is not easy to overfit, and it has achieved good results on learning tasks such as multiclassification, prediction and ranking. To obtain high accuracy, the GBDT method needs to traverse all data for each split point of each feature to calculate the information gain, i.e., each iteration needs to traverse all data several times, and the computational complexity will be affected by both the amount of data and the number of features, which makes it difficult for the GBDT method to meet the computational requirements in the face of high-dimensional features and a large amount of data [33].

To address the challenge of reducing the amount of data and features without compromising model accuracy, a variant of the GBDT algorithm, LightGBM, was proposed by the Microsoft team in 2017. LightGBM mainly incorporates two new techniques into the GBDT algorithm:

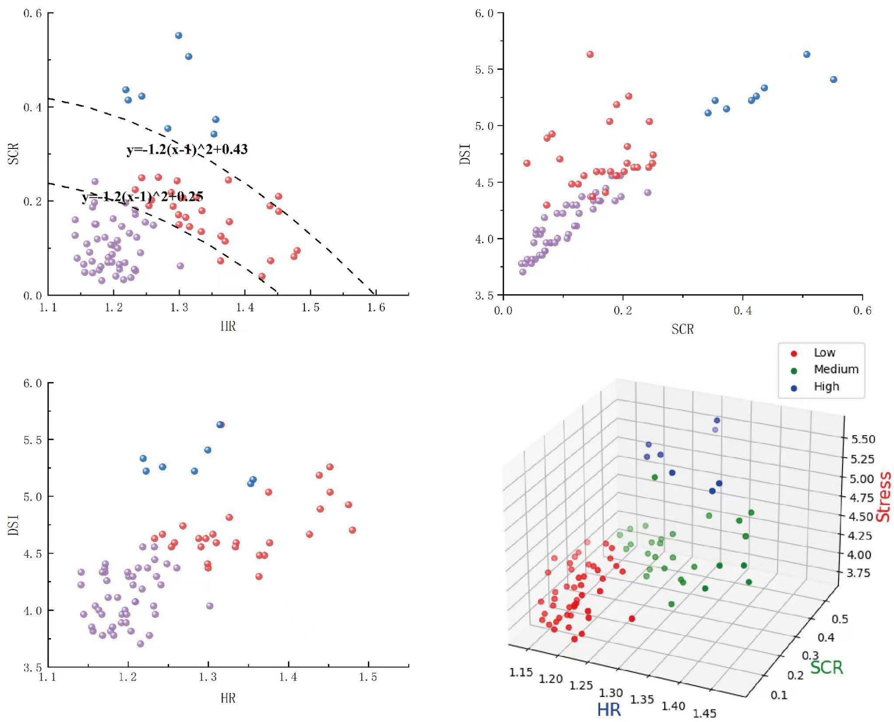

FIGURE 4. Driving stress evaluation result graphs based on K-means three-dimensional clustering analysis.

gradient-based one-side sampling (GOSS) and exclusive feature bundling (EFB).

GOSS is essentially an algorithm that balances the relationship between reducing the amount of data and ensuring accuracy [34]. In general, the common way to reduce the amount of sample data is to sort the samples by their weights and eliminate those with small weights, but this approach is not applicable to the GBDT algorithm without sample weights. However, the GBDT algorithm learns decision trees by fitting negative gradients (residuals) in each iteration, and the size of the sample gradient is inextricably linked to the training accuracy of the model. Therefore, GOSS downsamples based on the gradient values, but simply eliminating all samples with small gradients will change the distribution of the data and affect the training accuracy. In this step, GOSS retains samples with large gradients and uses a random sampling pattern for samples with small gradients to offset the effect of downsampling on the data distribution as much as possible and introduces a constant multiplier for small-gradient samples to amplify the information gain from the small-gradient samples when calculating the information gain to ensure that the data volume is reduced without degrading the model accuracy. Suppose there is a training dataset $O = (x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$, where $(x_1, x_2, \ldots, x_n)$ and $(y_1, y_2, \ldots, y_n)$are the independent and dependent variables of the prediction model, the maximum number of iterations is T, the loss function is L, and the negative gradient of the loss function of the model data variables is $(g_1, g_2, \ldots, g_n)$ for each gradient iteration. The GOSS algorithm first performs in a descending order according to the gradient of the variables, reserving the first data as the strongly influential data subset A, and then randomly samples from the remaining data to obtain the weakly influential data subset B with size b. Then, the information gain of feature j at splitting point d can be expressed as follows:

$$\begin{aligned}\tilde{v}_j(d) = \frac{1}{n}\Bigg(&\frac{\left(\sum_{x_i \in A: x_{ij} \leqslant d} g_i + \frac{1-a}{b}\sum_{x_i \in B: x_{ij} \leqslant d} g_i\right)^2}{n^j l(d)} \\ &+ \frac{\left(\sum_{x_i \in A: x_{ij} > d} g_i + \frac{1-a}{b}\sum_{x_i \in B: x_{ij} > d} g_i\right)^2}{n_r^j(d)}\Bigg) \end{aligned} \tag{4}$$

The goal of GOSS is to perform leafwise splitting by finding the maximum information gain point $\tilde{v}_j(d)$. In addition to reducing the sample data volume using GOSS, another core technique of LightGBM is feature dimensionality reduction through EFB without losing model accuracy. Since most high-dimensional datasets tend to be sparse, in the sparse feature space, many features exhibit the property of mutual exclusion, i.e., these features are never nonzero at the same time, and this property provides the possibility of feature dimensionality reduction. Therefore, the essential idea of EFB is to bundle multiple mutually exclusive features into one feature and reduce the computational complexity from O (data*feature) to O (data*bundle) by reducing the number of features, where bundle is the number of features after bundling and bundlefeature, which can greatly accelerate the GBDT training process.

The goal of the GBDT prediction model is to minimize the loss function L by continuously bifurcating the tree and finally obtain an actual model approximated as the sum of the outputs of a series of regression trees:

$$f(x)=\sum_{t=1}^{T}h_t(x) \tag{5}$$

Before LightGBM was proposed, XGBoost was widely used in various fields as one of the best performing variants of the GBDT method. The XGBoost algorithm adopts a levelwise tree growth method, i.e., the leaves of the same layer can be split at the same time when iterating. Although this approach can be optimized for multithreading, can better control the complexity of the model and is not easy to overfit, such an indiscriminate treatment of the leaves of the same layer without considering the information gain will cause the model to spend too much energy on the small gradient of leaves that have little impact on the accuracy, resulting in unnecessary time consumption and memory occupation. Therefore, LightGBM proposes adopting a more efficient leafwise tree growth approach. In this mode, only the leaf with the highest gain is found at each division, and then the child with the highest gain is found on top of this leaf for division, and the cycle continues in this way. Thus, in the case of the same number of splits, the leafwise method can reduce more errors and computational time consumption and obtain better accuracy. However, the disadvantage of leafwise is that it tends to produce deeper decision trees, which leads to overfitting of the model. Therefore, LightGBM needs to set a maximum depth parameter when using leafwise to obtain high efficiency and prevent overfitting of the model.

B. FEATURE SELECTION AND DATABASE CREATION

The purpose of this study is to solve the problem of predicting expressway driving stress under the influence of the vehicle, road and environment by building a LightGBM model. The model uses the driving stress values as its output target, which is calculated from the psychological data collected from the real driving experiments and the DSI questionnaire data based on the driving stress expression obtained from the K-means three-dimensional clustering and quantification classification. The model input variables are divided into three main categories: the road segment AADT and vehicle proportion as the vehicle driving behaviour input data, the road segment type, alignment design indexes and road condition indexes as the input feature values to characterize the road conditions, and the segmentation data of the driving video images extracted based on the DRN as the driving environment input data. The number of effective trips of the natural driving experiment is 83, and the natural driving data are sampled at a frequency of 1 sample/s. After sampling, 299 samples were obtained from each experiment according to the principle of road segmentation, and the initial database thus obtained has a total of 24,817 samples.

C. MODEL TRAINING

LightGBM is a fast, efficient and distributed machine learning algorithm based on a decision tree. Whether the setting of hyperparameters is reasonable or not is crucial to the training effect of a machine learning model. For LightGBM, there are two types of hyperparameters: one is the hyperparameters that affect the model structure, including max_depth and num_leaves, and the other is the hyperparameters that affect the model accuracy, including n_estimators and learning_rate. Max_depth represents the maximum depth of a single decision tree; in general, the larger the value is, the more complex the model is, and the easier it is to overfit; the smaller the value is, the simpler the model is but also the easier it is to underfit. Num_leaves refers to the maximum number of leaf nodes in a single decision tree; the larger the num_leaves value is, the more accurate the classification of the training datasets will be, but a larger num_leaves value can cause overfitting. N_estimators refers to the number of decision trees in the model; to some extent, the higher the value is, the higher the model accuracy, but too high of a value can reduce the accuracy. Learning_rate affects the speed of model training; the higher the value is, the faster the model converges, but the accuracy of the model is affected. To verify the training effect of the model, 80% of the samples from the dataset are randomly selected as the training set, and the remaining 20% are used as the validation set for testing the model. The following table lists the initial values of the model hyperparameter settings and the optimal values of each hyperparameter after comparing the training effects.

D. EVALUATION METRICS

In this study, the LightGBM model was used for the regression prediction task, and the evaluation of the prediction model was measured as the difference between the true and predicted values, so three indicators, the Mean Square Error (MSE), Mean Absolute Error (MAE), and R squared (R^2), were selected for the evaluation of the model accuracy.

$$MSE=\frac{1}{m}\sum_{i=1}^{m}(y_i-\hat{y}_i)^2 \tag{6}$$

The MSE is used to evaluate the degree of variation of the data and takes a value in the range of $[0, +\infty]$, and a smaller value indicates higher model accuracy for the description of the experimental data.

$$MSE=\frac{1}{m}\sum_{i=1}^{m}|y_i-\hat{y}_i| \tag{7}$$

The MAE reflects the true error between the actual value and the predicted value, and the smaller its value is, the higher the accuracy of the model.

$$R^2=1-\frac{\sum_{i=1}^{m}(y_i-\hat{y_i})^2}{\sum_{i=1}^{m}(y_i-\bar{y_i})^2} \tag{8}$$

R^2 is used to evaluate the regression fit of the model and takes a value in the range of [0,1], and the closer its value is to 1, the higher the degree of explanation of the dependent variable by the model independent variable.

TABLE 1. Summary of model characteristics.

Class	Category	Features	Description	Number
Input Attributes	Vehicle Operating	AADT	Annual average daily traffic of road sections, calculated from adjacent toll station data.	1
		Vehicle type ratio	The proportion of 5 vehicle types, including Proportion of type I cars,Proportion of type II ars,Proportion of type III cars,Proportion of type IV cars and Proportion of type V cars.	5
	Road	Section Type	Type of road sections, where 1 denotes Basic road sections,2 denotes Service area sections,3 denotes Tunnel sections and 4 denotes Interchange road sections	1
		Alignment Design Indicators	The alignment design indicators representing the road geometry, including Length of section,Curvature,Length of Horizontal Curve,Longitudinal Gradient,Continuous Downgrade Length,Continuous Upgrade Length,Median Width,Design Speed	8
		Pavement Conditions	Three parameters reflecting the condition of the pavement,including Pavement Surface Condition Index(PCI),Riding Quality Index(RQI),Skidding Resistance Index(SRI).	3
	Driving Environment	Proportion	The proportion of visual scene elements in images extracted from driving videos, including Road avg,Road min,Road max,Building avg, Building min,Building max,Vegetation avg,Vege tation min,Vegetation max,Sky avg,Sky min,Sky max	12
Output Target	Driving Stress Level	Stress level	Driving stress level is calculated from HR and SCR, where 1 denotes low stress, 2 denotes medium stress and 3 denotes high stress.	1

TABLE 2. Initial values of the model parameters and the range of optimal values for each iteration.

Name	max_depth	num_leaves	n_estimators	learning_rate
Initial Value	5/10/20	5/10/15	500/800/1000	0.1/0.02/0.01
Optimal Values	10	10	800	0.01

For all three indicators, m denotes the number of samples, y_i denotes the actual driving stress of the roadway, $\hat{y}_i$ denotes the predicted driving stress of the roadway calculated by the model, and $\bar{y_i}$ denotes the evaluation value of the driving stress of the roadway.

V. RESULTS

A. TRAINING RESULTS

This paper investigates the effects of the full range of highway vehicle, road, and environmental factors on driving stress. In constructing the model, the input feature variables cover all the influences that can characterize the vehicle, road, and environment as much as possible. Given the differences in the contribution of each factor to driving stress, the number of input variables to the model is not proportional to the training performance of the model. To ensure that the model achieves optimal performance, the MAE, MSE and R^2 values of the model are obtained iteratively in order of importance for different numbers of feature values according to the feature importance distribution obtained in the initial case of the model, as follows, to find the optimal set of input features for the model, and the comparison results are shown in Figure 5.

According to the above figure, the MAE of the model is relatively stable when the number of features is less than 22, remaining at approximately 0.042, and it starts to increase when the number of features is greater than 22; the MSE starts to decrease when the number of features is greater than 14, maintaining a more stable state, but the overall value is small, and the difference is not significant. The overall value of R2 shows a trend of rising and then falling, and its value reaches the maximum value when the number of features is 22. The reason may be that the model is in an underfitting state when the number of features is less than 22, and the model is overfitted when it is greater than 22. Therefore, the model reaches the optimal performance when the number of features is 22, and the optimal feature set contains the variables shown in Table 3.

B. MODEL PERFORMANCE COMPARED WITH BASELINES

Different models will show different prediction results on the same dataset, which is related to the dimensionality, type and computational power of the data that different models can handle. In this study, four commonly used regression prediction models, XGBoost, GBDT, a random forest

TABLE 3. Initial values of the model parameters and the range of optimal values for each iteration.

Category	Features	Number
Vehicle Operating	AADT	1
Road	Length of section Curvature Length of Horizontal Curve Longitudinal Gradient Continuous Downgrade Length Continuous Upgrade Length	6
	PCI RQI SRI	3
Driving Environment	Road avg Road min Road max Building avg Building min Building max Vegetation avg Vegetation min Vegetation max Sky avg Sky min Sky max	12

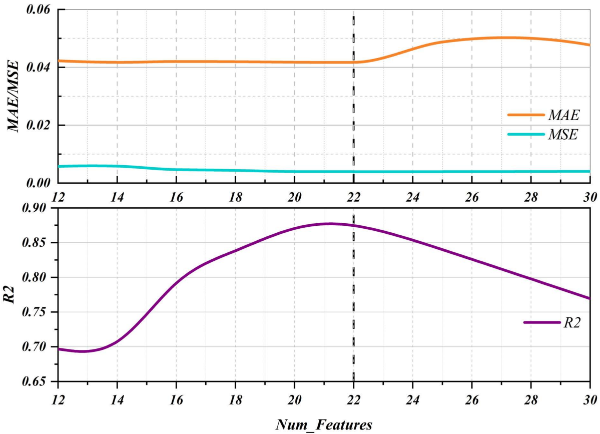

FIGURE 5. Optimal model accuracy for each iteration of the LightGBM model.

and SVM, were selected for comparison experiments with LightGBM, and the comparison results are shown in Table 4. The results show that LightGBM has the smallest error MAE and MSE and the largest R^2 value on the same dataset and equal hyperparameter settings, indicating the highest fit to the data, and overall, the model performance is better than other comparison models.

C. MODEL INTERPRETATION AND VISUALIZATION BASED ON SHAP

Machine learning algorithms have long been called "black boxes" because of their weak model interpretability. Especially when machine learning is applied to the field of traffic safety, researchers are more concerned about the interpretability of the model than the accuracy of the model prediction, and they often want to know how each independent variable affects the prediction result so that they can propose targeted measures to improve traffic safety.

Shapley Additive Explanation (SHAP) is a post hoc model explanation method inspired by cooperative game theory, whose core calculates the marginal contribution of features to the model output through the Shapley value for the purpose of explaining the predicted value. The greatest advantage of SHAP is that it can show the positive and negative correlation of features on the model results using positive and negative values. Although tree-based machine learning models such as a random forest, XGBoost and LightGBM already have good global explanations, little attention has been given to local explanations. Therefore, some researchers have proposed a Tree Explainer method specifically for tree models based on the Shapley value, which calculates the Shapley value using the nodes in the tree model, not only to obtain local explanations efficiently and accurately but also to mine the interactions within the model by calculating an interaction value. The global interpretation of a model can be obtained by combining many high-quality local interpretations.

1) GLOBAL INTERPRETATION

From the summary plot of the model, it can be found that the AADT has the greatest influence on driving stress, which is inversely related to driving stress; that is, the smaller the AADT is, the greater the driving stress. When the AADT value is small, the traffic flow is in a freer state, and the vehicle driving speed on the road will be correspondingly high. When the speed is higher, a driver's response to external stimuli and vehicle handling time will be correspondingly shortened. To ensure driving safety, the driver's attention will be more focused, thus leading to greater driving stress. The average road ratio of a road segment also greatly affects the driving stress. When the average road ratio of a road segment is larger, it means that the proportion of lanes in the visual scene is also larger, the driver has more freedom to operate while driving, and the traffic condition is more complicated, so the driving stress increases accordingly. The great correlation between curvature and driving stress is consistent with the expectation that a larger curvature means a smaller curve radius of the roadway, the driver needs to operate the steering wheel, throttle and brake more frequently, and the driving stress increases accordingly. Satisfactorily, the model results show that an increase in the longitudinal slope of the route will lead to an increase in driving stress, which directly confirms the principle that the maximum longitudinal slope needs to be controlled when designing a route. As an important indicator to characterize the road surface condition, the road surface resistance index (SRI) also has a significant impact on driving stress. This is because under the same vehicle operation, the larger the SRI value is, the greater the force of the road surface feedback on the vehicle, i.e., the greater the acceleration that the vehicle can obtain, and the driver needs to allocate more attention to complete smooth and comfortable driving of the vehicle, resulting in greater driving stress.

TABLE 4. Classification performance of this model with four other popular machine learning methods.

Model	num_features	n_estimators	max_depth	MAE	MSE	R^2
LightGBM	22	800	10	0.04196	0.00389	0.88108
XGBoost	22	800	10	0.04277	0.00463	0.80579
GBDT	22	800	10	0.05236	0.00599	0.66573
RF	22	800	10	0.04457	0.00466	0.80293
SVM	22	–	–	0.05027	0.00521	0.74517

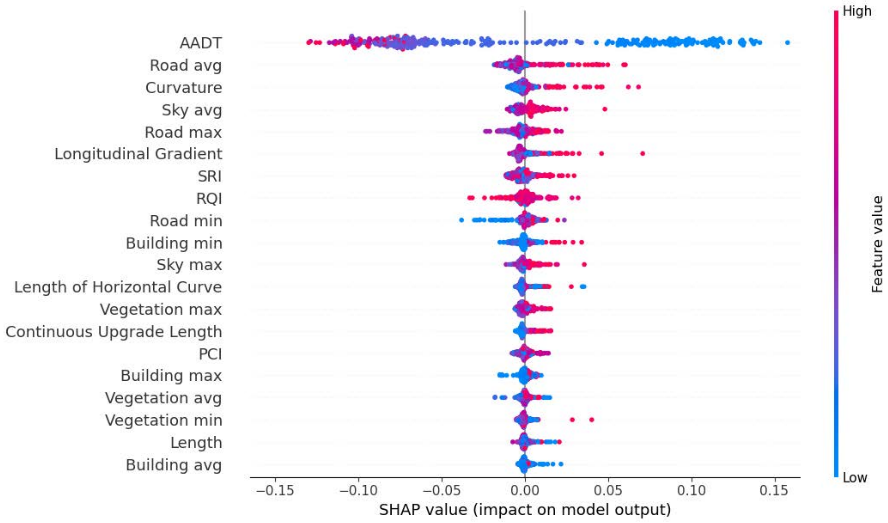

FIGURE 6. Summary plot of the SHAP values of the model variables.

2) LOCAL AND INTERACTION EXPLANATION

The SHAP method is an important method for local interpretation of a model. By calculating the SHAP interaction values and plotting the dependence the effect of the interaction between two feature variables on the prediction results of the model can be described. Figure 7 shows the SHAP plots for a few representative highway driving stress prediction models with two interactions of different eigenvalues.

First, the smaller the AADT and the greater the curvature of the route are, the greater the promotion of driving stress, which is fully consistent with the principle that the higher the design speed is, the greater the minimum radius of the curve required for highway alignment design.

Second, as the length of a continuous uphill or downhill increases, the contribution to driving stress also increases, and this result confirms the correctness of the empirical principle of avoiding long uphill and downhill sections when designing roads. The curvature of the road section also shows a clear demarcation phenomenon. When the curvature is greater than 0.0012, the driving stress will significantly increase, while when the curvature is less than 0.0012 and the length of the flat curve is greater than 1 km, the driving stress will be reduced, which is also consistent with the traditional perception that drivers need to be more cautious when driving on small radius curves. The above results show that the road design of a highway should be within a controllable range as far as possible to avoid the selection of limit indicators but should also pay attention to optimizing the combination of alignment to avoid traffic safety problems due to a surge in driver stress caused by bad alignment design.

Finally, roads, skies, buildings and vegetation are important scene elements of a highway landscape, and the proportion of their respective placement in the environment has a significant impact on driving stress to a certain extent. There is a clear demarcation phenomenon in the influence of road proportion on driving stress. When the average proportion of road is less than 0.22 and the maximum proportion of road is less than 0.24, the driving stress of the road section is reduced, and vice versa, driving stress is promoted. From the distribution diagram, there is a certain interaction between the sky and buildings. A low proportion of sky and a high proportion of building distribution will significantly reduce driving stress, while when the average proportion of sky is greater than 0.48, it will increase driving stress. From the interaction between the minimum and average proportion of plants, it is best to control the proportion of plants in the highway landscape to be greater than 0.1. This seems to be consistent with the theory that a certain proportion of plant placement can, to some extent, alleviate driver visual fatigue and driving fatigue, thus improving driving safety.

D. MODEL APPLICATIONS

Based on the model, an attempt was also made to explore the advantages and application prospects of the study.

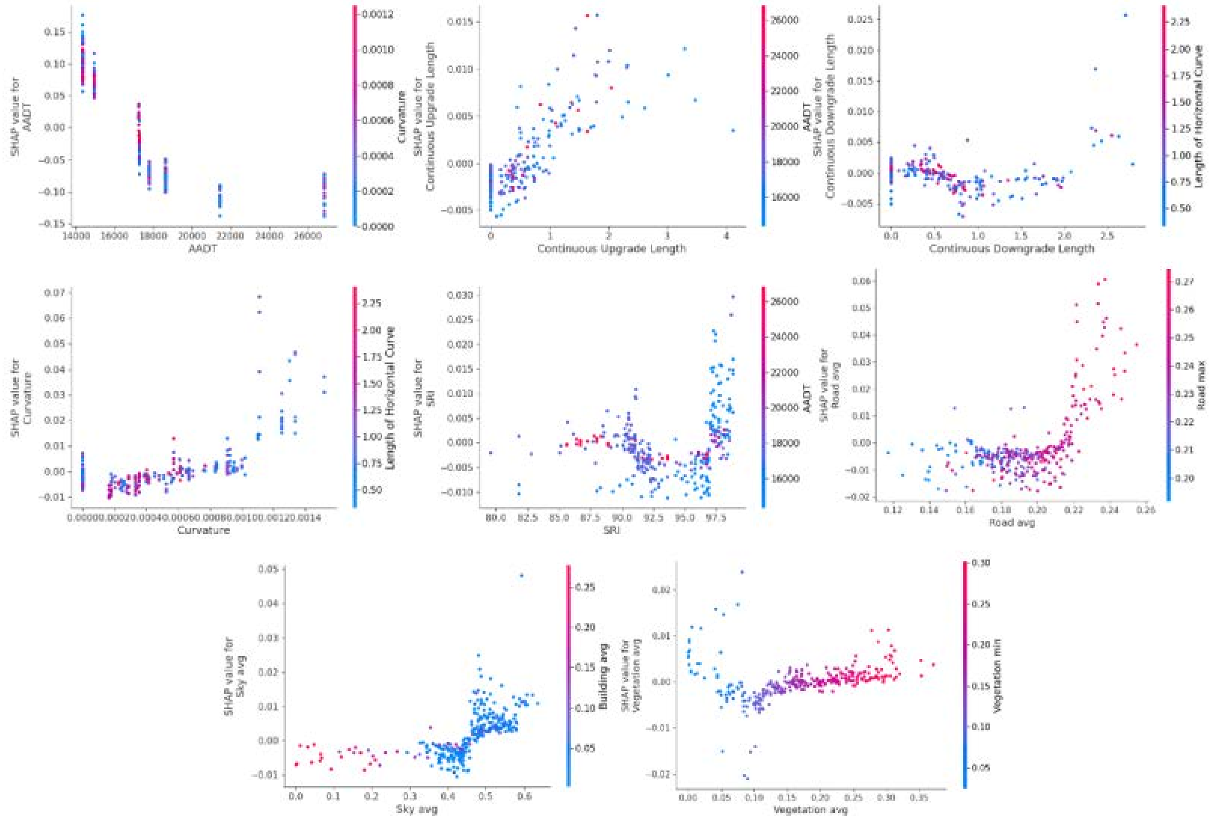

FIGURE 7. **SHAP correlation analysis.**

Figure 8 shows a stress prediction map of another highway outside the study data. To avoid the influence of the density of the collection points on the prediction results, the experimental data were extracted at 1 km intervals, and the driving stress load values were calculated based on the prediction model. Finally, the data of the main roads in this area were automatically extracted and evaluated for driving stress. The obtained highway stress prediction map has good evaluation and visualization effects and realizes the scale and efficient evaluation of the highway driving stress load.

VI. DISCUSSION

Driving stress has been proven to be an important factor affecting traffic safety, and assessing and controlling driving stress has become a key issue to improve traffic safety. Traditional stress prediction relies too much on psychological data, which is limited by the fact that psychological data collection technology is not widespread and cannot be applied on a large scale for daily use. Thanks to the wide application of deep learning in computer vision, the quantitative analysis framework of highway driving stress based on the factors of the vehicle, road and environment, and the construction of a highway driving stress prediction model based on multi-source data and machine learning algorithms provide a new perspective for exploring and predicting highway driving stress. The fusion of multisource data and the high accuracy

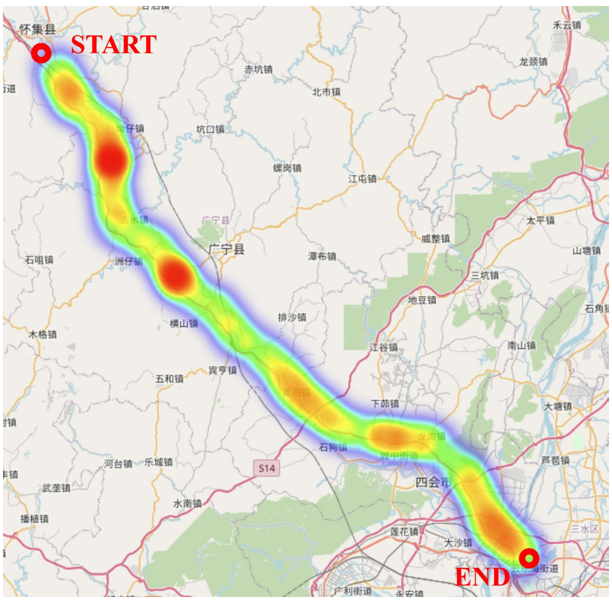

FIGURE 8. **Model application chart.**

of the model make it possible to evaluate highway driving stress on a large scale with high efficiency.

The SHAP algorithm is applied to the study of the importance and correlation analysis of model features, and the mechanism of driving stress influence is investigated from the factors of the vehicle, road and environment. Finally, we propose relevant suggestions for highway road design from the perspective of reducing driving stress. First, according to the importance ranking of the SHAP value of all factors, we know that the ranking of different factors on a driver's driving stress is vehicle>road>environment. (1) The AADT is the factor that has the greatest influence on driving stress. The data show that the greater the AADT on the highway is, the smaller the driving stress, the greater the traffic flow on the road and the slower the speed, the smaller the driving stress, which also shows that a road design that blindly expands the road will increase driving stress. (2) Road width and curvature are the road factors that have the greatest impact on driving stress; the greater the width of the road is, the higher the degree of freedom to drive, traffic conditions are more complex, and driving stress increases accordingly. (3) The influence of visual scene elements is low.

Second, the interaction between two different parameters was found by analysing the interaction of different eigenvalues. (1) The higher the SRI value of the road is, the higher the driving stress. This phenomenon may be related to the greater force of road feedback on the vehicle causing the driver to allocate higher attention to complete a smooth and compliant vehicle ride. (2) Driving stress will increase significantly when the road curvature is greater than 0.0012, while it will decrease when it is less than 0.0012 and the flat curve length is greater than 1 km, which is also consistent with the traditional perception that drivers need to be more cautious when driving on small radius curves. (3) An average road occupancy ratio less than 0.22 and a maximum occupancy ratio less than 0.24 will reduce the road driving stress, and vice versa will promote driving stress. (4) A low proportion of sky and a high proportion of building distribution significantly reduce driving stress, while when the average proportion of sky is greater than 0.48, driving stress increases. (5) The proportion of plants in the highway landscape should preferably be greater than 0.1, which seems to be consistent with the theory that a certain proportion of plants can alleviate driver visual fatigue and driving fatigue to some extent, thus improving driving safety.

Finally, the results of the study can be combined with some highway design-related recommendations. (1) The width of new expressway or highway expansion is not the wider the better, but an appropriate width should be designed according to the design traffic volume of the road to ensure that the driving stress is at a safe threshold. (2) The parameter index of the road surface is not the higher the better, and a parameter index that is too high will inadvertently increase driving stress. (3) The proportional information of different scene elements in the traffic environment can be changed appropriately to reduce driving stress. In addition, the results of the study were used for a large-scale evaluation of driving stress on highways, and the evaluation results were satisfactory.

The main contributions of this study are as follows:

1) A research framework using multisource data and a DRN model to describe the characteristics of all vehicle, road and environment factors on an expressway driver's stress is proposed, which provides a new way to study expressway driving stress.

2) Based on the LightGBM method, a prediction model for expressway driving stress was constructed. Multisource data and a high-precision machine learning algorithm were used to evaluate the expressway pressure load from the perspective of all factors and achieve ideal performance. The research results also showed the prospect of large-scale and efficient evaluation of expressway driving stress.

3) The SHAP algorithm was used to analyse the impact of different influencing factors on driving stress and to investigate the influence mechanism of expressway driving stress by analysing the importance of features in the model and the interaction and correlation between different features. The results of the study can be used to propose relevant recommendations for expressway design and planning from the perspective of reducing the stress load.

There are still some shortcomings in this study. The participants were recruited mainly through campus recruitment, so the age of the participants was generally young. Some studies have confirmed that driver age affects driver behaviour and responses to changes in the driving environment, which in turn affects driver psychological status. This study did not consider errors introduced by the age of the driver on the study results, which may have led to some degree of specificity in the results. In future studies, participants of different ages from 18 years old and above need to be recruited in the community to provide generalizability of the findings.

VII. CONCLUSION

This study attempts to eliminate the current situation that stress prediction technology cannot be applied on a large scale due to the unpopularity of psychological acquisition technology and proposes a prediction model for highway driving stress based on the full range of vehicle, road and environmental factors. The results show that the highway driving stress prediction model constructed using the LightGBM method achieves high accuracy with MAE, RMSE and R^2 values of 0.042, 0.004 and 0.881, respectively. The comparison results with four other mainstream machine learning methods showed that the LightGBM model is suitable for highway driving stress prediction modelling, and the model was proven to be useful for the scaled and efficient evaluation of highway stress loads without using physiological data. In addition, the SHAP method was used to analyse the importance of features in the model and the interaction and correlation between different features to identify the influencing factors that induce traffic accidents. This study provides a new way of thinking to quantitatively study the link between all road travel factors and driving stress and offers the possibility to efficiently assess highway driving stress conditions on a large scale, as well as suggesting relevant recommendations for highway design and planning from the perspective of stress load reduction.

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