A BOA-LightGBM hybrid model for estimating the dynamic friction coefficient of asphalt pavements

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ABSTRACT

The skid resistance of the pavement has a significant impact on road safety. To accurately evaluate the change mechanism of skid resistance, a hybrid model based on Bayesian optimization algorithm (BOA) and light gradient boosting machine (LightGBM) is proposed. Firstly, the electric sander is used to obtain the mean texture depth (MTD) of the asphalt pavement. Then, the friction coefficient of road surface under dry and wet conditions is measured by dynamic friction tester at corresponding positions. Finally, a BOA-LightGBM dynamic friction coefficient estimation model is proposed based on the mean texture depth, pavement water content, and vehicle speed. The BOA algorithm is used to adjust the optimal parameters of the model. Compared with the LightGBM model, the results show that the BOA-LightGBM model fits predicted and true values better through the above factors, and the R^2 value is 97.21%. It proves that the proposed model has strong stability and nonlinear fitting ability.

Keywords: Skid resistance; friction coefficient prediction; MTD; Bayesian optimization; light gradient boosting machine.

1. INTRODUCTION

Pavement skid resistance is a key factor affecting the safety performance of the road. Friction is an important index to measure skid resistance. The wet state reduces the contact force between a tire and a road surface in rainy weather. At this point, the friction provided by the road surface is reduced[1]. Therefore, it is necessary to analyze the key factors affecting pavement friction in order to accurately assess the skid resistance.

Some studies have analyzed the factors affecting skid resistance and constructed skid resistance evaluation models based on these factors[2-4]. Smith et al.[5] demonstrated in 1977 that texture and pavement drainage were important research objects for evaluating pavement surface skid resistance and reducing traffic accidents. Zhang et al.[6] first constructed a calculation model of water film thickness based on road type, MTD, rainfall intensity, porous layer thickness and other factors, and then constructed a numerical model of friction coefficient based on tire characteristics, road materials, and fluid material properties. Ahammed et al.[7] used digital image processing techniques to explore the impact of MTD on anti-slip performance. Hu et al.[8] extracted eight texture parameters. Meanwhile, a friction coefficient prediction model based on stepwise multiple linear regression was constructed.

Many of the above studies used finite element simulation models and numerical models to predict skid resistance. When the dimension of original data is large, the traditional method will produce large errors in the process of data analysis. In view of this, Yang et al.[9] designed a convolutional neural network model to predict friction coefficients. The results suggest that this model outperforms other traditional algorithms in terms of performance. Zheng et al.[10] proposed a method for forecasting the skid resistance performance based on GA-BP. The precision of the model was assessed using R^2 and mean absolute error (MSE). The MSE was 0.6239, and the R^2 was 0.99. Majidifard et al.[11] proposed a hybrid model of gene expression programming (GEP) and neural networks optimized by simulated annealing algorithm for predicting the fracture energy of asphalt mixture specimens. Yu et al.[12] discussed the effect of velocity and surface texture on the anti-slip properties. They built a friction coefficient forecasting model using the BP neural network method. Li et al.[13] proposed a full convolutional network (FCN) model for pixel-level multiple damage detection of pavement structures.

Machine learning algorithms are widely used in road traffic due to their high stability and generalization capabilities[14,15]. Therefore, the successful application of artificial intelligence in these fields provides a new development direction for the research of the skid resistance mechanism of asphalt pavements. In this paper, the boosting tree model in machine learning is applied to explore the skid resistance mechanisms of pavements. The major research contents of this study are as follows:

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- Using pavement water content, MTD and travel speed as input features, an accurate estimation framework of skid resistance based on the light gradient boosting machine model is constructed.
- On this basis, the BOA algorithm is employed to define the optimal values of the model hyperparameters. To assess the non-linear predictive ability of the model, regression model evaluation metrics are used to compare the prediction accuracy of the BOA-LightGBM model with the single model LightGBM.

2. METHODOLOGY

2.1 LightGBM model

LightGBM is a lifting framework that supports efficient parallel training to solve the time-consuming problem in large sample and high-dimensional data environments. Both XGBoost and LightGBM use decision trees as their base learners[16,17]. The initial form of the XGBoost objective function is shown in equation (1).

$$Obj = \sum_i (y_i - \hat{y}_i)^2 + \sum_i \Omega(f_i) \tag{1}$$

where f_i is a feature in the feature space; $\Omega(f_i)$ is the regularization term.

$$\Omega(f_i) = \frac{1}{2}\lambda \sum_{j=1}^{K} \omega_j^2 + \gamma T \tag{2}$$

where K is the number of leaf nodes of the regression decision tree; λ is the parameter that controls the score of the leaf node; ω_j is the value of the leaf node. XGBoost fits the residuals of the current prediction to the true value by iterations, continuously converging to the true value. the result of each iteration of XGBoost is shown in equation (3).

$$\hat{y}_i^{(t+1)} = \hat{y}_i^{(t)} + \sum_{j=1}^{N} f_j(x_i) \tag{3}$$

To determine the optimal structure of the tree, XGBoost selects $Gain$ as the feature splitting criterion and prioritizes the nodes with the largest $Gain$ to be split. The formula for $Gain$ is shown in equation (4).

$$Gain = \frac{1}{2}[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda}] - \gamma \tag{4}$$

The regression tree will continue to split until $Gain < 0$ or reaches the depth threshold of the tree. LightGBM and XGBoost have different ways of splitting leaf nodes. Figure 1a shows the splitting strategy of leaf nodes of XGBoost and LightGBM. The leaf node splitting method of XGBoost is level-wise, which increases the computation and time complexity by calculating the splitting gain when traversing each splitting point. The leaf node splitting method of LightGBM is leaf-wise. The leaf node with the greatest split gain is selected for splitting at each iteration. In addition, the decision tree algorithm based on histogram sorting is another advantage of LightGBM., as shown in figure 1b. The algorithm reduces memory consumption and improves the efficiency of model training.

2.2 BOA-LightGBM model construction

The core process of the BOA algorithm is to set the objective function to be optimized, and update the objective function by continuously adding new data points. Then, the next combination of hyperparameters to be sampled is selected based on the posterior distribution. Figure 2 shows the Bayesian-LightGBM model construction process. Firstly, a dataset is constructed for assessing the skid resistance of asphalt pavements. Secondly, the LightGBM model is trained. In this process, the initial values of the model parameters as well as the domain space need to be defined. Then, a BOA algorithm is used to search for the optimal values in the domain space.

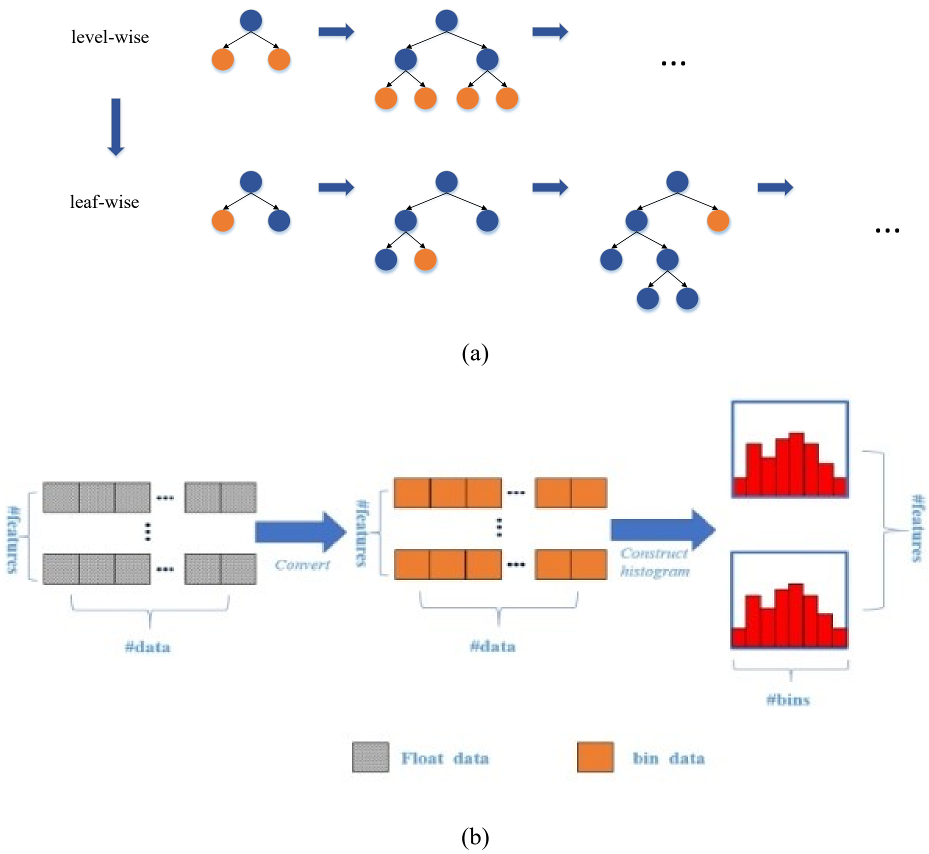


Figure 1. (a): Splitting strategy for leaf nodes; (b): Histogram optimization algorithm.

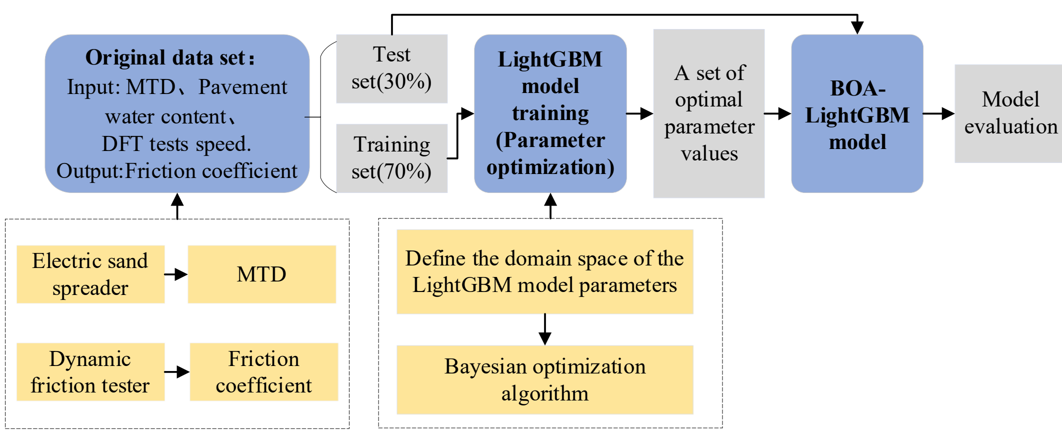


Figure 2. The Bayesian-LightGBM model construction process.

3. SKID RESISTANCE DATA COLLECTION AND ANALYSIS

3.1 Data measurement

(1) MTD data measurement. Pavement texture depth data is collected using an electric sand spreader as shown in figure 3a. The sand spreader needs to be calibrated during the test and the average value is recorded as L0 when the calibration is repeated three times. After calibration, the texture depth data is measured at the test location, and the same test point is

measured at least 3 times in parallel (All 3 test points are located on the wheel track). The average of three repeated tests is recorded as L. Finally, the texture depth value for this measurement point is calculated using equation (5).

$$TD = \frac{L_0 - L}{L_0 \bullet L} \times 1000 \tag{5}$$

(2) Dynamic friction coefficient data acquisition. To investigate the trend of the coefficient of friction under wet conditions and high and low speed conditions, skid resistance tests are designed for both dry and wet conditions. The wet condition is simulated by spraying a certain amount of water with a spray bottle in a fixed test area. The values of the pavement water content (ml) are 0, 16, 32, 48, 64, 80, 96, 112, 128, 144, and 160. The size of the spray area is 40 (cm) ×40 (cm). At the same time, the DFT as shown in Figure 3b is used to collect the pavement friction coefficient, which is mainly used for outdoor or indoor testing of large asphalt mixture specimens.

(a)

(b)

Figure 3. Data acquisition equipment. (a): Electric sand spreader; (b): DFT.

3.2 Data analysis

MTD reflects the height characteristics of the pavement texture structure and is one of the most significant factors impacting surface skid resistance. The Pearson correlation calculation method is used to analyse the degree of association between MTD and skid resistance under different DFT test speed conditions. The results are shown in Figure 4. There is a weak correlation between MTD and friction coefficient at low speeds. When the speed reaches 60 km/h, the correlation coefficient between MTD and friction coefficient is 0.802. The results show that MTD mainly affects the skid resistance at high speed.

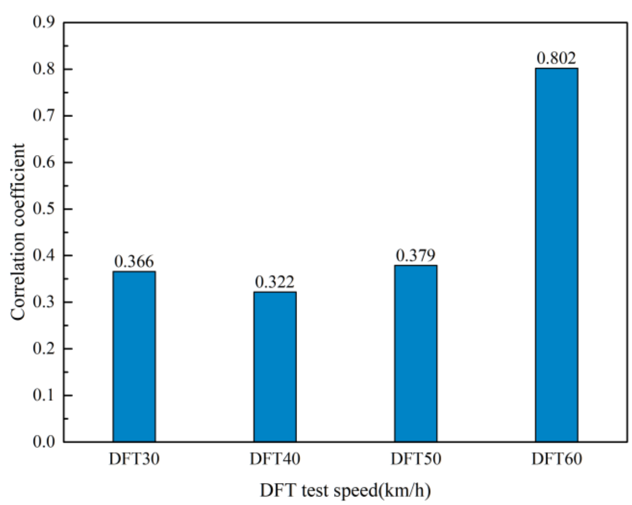


Figure 4. Pearson correlation features analysis results.

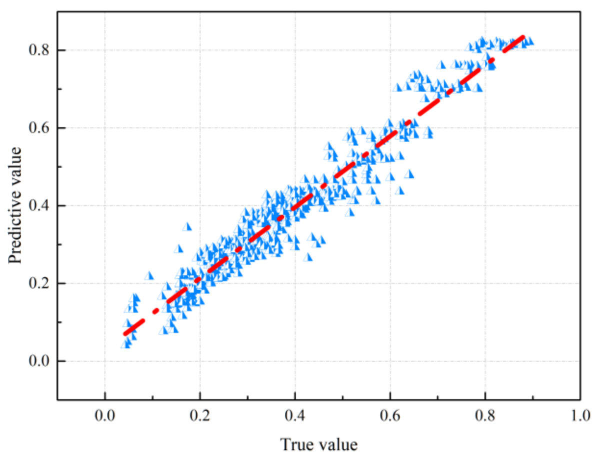
4. SKID RESISTANCE ASSESSMENT RESULTS AND DISCUSSION

4.1 Analysis of friction coefficient prediction results

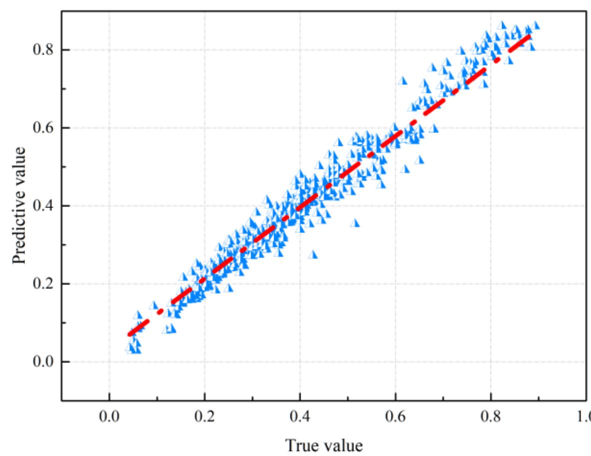
In this research, the 2333 sets of skid resistance evaluation data are divided into a 70% training set and a 30% test set. A BOA-LightGBM model is trained with MTD, pavement water content, and DFT test speed as input features to predict friction coefficient. Figure 5a shows the results of fitting the predicted values of LightGBM and true values. Figure 5b shows the fitting results of the predicted values of BOA-LightGBM and the true values. The more concentrated the scattered points are around the red line, the better the model prediction results. Analysis of figure 5 shows that the BOA-LightGBM model's predicted values are closer to the red line. Therefore, the optimized model constructed predicts better.

4.2 Evaluation of friction coefficient prediction results

Furthermore, R^2, root mean square error (RMSE), and mean absolute percentage error (MAPE) are used to quantitatively evaluate the prediction results of the model. The results are shown in table 1. Compared with LightGBM, the R^2 value of BOA-LightGBM increased by 2.7% and RMSE decreased by 1.2%. It indicates that the BOA-LightGBM model has higher prediction accuracy and the average deviation of its predicted values from the true values. At the same time, it is verified that the BOA algorithm can effectively enhance the precision of the LightGBM model.



(a)



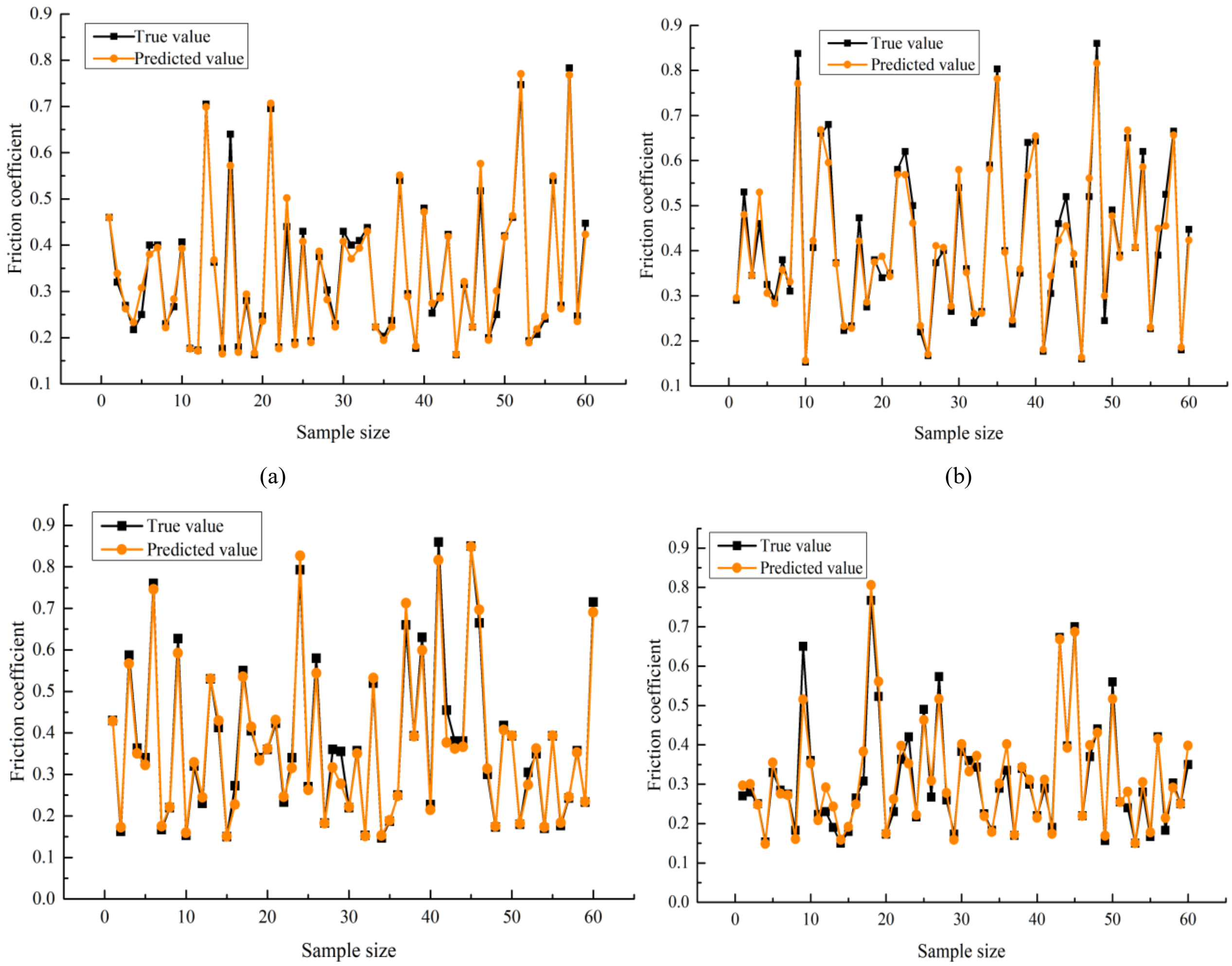
(b)

Figure 5. The fitting result of predicted value and real value. (a): LightGBM; (b): BOA- LightGBM.

Table 1. Predictive model evaluation.

Model	R^2	RMSE	MAPE
LightGBM	0.9449	0.0426	10.6742
BOA-LightGBM	0.9721	0.0303	6.3364

Thus, taking the predicted results of BOA-LightGBM model as an example, the trends of the predicted and true curves of pavement friction coefficient under DFT20-30 km/h, DFT30-40 km/h, DFT40-50 km/h and DFT50-60 km/h are analysed, and the prediction results are shown in Figure 6. The trends of the real and predicted values of the friction coefficient are basically the same. The BOA-LightGBM model has strong non-linear fitting performance in both low and high-speed conditions, and can accurately assess the pavement skid resistance.



(a) (b) (c) (d)

Figure 6. Forecasting results for dynamic friction coefficients using BOA- LightGBM. (a): DFT20-30 km/h; (b): DFT30-40km/h; (c) DFT40-50 km/h; (d) DFT50-60 km/h.

5. CONCLUSION AND FUTURE RESEARCH

In this research, we construct a dataset containing MTD, pavement water content, speed, and dynamic friction coefficients. Based on this, a model for assessing the skid resistance of asphalt pavements based on BOA-LightGBM is proposed. The BOA algorithm is employed to optimize the critical parameters of LightGBM. Compared to the pre-optimised model, the R^2 value of the optimised model increased by 2.7% to 97.12%. The research method improves the shortcomings of the traditional method such as low accuracy, sensitivity to parameter settings and poor non-linear fitting performance, and achieves accurate prediction of pavement friction performance.

Our future research efforts include: (1) collecting more data to enrich the original dataset and to better assist in model training; (2) collecting and extracting more 3D texture information to improve the accuracy of skid resistance assessment.

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