Adhesion Prediction Model for Reclaimed Asphalt Mixture Based on Machine Learning

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Abstract: The interfacial adhesion between reclaimed asphalt and aggregates is a critical factor determining the durability of the mixture, especially when a high proportion of reclaimed asphalt mixture is used. However, existing research is mostly limited to macroscopic tests and empirical models, lacking systematic investigation into the structure-property relationship between the microscopic composition of the asphalt system and its adhesion performance. In this study, a prediction model for reclaimed asphalt adhesion was constructed through multi-scale characterization techniques and based on machine learning. Convolutional Neural Network (CNN) and Elman Neural Network were selected for training, and the accuracy was evaluated using Mean Absolute Error (MAE), Relative Percentage Error (RPE), and coefficient of determination (R^2). Finally, the Elman Neural Network was selected as the reclaimed asphalt adhesion prediction model through a multi-index weighted scoring method, and adhesion evaluation indexes based on surface free energy and AFM force curves were preferred to construct a multi-scale adhesion evaluation parameter system. The results show that the Elman prediction model constructed in this paper has a relative percentage error RPE value of less than 1, a mean absolute error MAE value of less than 5, and a coefficient of determination R^2 value greater than 0.9, which can provide a reliable basis for RAP content optimization and further promote the application and development of reclaimed asphalt technology in engineering practice.

Keywords: Reclaimed Asphalt, Adhesion, Microscopic Composition Structure, Machine Learning, Elman Neural Network

1. Introduction

As China's highway infrastructure enters a period of large-scale maintenance, the annual production of Reclaimed Asphalt Pavement (RAP) exceeds 300 million tons. The efficient recycling and utilization of RAP has become a critical issue for the green development of the transportation sector. Driven by the "Dual Carbon" strategy, Warm Mix Asphalt (WMA) technology has emerged as an important direction for the sustainable development of asphalt pavements due to its ability to significantly reduce energy consumption and increase RAP content. However, the adhesion problem between the aged asphalt of RAP and the new and old aggregates is prominent, and the addition of warm mix additives may further change the interface characteristics of asphalt-aggregate [1,2]. Currently, research on the adhesion of recycled asphalt at home and abroad mostly focuses on macroscopic performance evaluation. There is still a lack of systematic research on the influence mechanism of the microscopic composition and structure of asphalt and aggregate on adhesion at the

micro scale, which restricts the application of high-percentage RAP recycling technology [3,4].

Currently, machine learning algorithms have been applied in the road field, including pavement distress analysis and prediction, asphalt mixture and asphalt material related research, etc [5]. In recent years, the methods researchers have established for asphalt precipitation models include: three Multilayer Perceptron (MLP) neural networks and three Radial Basis Function (RBF) neural networks, fuzzy C-means clustering method, genetic algorithm, hybrid support vector machine, etc [6]. Some scholars have also studied the relationship model of asphalt viscosity. Sheng et al. [7] combined an adaptive neuro-fuzzy inference system with a particle swarm optimization algorithm as a simple model for asphalt viscosity estimation. Tang [8] predicted the relationship between asphalt viscosity and tetradecane mixture based on the Least Squares Support Vector Machine (LSSVM) algorithm. Sheng et al. [9] used easily obtained compaction temperature, voids, and ITS as input variables to predict the degree of binder activity of recycled asphalt pavement samples. In this study, three techniques, namely Multiple Polynomial Regression (MPR), Artificial Neural Network (ANN), and random forest regression (RFR), were applied to fit the data into mathematical functions. The training accuracy of the three types of models was summarized and compared based on the maximum indirect tensile strength, average MAE, accuracy, and correlation coefficient of DoA prediction of the recycled asphalt pavement samples.

Based on this, this study established a database of asphalt adhesion performance and microstructure based on the microstructure of recycled asphalt and aggregate. Then, Convolutional Neural Network (CNN) and Elman Neural Network were used as models to construct a machine learning-based asphalt adhesion prediction model, and the Elman Neural Network was selected as the final recycled asphalt adhesion prediction model using the multi-index weighted average method. This model has important theoretical significance and application value for RAP content optimization, warm mix additive type selection, and aggregate compatibility.

2. Parameter Preprocessing

This paper selects different microscopic characteristic parameters of reclaimed asphalt (roughness, functional groups, and molecular weight), microscopic characteristic parameters of basalt and limestone aggregates (roughness and chemical composition), and adhesion characteristic parameters (spreading coefficient, adhesion work, and interfacial energy, etc.) as the database. However, in the process of machine learning modeling, the original features may have redundancy, collinearity, or little impact on the prediction target. Directly using all features may increase model complexity, computational cost, and reduce robustness. Therefore, feature extraction is usually required before modeling to remove irrelevant or redundant features and improve the generalization ability and computational efficiency of the model.

2.1 Feature Parameter Standardization Processing

Standardization processing is one of the important methods for original data. It can eliminate the dimensional differences and numerical distribution differences between features, so that different features can be analyzed on the same scale, thereby improving the stability, training efficiency, and prediction accuracy of the model. In this study, normalization and standardization methods are used to preprocess the characteristic parameters of the asphalt adhesion prediction model. First, the feature values are uniformly scaled to the range of [0, 1] through normalization processing to eliminate the influence of dimensional differences on the model. The normalization Equation is as follows:

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

where X is the original feature value. Through normalization processing, all features are mapped to the same numerical range, thereby providing a more consistent and comparable data basis for subsequent feature extraction and model training.

However, although normalization eliminates dimensional differences, the numerical distribution range between features may still vary greatly. This inconsistency in distribution may cause the model to be overly sensitive to certain features during the training process, thereby affecting the model's stability and prediction performance. Therefore, we further use standardization processing to convert the numerical distribution of features into a standard normal distribution with a mean of 0 and a standard deviation of 1. The Equation for standardization processing is as follows:

$$z = \frac{X - \mu}{\sigma}$$

where X is the original feature value, μ is the mean of the feature, σ is the standard deviation of the feature, and z is the standardized feature value. Through standardization processing, the numerical distribution differences between features can be further eliminated, and the training efficiency and prediction accuracy of the model can be improved. By combining normalization and standardization processing, we eliminate the dimensional differences between features, unify the numerical distribution range of features, and improve the training efficiency and prediction performance of the model.

2.2 Feature Extraction

Following feature processing, the data exhibits considerable inter-sample variability, which significantly influences the model's predictive performance. While high-variance features are present, they do not inherently demonstrate a strong correlation with the target variable. Consequently, the Pearson correlation coefficient method is employed to screen feature parameters for the asphalt adhesion prediction model. This approach evaluates the linear correlation between each feature and the target variable, facilitating the removal of redundant or irrelevant features. The Pearson correlation coefficient, a statistical measure of the linear relationship between two variables, yields values ranging from -1 to 1. A coefficient approaching 1 signifies a strong positive correlation, while a value near -1 indicates a strong negative correlation. A coefficient close to 0 suggests a negligible linear correlation. By computing the Pearson correlation coefficient between each feature and the target variable, the significance of each feature in predicting the target can be quantified, enabling the selection of features that substantially contribute to the model's performance. The Pearson correlation coefficient is calculated using the following equation:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

where x_i and y_i represent the feature value and target value of the i-th sample, respectively, $\bar{x}$ and $\bar{y}$ represent the mean of the feature and target variable, respectively, and n is the number of samples.

The correlation coefficients calculated according to the Pearson correlation coefficient equation will be divided to screen the features, and the weakly correlated and extremely weakly correlated features will be eliminated to reduce noise and redundancy [10]. The calculation results are shown in

Table 1. According to the results, this study finally retains the following feature parameters: asphalt roughness parameters $L-Ra$ and $L-Rz$, molecular weight parameter Mw, functional group parameters $R_{C=C}$, $R_{C=O}$, $I_{C=C}$, $I_{C=O}$, aggregate roughness parameter $J-Ra$, chemical composition parameters CaO and SiO_2, a total of 10 kinds, and 7 kinds of adhesion characteristic parameters, as the database of the asphalt adhesion prediction model.

Table 1: Person Coefficient.

	L-Ra	L-Rq	L-Rz	L-Rmax	Mw	d	R_{Mw}	$I_{C=O}$	$R_{C=O}$
L-Ra	1.00	0.76	0.81	0.71	0.32	-	-	0.54	0.53
L-Rq	0.76	1.00	0.86	0.76	0.58	0.53	0.50	0.69	0.64
L-Rz	0.81	0.85	1.00	0.81	0.72	0.65	0.63	0.80	0.72
L-Rmax	0.71	0.76	0.81	1.00	0.63	0.58	0.53	0.63	0.50
Mw	0.32	0.72	0.72	0.63	1.00	0.94	0.98	0.85	0.64
d	-	0.53	0.58	0.58	0.32	1.00	0.96	0.87	0.76
R_{Mw}	-	0.50	0.63	0.53	0.98	0.96	1.00	0.87	0.70
$I_{C=O}$	0.54	0.69	0.80	0.63	0.85	0.87	0.87	1.00	0.86
$R_{C=O}$	0.53	0.64	0.64	0.64	0.64	0.76	0.70	0.86	1.00
	J-Ra	SiO_2	CaO	Fe_2O_3	O	Si	Ca		
J-Ra	1.00	0.60	-0.60	0.60	0.60	0.60	-0.60		
SiO_2	0.60	1.00	-0.50	0.80	0.80	0.80	-0.50		
CaO	-0.60	-0.50	1.00	-0.50	-0.50	-0.50	0.80		
Fe_2O_3	0.60	0.80	-0.50	1.00	0.80	0.80	-0.50		
O	0.60	0.80	-0.50	0.80	1.00	0.80	-0.50		
Si	0.60	0.80	-0.50	0.80	0.80	1.00	-0.50		
Ca	-0.60	-0.50	0.80	-0.50	-0.50	-0.50	1.00		

2.3 Evaluation Metrics

Relative Percentage Error (RPE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2) are used as evaluation metrics for model accuracy to assess the accuracy of the model's predictions and to identify the optimal asphalt adhesion prediction model.

RPE has normalization characteristics, which can measure the ratio of error to the true value. It is suitable for data of different orders of magnitude, facilitates the comparison of error sizes, especially when the data distribution is wide or the scale difference between different variables is large. The calculation Equation is as follows:

$$\mathrm{RPE} = \frac{|\hat{y} - y|}{y} \times 100\%$$

where $\hat{y}$ is the model predicted value and y is the true value.

MAE is used to measure the average deviation between the predicted value and the true value, which can directly reflect the actual magnitude of the model error. Since MAE measures the error size in absolute terms, its calculation results are not as severely affected by extreme values compared to Mean Squared Error (MSE). The calculation Equation is as follows:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |\hat{y} - y|}{n} \times 100\%$$

R^2 is used to measure the goodness of fit between the model's predicted values and the true

values. The closer R^2 is to 1, the stronger the model's predictive ability and the better it can explain the changes in the true values.

Combining RPE, MAE, and R^2, the prediction performance of the model can be comprehensively evaluated from three perspectives: relative error, absolute error, and goodness of fit. RPE is suitable for comparing data of different dimensions, reflecting the relative magnitude of the prediction error; MAE is suitable for comparing data of the same dimension, reflecting the absolute magnitude of the prediction error; R^2 measures the model's ability to explain the changes in the true values, reflecting the model's fitting effect. Comprehensive analysis of the three parameters can provide a more comprehensive and reliable evaluation of model performance, ensuring the accuracy and stability of the model in practical applications.

3. Adhesion Prediction Model for Reclaimed Asphalt Mixture

3.1 Adhesion Prediction Model Based on CNN

The core idea of CNN is to extract local features through convolution operations and reduce data dimensionality through pooling operations, thereby achieving efficient processing of input data. The processing procedure is as follows:

(1) Construction of the Adhesion Prediction Model

Input Layer: Input data is converted into a multi-dimensional tensor.

Convolutional Layer: Convolution kernels are used to perform convolution operations on the input data, extracting local features. The Equation is as follows:

$$y_{i,j} = \sum_{m=1}^{k} \sum_{n=1}^{k} x_{i+m-1,j+n-1} \bullet \omega_{m,n} + b$$

where x is the input data, ω is the convolution kernel, and x is the bias term.

Activation Function: A non-linear activation function is applied to the convolution result. The Equation is as follows:

$$Relu(x) = \max(0, x)$$

Pooling Layer: A pooling operation is performed on the convolution result to reduce data dimensionality. The Equation is as follows:

$$y_{i,j} = \max(x_{i:i+k:j+k})$$

Fully Connected Layer: The pooled feature map is flattened and input into a fully connected layer for classification or regression.

Output Layer: Outputs the final prediction result.

Loss Function and Optimization: The error between the predicted value and the true value is calculated, and the model parameters are updated through backpropagation.

(2) CNN Prediction Model Evaluation Results

The error analysis results of the seven adhesion prediction models constructed based on the CNN method, as well as the comparison effect between the predicted values and the actual values, are shown in Tables 2 and 3, respectively, to more intuitively evaluate the generalization ability and prediction accuracy of the models.

Table 2: Evaluation Results of CNN Prediction Model.

Evaluation Index	$S_{a/s}$	W_{as}	W_{aws}	E_1	E_2	W_{AB}	γ_{AB}
RPE	0.41	0.41	0.60	4.08	0.03	0.02	2.79

MAE	6.57	1.04	1.01	3.77	3.13	3.75	4.16
R^2	0.95	0.95	0.97	0.83	0.50	0.47	0.88

Table 2 shows the error values of the prediction models. The smaller the values of RPE and MAE, the higher the accuracy of the model. The closer the R^2 value is to 1, the higher the accuracy of the model. The seven CNN models generally perform well in terms of prediction performance. Among them, the $S_{a/s}$, W_{as}, W_{aws}, and γ_{AB} models have smaller errors and higher goodness of fit. The RPE is less than 3%, the MAE is also small, and the R^2 coefficient of determination is greater than 0.88, indicating that these models can well explain the changes in the true values and have high prediction accuracy. In particular, the W_{aws} model has an R^2 of 0.97, showing a high degree of fitting.

However, the performance of the E_1, E_2, and W_{AB} models is relatively poor. The RPE of the E_1 model is 4.08%, which is a relatively large error. Although its MAE and R^2 values are reasonable, further optimization is needed to reduce prediction bias. The E_2 and W_{AB} models have low RPE and MAE, indicating high prediction accuracy, but their R^2 values are 0.50 and 0.47, respectively, which is a low degree of fitting, indicating that the model's ability to explain the changes in the true values is weak, and the model structure may need to be adjusted to improve the fitting effect.

Table 3: Prediction Results of the CNN Model.

	Actual value	Predicted value		Actual value	Predicted value		Actual value	Predicted value		Actual value	Predicted value
	40.0	40.5		105	110		0.36	0.37		53.5	52.2
	41.0	41.0		100	103		0.38	0.39		51.5	52.1
$S_{a/s}$	40.0	39.5	W_{as}	104	108	E_2	0.37	0.38	γ_{AB}	52.5	52.1
	37.0	38.0		90	88		0.41	0.40		48.5	50.2
	44.0	43.5		115	120		0.35	0.38		52.6	54.3
	59.5	59.0		0.55	0.54		52.0	52.5			
	59.0	58.7		0.58	0.57		52.0	50.3			
W_{as}	57.2	57.5	E_1	0.55	0.54	W_A	52.5	50.4			
	55.5	55.0		0.59	0.60		51.2	50.3			
	64.0	64.5		0.58	0.56		53.6	52.5			

Table 3 shows the prediction results of the CNN model. It can be seen that in these seven adhesion prediction models, the predicted values of $S_{a/s}$ and W_{as} basically coincide with the actual values in the first few data points, and the prediction effect is better. As the number of data points increases, the deviation between the predicted value and the actual value increases slightly, but the overall deviation is small. The deviation between the predicted values of γ_{AB} and W_{AB} and the actual values changes the least with the increase of data points, basically remaining unchanged. However, W_{aws} performs the worst among the seven prediction models. Not only is the deviation between the predicted value and the actual value large, but the change in deviation is most obvious as the number of data points increases. Comprehensive analysis of the error values of the CNN model and the model effect comparison chart of predicted values and actual values shows that the prediction effects of the three prediction models $S_{a/s}$, W_{as} and γ_{AB} are the best, with small errors. The prediction effect of the W_{aws} prediction model is the worst.

3.2 Adhesion Prediction Model Based on Elman Neural Network

The Elman Neural Network is a type of Recurrent Neural Network (RNN) that has a context layer (memory unit) and can process sequence data.

(1) Construction of the Adhesion Prediction Model

Input layer: Input sequence data.

Hidden layer: The input data is weighted, summed, and passed through an activation function to the hidden layer, according to the following Equation:

$$h_t = f(\sum_{i=1}^{n} \omega_{hi} x_{t,i} + \sum_{j=1}^{m} \omega_{hh} h_{t-1,j} + b_h)$$

where h_t is the hidden state at the current time, and h_{t-1} is the hidden state at the previous time.

Context layer: Stores the hidden state h_{t-1} from the previous time and passes it as input to the current time.

Output layer: The output of the hidden layer is weighted, summed, and passed through an activation function to the output layer, according to the following Equation:

$$y_t = f(\sum_{j=1}^{m} \omega_{oj} h_{t,j} + b_o)$$

Loss function: Calculate the gradient of the loss function with respect to the weights and biases, and update the parameters, according to the following Equation:

$$E = \frac{1}{2} \sum_{t=1}^{T} (y_t - t_t)^2$$

Backpropagation: Calculate the gradient of the loss function with respect to the weights and biases, and update the parameters, according to the following Equation:

$$\omega_{hi} \leftarrow \omega_{hi} - \eta \frac{\partial E}{\partial \omega_{hi}}, \omega_{hh} \leftarrow \omega_{hh} - \eta \frac{\partial E}{\partial \omega_{hh}}$$

Iterative training: Repeat forward propagation and backpropagation until the model converges.

(2) Evaluation Results of the Elman Neural Network Prediction Model

The error analysis results of the seven adhesion prediction models constructed based on the Elman Neural Network method, as well as the comparison between predicted and actual values, are shown in Tables 4 and 5, respectively, allowing for a more intuitive evaluation of the model's generalization ability and prediction accuracy.

Table 4: Evaluation Results of the Elman Neural Network Prediction Model.

Evaluation Index	$S_{a/s}$	W_{as}	W_{aws}	E_1	E_2	W_{AB}	γ_{AB}
RPE	0.51	0.24	1.27	2.68	0.02	0.02	0.87
MAE	6.19	0.57	2.10	2.46	1.01	1.77	1.83
R^2	0.92	0.98	0.88	0.91	0.94	0.89	0.95

Table 4 shows the error values of the Elman Neural Network prediction model, and a comprehensive analysis is performed on the RPE, MAE, and R^2 indicators of the seven adhesion prediction models. First, looking at the relative percentage error RPE, the RPE values of the seven models are all less than 3, and the RPE values of E_2 and W_{AB} are 0.02, indicating that the prediction error of the model is small. Secondly, except for the MAE value of $S_{a/s}$, which is 6.19 and slightly

higher than the normal range, the MAE values of the remaining adhesion evaluation indicators are all less than 3. Finally, looking at the R^2 coefficient, the R^2 values of all models are between 0.88 and 0.98, and the fitting degree between the prediction results of these seven models and the actual values is very good.

In summary, except for $S_{a/s}$ which performs poorly on the MAE indicator, the other adhesion prediction models perform well in terms of error and fitting degree. Compared with other models, the Elman Neural Network prediction model shows the best error analysis results and the best fitting degree between the prediction results and the actual values.

Table 5: Prediction Results of the Elman Neural Network Model.

	Actual value	Predicted value		Actual value	Predicted value		Actual value	Predicted value		Actual value	Predicted value
	40.0	39.5		106	110		0.36	0.37		51.5	49.2
	40.0	40.5		101	103		0.39	0.38		51.5	52.1
$S_{a/s}$	39.0	39.0	W_{as}	104	105	E_2	0.37	0.37	γ_{AB}	52.5	51.6
	37.0	37.0		90	88		0.41	0.40		43.8	52.0
	43.0	43.5		115	118		0.35	0.37		51.1	52.0
	59.5	58.5		0.53	0.54		51.5	50.5			
	60.0	58.7		0.58	0.57		51.0	50.3			
W_{as}	58.1	57.5	E_1	0.56	0.56	W_{AB}	53.5	52.5			
	55.5	55.0		0.58	0.60		51.2	51.2			
	64.0	65.5		0.56	0.55		53.6	52.5			

Among these seven adhesion parameters, the difference between the predicted and actual values of the Elman Neural Network prediction model is generally small, showing good prediction ability. However, as the number of data points increases, the predicted values of $S_{a/s}$, W_{as}, W_{aws}, and E_2 in the last few data points deviate slightly more compared to the first few data points, and there are some fluctuations in the prediction results. In contrast, the changes in E_1, W_{AB}, and γ_{AB} in all data points are relatively stable, and the prediction results are more accurate and stable. Comprehensive analysis of the error values of the Elman Neural Network prediction model and the comparison chart of predicted values and actual values reveals that although some parameters show slight deviations when the number of data points increases, the overall prediction effect of the model is ideal.

4. Optimal Selection of the Prediction Model

To select the best model from CNN and Elman Neural Network, this study uses a multi-index weighted scoring method for comprehensive evaluation [11]. This method combines multiple error indicators (RPE, MAE) and goodness-of-fit indicators (R^2) to quantitatively score the performance of the models, thereby scientifically and objectively selecting the optimal model.

4.1 Model Normalization Processing

Since the dimensions and value ranges of RPE, MAE, and R^2 are different, they need to be normalized to be compared on the same scale. The smaller the RPE and MAE values, the better, so their normalization Equation is:

$$X'_{RPE} = 1 - \frac{RPE}{\max(RPE)}, X'_{MAE} = 1 - \frac{MAE}{\max(MAE)}$$

The larger the R^2 is, the better, and its normalization Equation is:

$$X'_{R^2} = \frac{R^2}{\max(R^2)}$$

The accuracy evaluation result after normalization is shown in Table 6.

Table 6: Normalized Processing Values of Accuracy Evaluation Indicators.

Neural Network	Evaluation Index	$S_{a/s}$	W_{as}	W_{aws}	E_1	E_2	W_{AB}	γ_{AB}
CNN	RPE	0.91	0.91	0.87	0.01	1.01	1.01	0.33
	MAE	0.01	0.85	0.86	0.44	0.53	0.44	0.38
	R2	0.98	0.98	1.02	0.86	0.52	0.49	0.92
Elman	RPE	0.89	0.95	0.70	0.35	1.01	1.01	0.80
	MAE	0.07	0.92	0.69	0.64	0.86	0.74	0.73
	R2	0.96	1.03	0.91	0.95	0.97	0.93	0.98

4.2 Comprehensive Scoring Calculation of the Model

Based on actual needs and research objectives, weights need to be assigned to RPE, MAE, and R^2. In the optimal selection process of the asphalt adhesion prediction model, the weight allocation of $RPE:MAE:R^2 = 3:3:4$ is adopted [12]. RPE and MAE each account for 30% of the weight, which can balance the importance of relative error and absolute error, ensuring that the model performs balanced on different error indicators. R^2 accounts for 40% of the weight, emphasizing the importance of fitting ability in model evaluation, ensuring that the selected model not only has small errors but also can well explain the changes in the data. The Equation for calculating the comprehensive score of different models is as follows [12]:

$$S = (X'_{RPE} \times 0.3) + (X'_{MAE} \times 0.3) + (X'_{R^2} \times 0.3)$$

The comprehensive scoring results are shown in Table 7:

Table 7: Comprehensive Scoring Results of the Prediction Model.

Neural Network	$S_{a/s}$	W_{as}	W_{aws}	E_1	E_2	W_{AB}	γ_{AB}
CNN	0.66	0.92	0.91	0.47	0.66	0.62	0.57
Elman	0.66	0.97	0.77	0.67	0.94	0.89	0.85

According to the content of Table 7, it can be seen that among these 7 adhesion evaluation indicators, Was, Waws, E2, and WAB show relatively stable and high scores in the scoring, indicating that they have a strong correlation with adhesion. Therefore, we choose these four indicators as the final adhesion evaluation model. Furthermore, according to the comparison and analysis of the model scores of CNN and Elman based on these four adhesion indicators, the Elman prediction model scores are higher than those of the CNN prediction models in the W_{as}, E_2, and W_{AB} adhesion prediction models. In the Waws adhesion prediction model, the CNN model's score is slightly higher than the Elman prediction models. Therefore, a comprehensive analysis indicates that the Elman model has the best prediction effect.

In summary, the Elman prediction model is the best choice for adhesion prediction due to its

high comprehensive score, and the four characteristic parameters for evaluating adhesion, Was, Waws, E2, and WAB, are more suitable for key indicators for adhesion prediction. This combination can provide more accurate and reliable prediction results for adhesion analysis.

5. Conclusion

In response to the limitations of existing methods for studying the adhesion of reclaimed asphalt, which are relatively singular, and the lack of systematic research on the influence mechanism of the micro-composition structure of asphalt and aggregate on adhesion at the micro- and multi-scale levels, this paper constructs a prediction model database based on 10 key input features and 7 adhesion output features. This is achieved through systematic feature parameter extraction and screening methods, according to the correlation between different characteristic parameters and adhesion indicators. Then, a prediction model based on a CNN and an Elman neural network was built using the Python programming language. The performance of the model was systematically evaluated using three evaluation indicators: RPE, MAE, and R^2, and the Elman neural network was selected as the reclaimed asphalt adhesion prediction model. Finally, the optimized adhesion prediction model based on the Elman neural network was evaluated. The results show that the relative percentage error RPE value of the model is less than 1, the average absolute error MAE value is less than 5, and the coefficient of determination R^2 value is greater than 0.9, all of which meet the accuracy requirements. The prediction model established in this study provides a new technical means for the adhesion evaluation of reclaimed asphalt, and its prediction results can provide data support for the material design and performance optimization of reclaimed asphalt pavements.

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