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Freeze-thaw Damage Model for Compressive Strength of Flowable Solidified Soil Based on Machine Learning

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Abstract : Freeze-thaw cycling is a critical factor triggering durability degradation of flowable solidified soil in cold-region engineering, and its damage evolution process is affected by multi-factor coupling with obvious nonlinear characteristics. Based on experimental compressive strength data of flowable solidified soil under freeze-thaw cycles, four influencing factors, namely solidifier dosage (SD), admixture dosage (AD), water-solid ratio (WS) and freeze-thaw cycle number (F-T), are selected as input variables. Four machine learning algorithms including Decision Tree (DT), BP Neural Network (BP), Support Vector Regression (SVR) and XGBoost are adopted to establish freeze-thaw damage prediction models for the compressive strength of flowable solidified soil. The SHAP interpretable framework is further employed for feature sensitivity analysis to quantify the contribution and nonlinear effect of each input factor on prediction results. The results reveal that the DT model suffers severe overfitting with drastic error fluctuations on the test set; BP and SVR exhibit stable generalization performance; the ensemble tree model XGBoost achieves the optimal fitting capacity and superior overall prediction balance. SHAP analysis indicates the feature importance ranking: F-T > SD > AD > WS. Freeze-thaw cycle number (F-T) acts as the dominant control factor, and high/low values of each factor impose distinct positive and negative effects on model outputs. The proposed modeling and interpretive analysis method can provide technical references for rapid prediction of mechanical indices of similar compression specimens and identification of primary influencing factors.

Keywords: freeze-thaw cycles; flowable solidified soil; compressive strength; machine learning; prediction model

1. Introduction

Flowable solidified soil is a new type of geotechnical engineering material formed by improving waste soft soil, muck, industrial solid waste and other soils via solidification technology. It has been widely applied in civil engineering fields including subgrade backfilling, foundation pit backfilling, soft soil foundation treatment and gap filling of underground engineering, serving as one of the core materials for the resource utilization of geotechnical solid waste and the development of green infrastructure^[1-3]. Soil freeze-thaw damage is a complex nonlinear evolution process under the coupling effect of multiple factors. Traditional empirical formulas and statistical models fail to accurately fit the nonlinear mapping relationship between

multiple variables and strength damage, exhibiting limited generalization ability and prediction accuracy, and cannot meet the demand for precise prediction of the freeze-thaw compressive strength damage of flowable solidified soil under complex working conditions^[4-8]. Therefore, constructing an efficient, accurate and adaptable prediction model to replace traditional tests and empirical models and realize the rapid prediction of freeze-thaw compressive strength damage of flowable solidified soil has become a key research focus in this field.

With the rapid development of artificial intelligence and big data technologies, machine learning algorithms, endowed with powerful capabilities in nonlinear fitting, multi-variable coupling analysis and data mining, have become mainstream technical tools for predicting the mechanical properties of civil engineering materials. They are widely adopted in strength prediction research of geotechnical and construction materials, effectively breaking through the technical bottlenecks of traditional modeling methods. Vijaya et al. verified the feasibility of supervised machine learning algorithms in parameter fitting and performance prediction, providing fundamental methodological support for intelligent performance prediction of various engineering materials^[8]. Li et al. adopted machine learning to accurately predict the axial compressive strength of circular double-skin concrete-filled steel tubular columns and demonstrated the advantages of machine learning in predicting mechanical behaviors of composite structures^[9]. Santhosh et al. established compressive strength prediction models for lime mortar using multiple supervised learning algorithms, which effectively addressed the insufficient fitting accuracy of traditional models for the nonlinear variation of binder strength^[10]. Ahadian et al. introduced interpretable machine learning methods to achieve precise prediction of compressive strength for fly ash-based geopolymers concrete, offering new insights into the optimization of intelligent prediction models for material properties^[11].

Beyond cemented geotechnical materials, machine learning techniques have been extended to the mechanical property prediction of metals, polymers, welded components, composite materials and other fields, exhibiting excellent generality and robustness. Klimenko et al. realized the accurate strength prediction of high-entropy alloys based on machine learning algorithms, verifying the applicability of such techniques in material performance modeling scenarios with multiple components and influencing factors^[12]. Fang et al. constructed a hybrid machine learning model, which effectively improved the prediction stability and accuracy of undrained shear strength of soil, providing a novel method for the prediction of geotechnical mechanical parameters^[13]. Combining physical information constraints, Li et al. developed a theory-guided machine learning model to accurately predict the strength characteristics of polymer materials under different temperatures and strain rates, realizing the organic integration of data-driven methods and physical mechanisms^[14]. Meanwhile, machine learning has been successfully applied in various prediction scenarios, including electromagnetic field intensity, bond strength between FRP bars and ultra-high-performance concrete, compressive strength of high-performance concrete, tensile strength of welded components, mechanical properties of high-strength steel welded joints, and strength of composite joints in hygrothermal

environments. These applications fully prove that machine learning algorithms can effectively explore the complex correlations between multiple variables and material mechanical properties, and possess higher prediction accuracy and broader applicability than traditional statistical models^[15-22]. Existing studies have fully demonstrated that machine learning techniques are suitable for nonlinear prediction of mechanical properties of various engineering materials. However, targeted prediction models dedicated to the freeze-thaw compressive strength damage of flowable solidified soil are still lacking, which cannot meet the requirements for rapid durability evaluation of flowable solidified soil engineering in cold regions.

In view of the above research status and existing technical shortcomings, this study focuses on the compressive strength damage characteristics of flowable solidified soil under freeze-thaw cycles, and develops a machine learning-based prediction model for freeze-thaw damage in the compressive strength of flowable solidified soil. By sorting out key influencing parameters, including freeze-thaw cycle number, solidifier dosage, admixture dosage, and water-solid ratio, the model is trained, validated, and optimized using experimental datasets to analyze the nonlinear degradation law of the compressive strength of flowable solidified soil under multi-factor coupling effects. This study aims to overcome the limitations of low efficiency in traditional experimental methods and low prediction accuracy of conventional empirical models, thereby achieving efficient and precise prediction of freeze-thaw compressive strength damage of flowable solidified soil. The research outcomes can provide innovative technical support and theoretical references for the durability evaluation, material proportion optimization, and long-term service safety guarantee of flowable solidified soil engineering in cold regions.

2. Database Establishment

2.1 Parameter Selection

Silty clay was adopted in the indoor test, with a wet density of 1.76 g/cm^3 and a natural water content of 32.16%. A photoelectric liquid-plastic limit combined tester was used to measure the liquid limit and plastic limit of the soil, which were 45.52% and 23.65%, respectively. The calculated plasticity index and liquidity index were 21.87 and 0.39. The particle size distribution curve is shown in Figure 1. The soil solidifier was prepared using industrial solid wastes such as fly ash and slag powder as the main raw materials, mixed with composite activators. Polycarboxylate high-performance water reducer was selected as the admixture in this test.

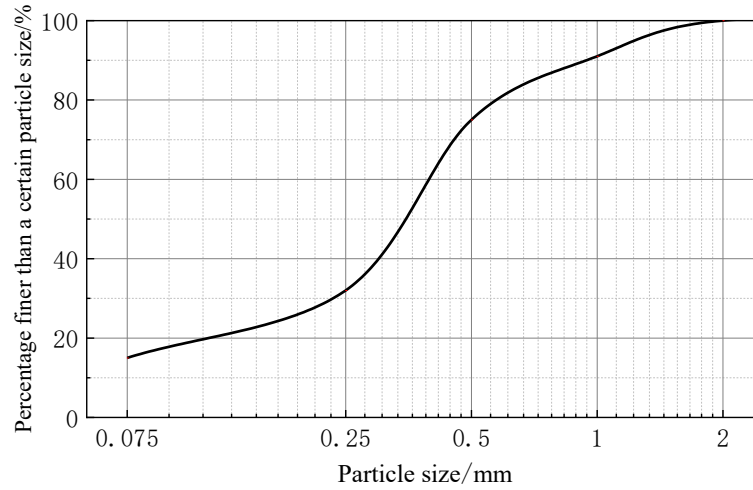


Fig 1 Particle size grading curve

To obtain the strength data of flowable solidified soil under freeze-thaw cycles, cubic specimens with a size of 5 cm × 5 cm were prepared with different mix proportions. The selected solidifier dosages were 5%, 10%, 15%, 20% and 25%, the admixture dosages were 0%, 0.2%, 0.5%, 1.0% and 1.5%, and the water-solid ratios were 40%, 45%, 55%, 60% and 70%. A total of 50 freeze-thaw cycles and compressive strength tests were carried out. In the freeze-thaw cycle test, the freezing temperature was set to -10 °C and the thawing temperature was set to 20 °C. The test procedure is illustrated in Figure 2.

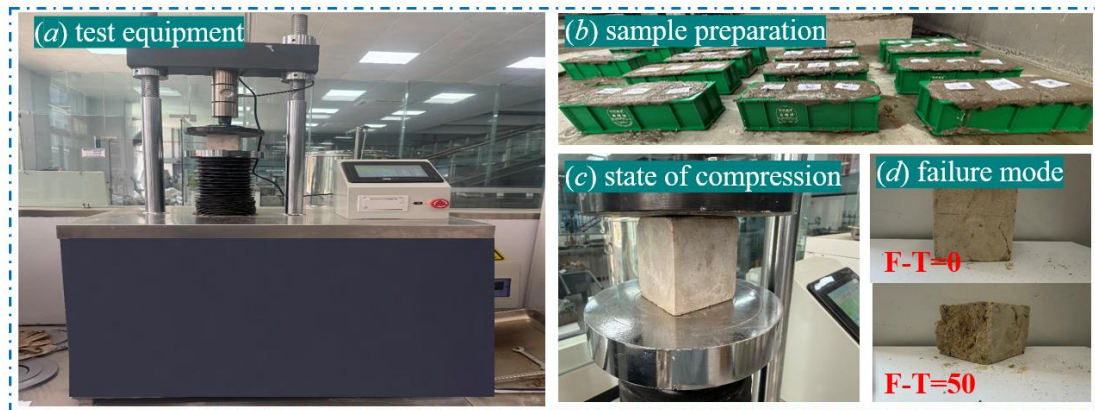


Fig 2 Test procedure

2.2 Data Analysis

Figure 3 presents the frequency distribution of test parameters and compressive strength of flowable solidified soil. Three input variables, namely solidifier dosage (SD), admixture dosage (AD), and water-solid ratio (WS), approximately follow a normal distribution. The samples are mainly concentrated at an SD of 15%, an AD of 0.5%, and a WS of 55%, while the samples of freeze-thaw cycle number are uniformly distributed at each preset level. The compressive strength also exhibits an approximate normal distribution, with most samples concentrated in the range of 3.0–3.5 MPa. The established dataset fully covers the value ranges of each variable in practical engineering with complete variable gradients and clear sample distribution characteristics. The reasonable data structure is suitable for machine learning model

training, enabling the model to adequately learn the evolution law of compressive strength of flowable solidified soil under diverse parameter conditions.

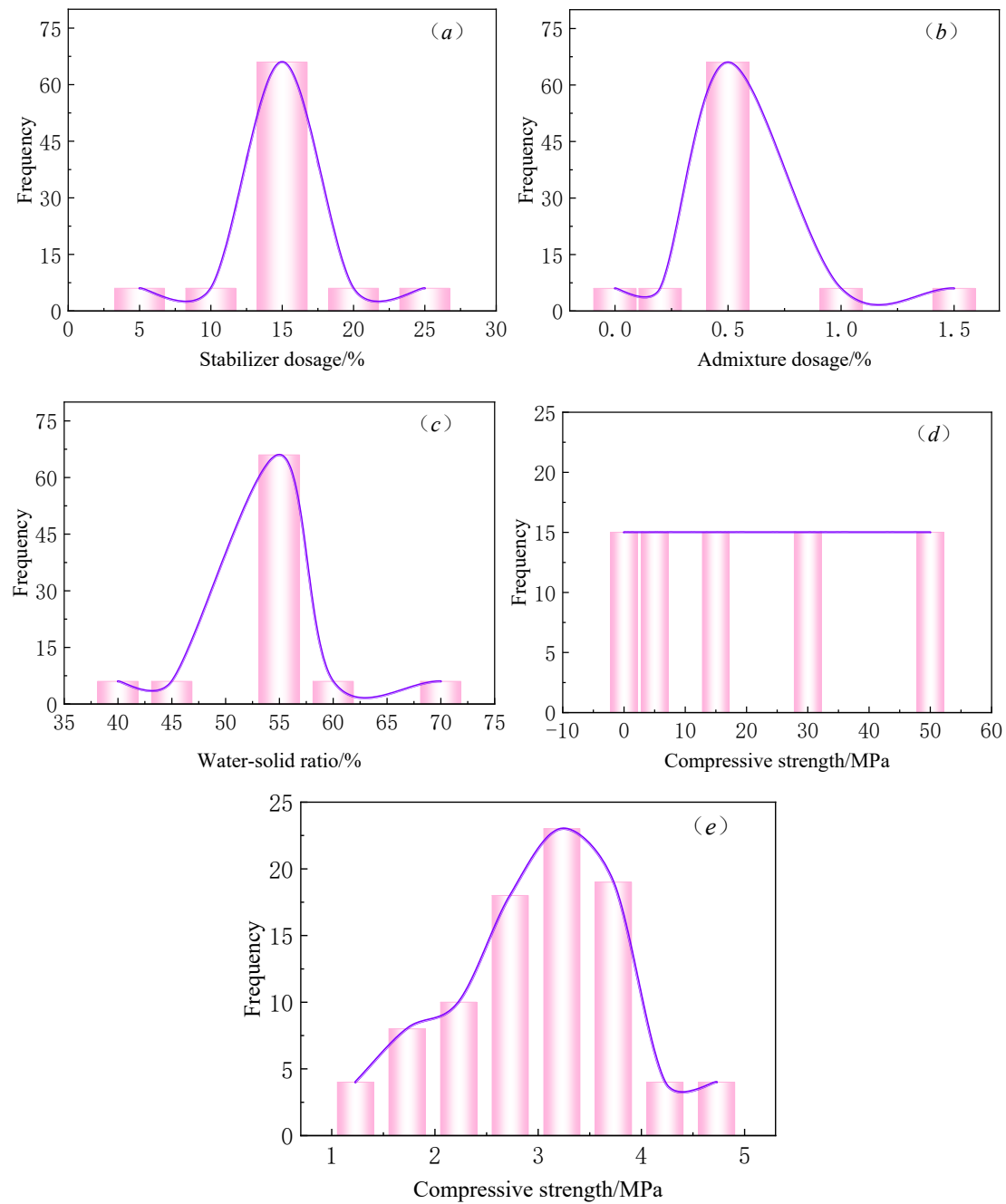


Fig 3 Frequency distribution of parameters

3. Model Construction and Evaluation

3.1 Construction of Machine Learning Models

Four machine learning models were adopted for model construction in this study: Decision Tree (DT), Back Propagation Neural Network (BP), Support Vector Regression (SVR), and Extreme Gradient Boosting (XGBoost). The experimental dataset was employed for model training, in which 80% of the data was randomly assigned as the training set and the remaining 20% as the test set^[23-25]. The optimal hyperparameters of each model are presented in Figure 4.

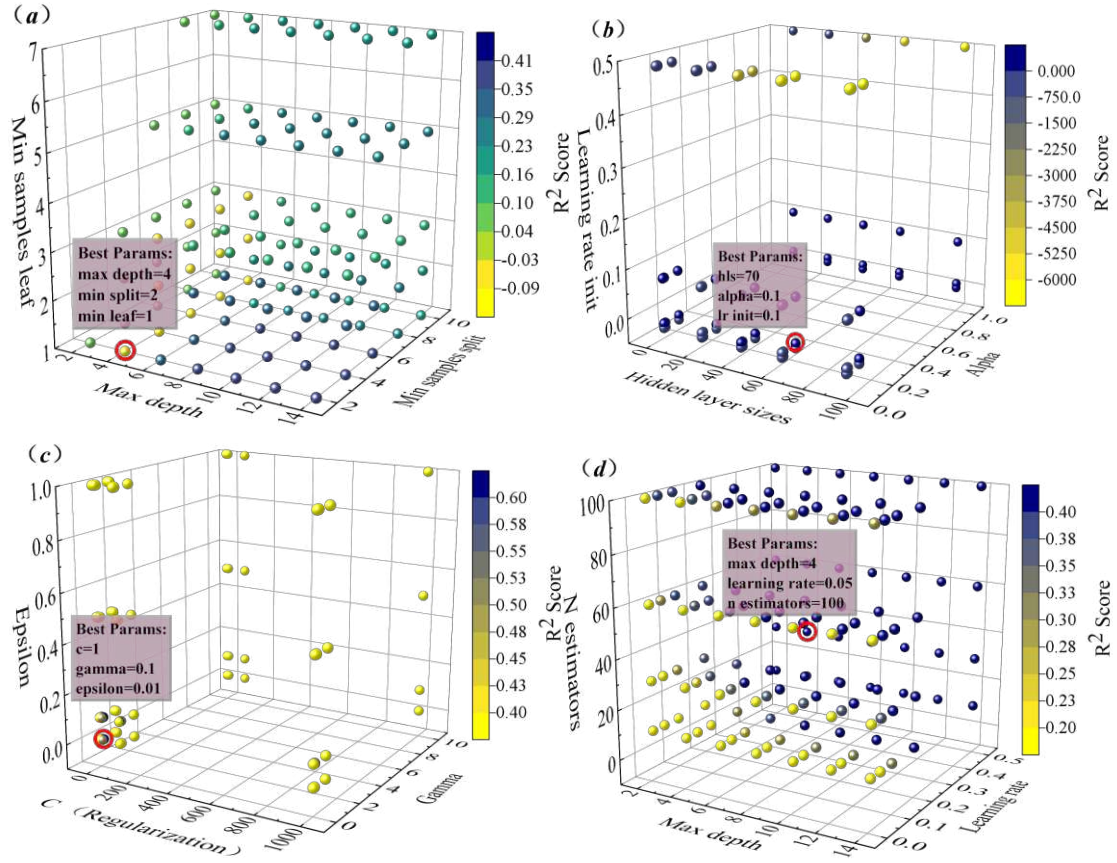
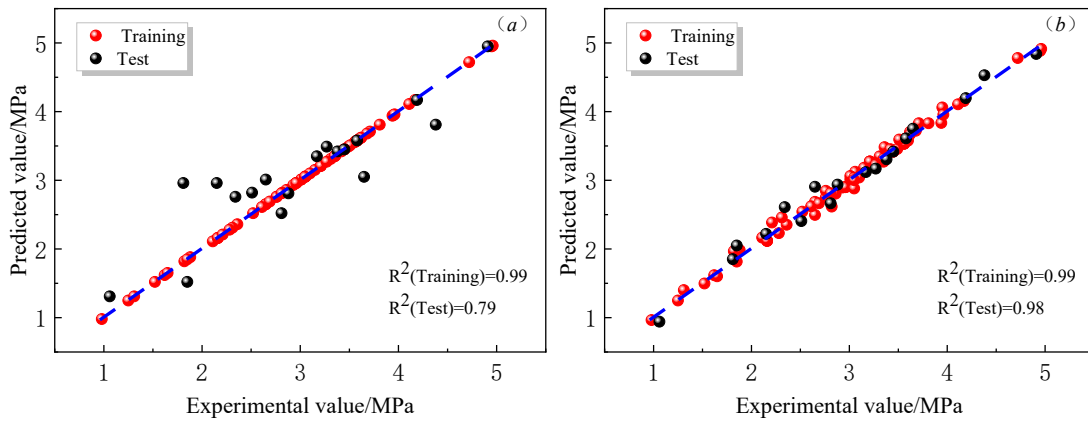


Fig 4 Optimal hyperparameter search of models: (a) *DT*, (b) *BP*, (c) *SVR*, (d) *XGBoost*

Figure 5 shows the scatter plots comparing the predicted and experimental values of the established models. All four models achieve a coefficient of determination R^2 higher than 0.99 on the training set, indicating satisfactory fitting performance on training samples. Nevertheless, significant differences in prediction accuracy are observed on the test set. The *DT* model yields a low test-set R^2 of 0.79 with considerable discrete data points. Both *BP* and *SVR* models obtain a test-set R^2 of 0.98, and their predicted values are densely distributed along the ideal diagonal reference line. The *XGBoost* model achieves a test-set R^2 of 0.95, exhibiting slightly lower prediction accuracy than *BP* and *SVR* but distinctly superior performance compared with the *DT* model.



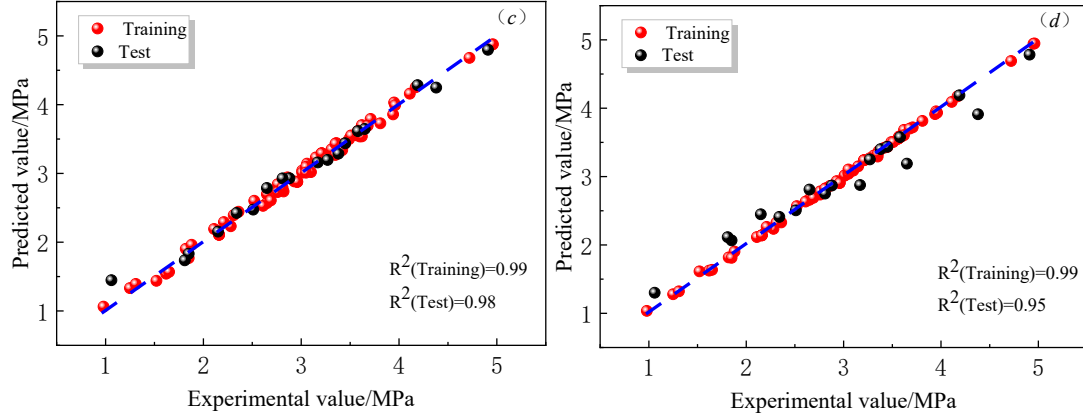


Fig 5 Predicted and experimental values: (a) *DT*, (b) *BP*, (c) *SVR*, (d) *XGBoost*

3.2 Model Evaluation

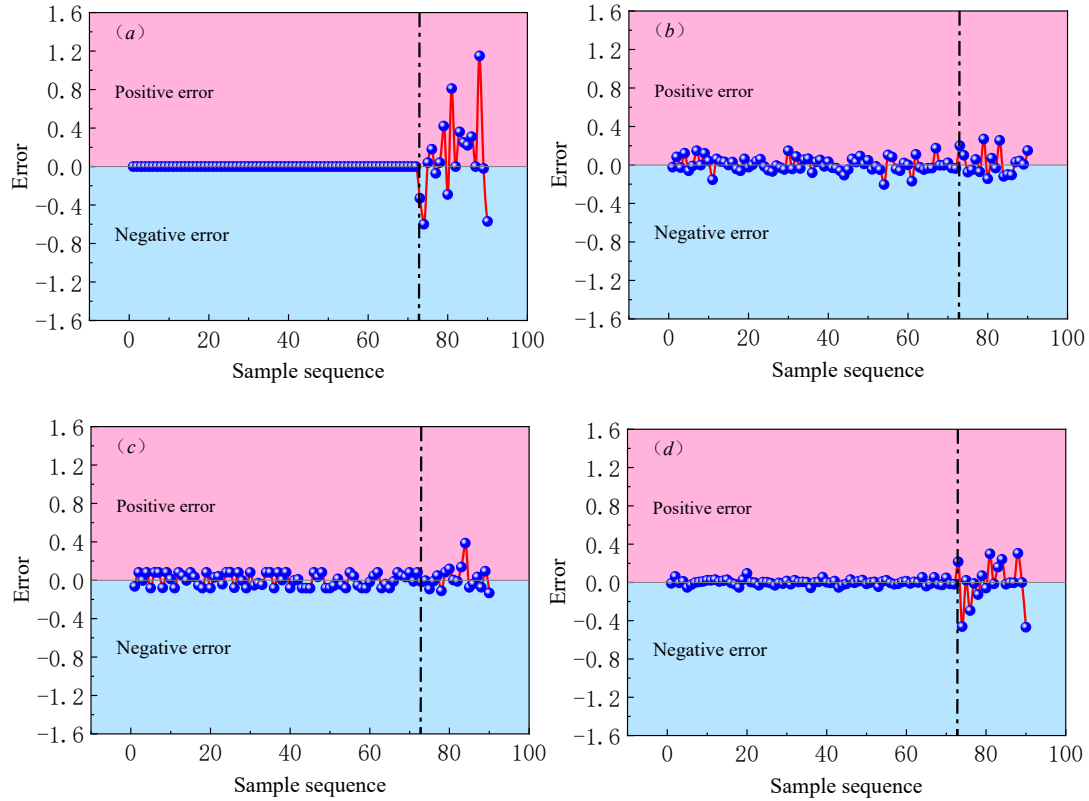


Fig 6 Distribution of differences between predicted and experimental values: (a) *DT*, (b) *BP*, (c) *SVR*, (d) *XGBoost*,

Figure 6 illustrates the distribution characteristics of model prediction errors along the sample sequence, where the vertical dashed line divides the intervals of training samples and test samples. The DT model exhibits severe positive and negative error fluctuations in the test sample interval, with the maximum error extremum and the poorest generalization stability. The errors of BP and SVR models are generally close to the zero line, while positive and negative deviations still exist in overall samples, resulting in unsatisfactory generalization stability. For the XGBoost model, the training set errors remain basically stable near zero, and only limited error fluctuations occur in the test interval, with the error amplitude significantly lower than

that of the DT model. Comprehensive comparison indicates that XGBoost effectively suppresses the drastic fluctuation of prediction errors compared with the single decision tree, presenting excellent robustness and balanced performance in comprehensive fitting ability and generalization capacity.

Figure 7 presents the distribution of the ratios of predicted values to experimental values for each model, in which subgraph (a) corresponds to the training set and subgraph (b) corresponds to the test set. In the training set, the ratios of all four models are concentrated around 1. The DT model shows the best concentration performance, followed by the XGBoost model, while BP and SVR exhibit relatively larger dispersion. In the test set, the DT model possesses the widest dispersion range of ratios with significant fluctuations, indicating severe prediction deviation. Although the dispersion degrees of BP and SVR are reduced, obvious abnormal samples deviating from 1 can still be observed. By contrast, the XGBoost model delivers a more compact ratio interval and a median value highly close to 1 on the test set, with the lowest dispersion among all the established models. The results demonstrate that the XGBoost model possesses higher prediction stability and superior generalization performance, and can effectively reduce the deviation between predicted values and experimental values.

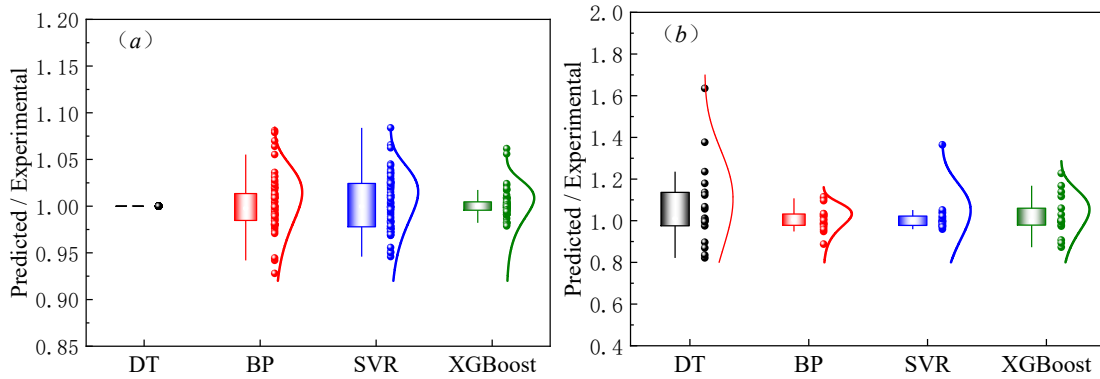


Fig 7 Distribution of ratios between predicted and experimental values: (a) Training, (b) Test

Table 1 lists the root mean square error (RMSE) and mean absolute error (MAE) evaluation metrics of the four models on the training and test sets. The training set errors of DT and XGBoost are nearly close to zero, indicating adequate fitting for training samples. However, the DT model exhibits a substantial increase in RMSE and MAE on the test set, demonstrating significant overfitting. The BP neural network and SVR maintain moderate training errors and desirable generalization ability. As an ensemble tree model, XGBoost can effectively alleviate the overfitting problem of a single decision tree and achieves the minimum prediction error among all the four models. The comprehensive evaluation metrics indicate that XGBoost obtains the optimal prediction performance with a good balance of fitting capability and generalization ability, followed by SVR and BP neural network, while the single decision tree DT has the poorest generalization performance.

Table 1 Model performance

Model	Training		Test	
	RMSE	MAE	RMSE	MAE
DT	1.282e-16	3.701-17	0.435	0.314
BP	0.070	0.055	0.127	0.104
SVR	0.087	0.061	0.119	0.082
XGBoost	0.038	0.029	0.147	0.109

3.3 Sensitivity Analysis of Influencing Factors

Figure 8 shows the feature importance of each parameter. The feature importance ranking from high to low is F-T > SD > AD > WS. Among all factors, F-T exerts the most significant influence on the model prediction results and serves as the dominant factor, followed by SD. In contrast, AD and WS contribute relatively less to the prediction performance. The findings quantitatively reveal the influence magnitude of each factor on the target output, providing a reliable basis for the feature sensitivity analysis of the prediction model.

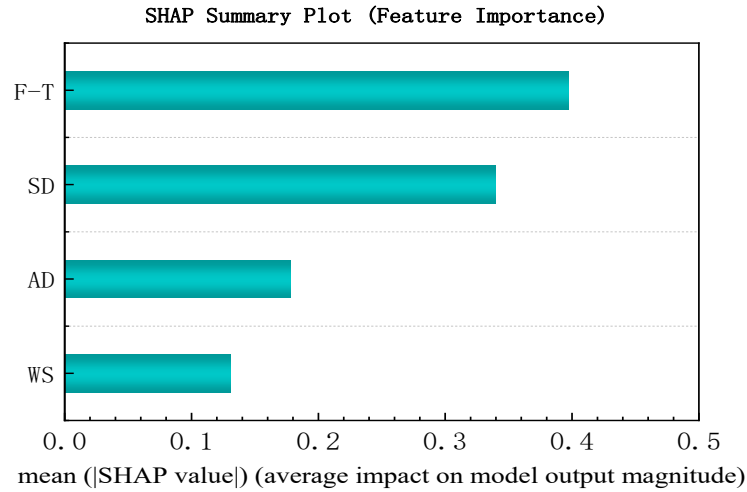
**Fig 8 Parameter importance ranking**

Figure 9 presents the parameter sensitivity analysis results based on SHAP values. The horizontal axis represents the SHAP value, where positive values increase the predicted results and negative values decrease the predicted results. The color of each dot denotes the feature value: blue corresponds to low feature values, and red corresponds to high feature values. For F-T, high F-T values (blue) correspond to positive SHAP values and increase the model output, while low F-T values (red) produce negative effects and reduce the predicted values. F-T exhibits the widest influence range and acts as the primary influencing factor. For SD, high SD values (red) significantly increase the model prediction results, whereas low SD values (blue) generate negative or weakly positive effects. For AD, low AD values (blue) mainly impose an inhibitory effect, while high AD values (red) slightly promote the model output. For WS, low WS values (red) correspond to negative SHAP values, and high WS values (blue) yield positive effects, though the overall influence amplitude is limited. Combined with the feature importance ranking, each variable differs not only in influence magnitude but also exhibits distinct nonlinear effects on the prediction

results with the variation of feature values.

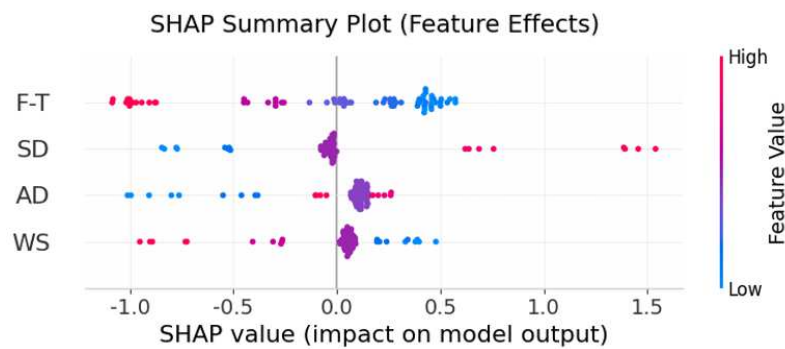


Fig 9 Parameter Sensitivity

4. Conclusions

Based on the experimental dataset of the compressive strength of flowable solidified soil under freeze-thaw cycles, four machine learning prediction models including DT, BP, SVR and XGBoost were constructed in this study. The fitting capability, prediction accuracy and generalization performance of each model were systematically evaluated, and the SHAP method was adopted to reveal the influence mechanism of input features on strength damage. The main conclusions are summarized as follows::

(1) Both DT and XGBoost achieved near-zero errors on the training set, whereas the DT model exhibited a sharp accuracy decline on the test set with an R^2 of 0.79, indicating significant overfitting. The BP and SVR models presented high prediction accuracy with a test-set R^2 of 0.98 but still suffered from certain prediction deviations and fluctuations. The XGBoost model yielded a test-set R^2 of 0.95, achieving the optimal overall prediction performance among the four models with a well-balanced fitting ability and generalization performance.

(2) The XGBoost model exhibited the smallest fluctuation range of prediction errors on the test set. Its median ratio of predicted values to experimental values was closest to 1.0 with the lowest data dispersion, which was significantly superior to the DT, BP and SVR models. The results verify that XGBoost possesses stronger robustness and generalization capacity in solving multivariate nonlinear coupling regression problems.

(3) The feature importance ranking and SHAP sensitivity analysis consistently demonstrate that the importance of influencing factors follows the order of $F-T > SD > AD > WS$. Freeze-thaw cycle number (F-T) exerts the most prominent effect on model outputs and serves as the dominant factor controlling the freeze-thaw compressive strength damage of flowable solidified soil.

(4) The established XGBoost freeze-thaw damage prediction model realizes the rapid and accurate prediction of freeze-thaw compressive strength damage of flowable solidified soil, which can provide reliable technical support and theoretical references for the long-term service safety guarantee of flowable solidified soil engineering in cold regions.

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Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

All data from the study used to support the findings of this study are available from the corresponding author upon request.

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