

Research on an Intelligent Early Warning Model for Coal Spontaneous Combustion Based on Stacking Ensemble Learning

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Abstract: To address the challenge of accurately predicting the spontaneous combustion temperature of water-immersed and air-dried coal, and to enhance the reliability of early warning systems for coal spontaneous combustion hazards, this paper constructs a coal spontaneous combustion temperature prediction model based on Stacking-based ensemble learning. Based on multi-stage indicator data derived from water-immersed and air-dried coal samples—obtained through programmed-temperature coal spontaneous combustion experiments—Grey Relational Analysis was employed to identify CO, CO₂, C₂H₄, C₂H₆, and the alkane-to-alkene ratio (C₂H₄/C₂H₆) as the core early-warning indicators. Data preprocessing was subsequently completed through normalization and linear interpolation. A two-layer ensemble prediction model was then constructed by selecting Random Forest (RF), Support Vector Machines with Radial Basis Function kernels (RBF-SVM), and Extreme Gradient Boosting (XGBoost) as the base learners for a Stacking framework, with Gradient Boosting Decision Trees serving as the meta-learner; this ensemble model was subsequently validated through comparison against each of the individual models. The results indicate that the RF model exhibits optimal generalization capability, achieving a coefficient of determination (R²) of 0.9027 on the test set. The Stacking ensemble model demonstrates excellent fitting performance on the training set, with a Mean Squared Error (MSE) of 0.3234 and an R² of 0.99; on the test set, it yields an R² of 0.9019 and a Root Mean Squared Error (RMSE) of 23.9473. Its generalization performance is on par with the RF model and superior to the XGBoost model, effectively integrating the strengths of the individual base learners to achieve a dual balance between fitting accuracy and generalization capability. Conversely, the SVM model demonstrates poor adaptability within the specific data context of this study and fails to meet the requirements for coal temperature prediction. The Stacking ensemble learning model constructed in this paper is capable of accurately predicting the spontaneous combustion temperature of water-immersed and air-dried coal, thereby providing reliable technical support for the early warning of spontaneous combustion hazards in the goafs of shallow-buried, closely spaced coal seams.

Keywords: Coal Spontaneous Combustion; Temperature Prediction; Stacking Ensemble Learning; Feature Selection; Machine Learning.

1. Introduction

As a vital component of our national energy system, coal plays an irreplaceable role in safeguarding energy supplies and supporting industrial production. Spontaneous combustion of coal ranks among the most severe hazards encountered during mining operations; not only does it result in resource wastage and environmental pollution, but it can also trigger cascading accidents—such as gas explosions—thereby posing a grave threat to the safety of underground personnel. Furthermore, the process of spontaneous coal combustion generates substantial carbon emissions, running counter to our nation's strategic objectives of achieving "carbon peaking" and "carbon neutrality." To foster high-quality development within the coal industry and enhance mine safety standards, the application of intelligent algorithms and machine learning techniques to the field of spontaneous coal combustion early warning—with the aim of continuously improving prediction accuracy—has emerged as a key research priority for scholars both domestically and internationally.

Currently, various optimized machine learning models are widely applied in research on predicting coal spontaneous combustion temperatures and ignition risks; the resulting findings provide crucial technical support for intelligent early

warning systems for coal spontaneous combustion. Gao Fei [1] employed Grey Relational Analysis to select key indicator gases characteristic of different stages of coal spontaneous combustion, and proposed a coal spontaneous combustion prediction model based on a Radial Basis Function (RBF) neural network optimized by the Sparrow Search Algorithm (SSA), thereby effectively enhancing prediction accuracy. Muhammad Kamran [2] proposed utilizing CatBoost and Light Gradient Boosting Machine (LightGBM) methods to analyze mine fire data, constructing an intelligent decision-making model for fire risk prevention and early warning systems applicable to underground engineering projects. The findings indicated that, compared to CatBoost, the LightGBM algorithm achieved more comprehensive performance, yielding prediction accuracies of 92% and 89%, respectively. Zhou Xu [3] utilized data on gas volume fractions and their ratios obtained from spontaneous combustion experiments; by employing the Particle Swarm Optimization (PSO) algorithm to fine-tune the key parameters within the Extreme Gradient Boosting (XGBoost) framework, a PSO-XGBoost model for predicting coal spontaneous combustion temperatures was established, offering a novel approach to the prediction of coal spontaneous combustion temperatures. Zhang Lidong [4] developed regression prediction models—utilizing Multi-Layer Perceptrons (MLP) and Random Forests (RF)—that correlate junction temperatures with 13

input features, thereby achieving effective prediction of the characteristic temperatures associated with coal spontaneous combustion. Deng Jun et al. [5] employed the Analytic Hierarchy Process (AHP) and fuzzy mathematics to construct a multi-level hazard assessment index system encompassing the various stages influencing coal spontaneous combustion; by calculating the weights of these assessment indices, they determined the hazard levels for coal spontaneous combustion, thereby providing a quantitative methodology for risk classification. Zan Juncai [6] established a BP neural network prediction model by integrating gas composition analysis with neural network algorithms, offering guidance of paramount importance for the early-stage forecasting of coal spontaneous combustion. Wang Wei [7] developed a dynamic prediction index system for assessing the spontaneous combustion hazard of residual coal in goafs, based on 15 predictive indicators; furthermore, the author proposed an index weight calculation model utilizing an improved CRITIC-G2 method, thereby enhancing the scientific rigor and rationality of the weight allocation process. Lin Kaiyi [8] introduced a dynamic data fusion method for multi-feature coal spontaneous combustion indices based on deep learning (DMCNN) and integrated a deep neural network-based temperature prediction method into an early warning system, thereby realizing predictive and early-warning capabilities regarding the hazards of coal spontaneous combustion.

In the process of monitoring and predicting coal spontaneous combustion, air leakage directly affects the volume fractions of gases within the goaf, leading to inaccuracies in the detection of indicator gases for spontaneous combustion. Consequently, this factor becomes a critical constraint hindering improvements in prediction accuracy. To mitigate the impact of air leakage, researchers both domestically and internationally have adopted various approaches to achieve the collaborative and precise prediction of coal spontaneous combustion risk levels. In a study by Zhai Xiaowei [9], the impact of air leakage on CO concentrations within the goaf was determined through a combination of bundle-tube monitoring and tracer gas leakage testing. The functional relationship between CO volume fraction and coal temperature was subsequently corrected across various ranges of oxygen volume fractions. By utilizing these corrected functional equations to calculate CO early-warning thresholds for spontaneous combustion—and integrating these results with the early-warning thresholds of other indicator gases—a hierarchical early-warning system for coal spontaneous combustion in the goaf under air leakage conditions was successfully established. Other scholars have proposed utilizing alkane and alkene gases—along with their ratios—as auxiliary gas data to facilitate synergistic prediction. For instance, Deng Jun et al. [10], [11] employed C_2H_6 , C_2H_4/C_2H_6 , $CO/\Delta O_2$, and alkane ratios as auxiliary gas parameters to construct a coal spontaneous combustion early warning system; this approach effectively enhanced prediction accuracy under conditions involving air leakage. Lei Changkui [12] introduced Grey Comprehensive Relational Analysis to quantitatively assess the degree of correlation between the upper limit of air leakage intensity and its influencing factors. Based on this analysis, he established a prediction model for the limit parameters of coal spontaneous combustion that utilizes an improved Particle Swarm Optimization algorithm to fine-tune Support Vector Regression parameters, thereby mitigating the disruptive impact of air leakage on prediction results. In summary, while

existing research has achieved significant progress in optimizing coal spontaneous combustion prediction models and correcting for the effects of air leakage, there remains room for improvement regarding the precise prediction of coal spontaneous combustion temperatures under conditions involving the coupling of multiple influencing factors. Building upon this foundation, the present study integrates existing research findings to further explore intelligent models suitable for predicting coal spontaneous combustion temperatures, with the aim of providing more reliable technical support for the precise early warning of coal spontaneous combustion.

2. Theoretical Basis

2.1. RF

Random Forest (RF) is a classic machine learning algorithm developed based on the principles of ensemble learning. This algorithm operates by independently training multiple decision trees and aggregating their outputs to produce a final result. Characterized by its strong resistance to overfitting, robust performance, and exceptional capability in handling high-dimensional data, RF is widely applied across various classification and regression analysis tasks. During the model construction process, the RF algorithm employs bootstrap sampling to randomly draw multiple subsets of samples from the original dataset, training a distinct decision tree—serving as a base model—for each specific subset. Concurrently, during the node-splitting phase of each decision tree, a random subset of features is selected to participate in the computation of the optimal split node; this strategy further enhances the diversity among the base models and strengthens the algorithm's overall generalization capability. Upon completion of model training, the outputs from all decision trees are aggregated—utilizing a voting mechanism for classification tasks and an averaging method for regression tasks—to yield the final predictive result of the Random Forest algorithm.

2.2. SVM

The Support Vector Machine (SVM) is a classic machine learning algorithm developed based on statistical learning theory. Primarily applied to classification and regression analysis tasks, it demonstrates excellent generalization performance in scenarios involving small sample sizes, high dimensionality, and nonlinear data. The core principle of the algorithm lies in identifying an optimal classification hyperplane within the feature space; by maximizing the margin between samples of different classes, it achieves enhanced classification accuracy and robustness. To address data analysis problems that are linearly inseparable, SVM utilizes kernel functions to map original low-dimensional data into a higher-dimensional feature space, thereby transforming the inherently nonlinear problem into a linearly separable one to facilitate classification decisions or regression fitting. This study selects the Radial Basis Function (RBF) as the kernel type; this function is highly effective in processing nonlinear and strongly coupled feature data, exhibiting strong adaptability and stability in fitting complex datasets. Consequently, it is incorporated as one of the base learners within the Stacking ensemble model.

2.3. XGBoost

XGBoost (eXtreme Gradient Boosting) is a highly efficient

ensemble learning algorithm situated within the gradient boosting decision tree framework. Boosting advantages such as high predictive accuracy, rapid convergence, and robust resistance to overfitting, it has been widely applied across numerous practical scenarios, including classification, regression analysis, and risk prediction. The algorithm employs decision trees as its base learners and utilizes a forward-stage additive training approach to construct an ensemble of trees; in each iteration, it fits the model's residuals by moving in the direction of the negative gradient of the loss function, thereby progressively reducing the model's predictive error. Furthermore, XGBoost incorporates regularization terms into its objective function to judiciously control model complexity, thereby mitigating the occurrence of overfitting at its source. By performing a second-order Taylor expansion of the loss function, the algorithm enhances the precision of model optimization; additionally, through the integration of strategies such as feature sampling and column sampling, it further bolsters the model's generalization capability and operational stability. For problems such as coal spontaneous combustion early warning—which are characterized by nonlinear features, the coupling of multiple indicators, and complex data distributions—XGBoost demonstrates the ability to effectively uncover the intrinsic interdependencies among various monitoring indicators, yielding stable and reliable predictive results. Consequently, in this study, XGBoost was selected as one of the base learners for the Stacking ensemble model.

2.4. Stacking Model

Stacking is a classic two-layer ensemble learning algorithm that fundamentally enhances a model's overall predictive performance by integrating the predictions of multiple base learners and employing a meta-learner to perform decision fusion. This algorithm features a two-tier structure: the first layer consists of multiple independent base learners responsible primarily for feature extraction and learning from the raw data, yielding preliminary predictions; the second layer takes these preliminary predictions from the base learners as input and utilizes a meta-learner to execute subsequent decision fusion and optimization, ultimately generating the final model predictions. This two-layer architecture effectively leverages the distinct modeling strengths of the various base learners, thereby significantly improving the model's predictive accuracy and robustness in complex scenarios—making it highly suitable for constructing intelligent early-warning models for coal spontaneous combustion hazards.

3. A Stacking-Based Intelligent Early Warning Model for Coal Spontaneous Combustion

3.1. Data Collection and Processing

3.1.1. Collection of Experimental Data

The data utilized in this study were primarily obtained through programmed-temperature coal spontaneous combustion experiments. This dataset encompasses characteristic temperatures, concentrations of indicator gases—such as O_2 , CO , CO_2 , C_2H_4 , and C_2H_6 —and relevant environmental parameters for water-immersed and air-dried coal samples across various oxidation stages.

First, a correlation analysis was conducted between the characteristic gases and characteristic temperatures. Based on

the experimentally measured data, the Grey Relational Analysis method was employed; with coal temperature designated as the reference sequence and each indicator gas as a comparative sequence, the grey relational degrees between the coal temperature and each gas were calculated for each distinct oxidation stage. This process served to clarify the strength of the correlation between the indicator gases and coal temperature fluctuations at each stage, thereby providing a basis for the subsequent selection of key indicators.

3.1.2. Data Preprocessing

(1) Normalization

Since the various feature indicators within the monitoring data exhibit significant differences in dimensions, units, and numerical ranges, directly inputting them into the model would lead to unbalanced parameter updates, thereby compromising both the model's convergence speed and predictive accuracy. Consequently, this paper employs the Min-Max normalization method to standardize the data:

$$x^* = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

(2) Handling Missing Values

During the data acquisition process, the raw data inevitably contains a small number of missing values; if used directly for model training, this would compromise data integrity and subsequently impair the predictive performance of the early warning model. To address this, this paper employs linear interpolation to impute the missing data, thereby maximizing the preservation of the data's original variation patterns and ensuring the dataset remains complete and reliable. The formula for linear interpolation is as follows:

$$y = y_1 + \frac{(y_2 - y_1)}{(x_2 - x_1)} \times (x - x_1)$$

3.2. Analysis of Model Early Warning Indicators

The process of coal spontaneous combustion is accompanied by the generation and variation of various gases; the concentrations of different indicator gases are closely correlated with the oxidation stage and temperature fluctuations of the coal body, serving as a crucial basis for assessing the severity of the spontaneous combustion hazard. Under conditions involving water immersion followed by air-drying, the pore structure and oxidation characteristics of the coal body undergo alterations, leading to corresponding changes in the generation patterns of indicator gases; consequently, a systematic analysis of these warning gases is essential. Through programmed temperature-rise experiments, typical gases—including O_2 , CO , CO_2 , C_2H_4 , and C_2H_6 —were continuously monitored. The results indicate that CO and CO_2 are generated distinctly even during the low-temperature oxidation stage and continue to increase as the temperature rises, thereby effectively reflecting the early self-heating status of the coal body. Conversely, olefin and alkane gases—such as C_2H_4 and C_2H_6 —show a significant increase only after the coal body enters the rapid oxidation stage; thus, they serve as key markers for assessing the progression of spontaneous combustion. To further enhance the effectiveness of these indicators, this study employs Grey Relational Analysis to calculate the degree of correlation between each gas and the coal temperature, thereby identifying and selecting gases that

are highly sensitive to temperature changes and exhibit timely responses to serve as core early-warning indicators. Furthermore, recognizing that air leakage is pronounced in the goafs of shallow-buried, closely spaced coal seams—where individual gas concentrations are susceptible to dilution by airflow—the C_2H_4/C_2H_6 ratio (alkene-to-alkane ratio) is introduced as an auxiliary indicator to mitigate the interference caused by air leakage and to improve the stability and accuracy of the early-warning system. The resulting set of optimized and combined early-warning indicators comprehensively reflects the spontaneous combustion status of water-immersed and air-dried coal across various oxidation stages, thereby providing reliable and stable input features for the development of subsequent intelligent early-warning models.

3.3. Construction of the Stacking Model for Coal Temperature Prediction

To enhance the prediction accuracy and generalization capability of coal spontaneous combustion temperatures, this paper constructs a Stacking ensemble learning model for coal temperature prediction, optimized via the Sparrow Search

Algorithm (SSA). This model employs a two-layer ensemble architecture: the first layer selects Random Forest (RF), Support Vector Machines (SVM) with an RBF kernel, and Extreme Gradient Boosting (XGBoost) as base learners to perform primary learning and prediction on preprocessed and augmented indicator data; the second layer utilizes Gradient Boosting Decision Trees (GBDT) as a meta-learner to fuse the outputs from the base learners, thereby yielding the final predicted coal temperature. To mitigate the subjectivity and limitations associated with manual parameter tuning, the Sparrow Search Algorithm (SSA) is employed—with the objective of minimizing prediction error—to conduct a global search for the optimal parameters of the RF, SVM, XGBoost, and GBDT components, thereby securing the optimal parameter combination to boost the model's overall performance. With the selected warning indicators serving as inputs and the coal body temperature as the output, the model—following data partitioning, parameter optimization, hierarchical training, and result fusion—achieves accurate and stable prediction of coal spontaneous combustion temperatures, thereby providing a reliable basis for subsequent intelligent early warning systems. The structure of the Stacking model is illustrated below:

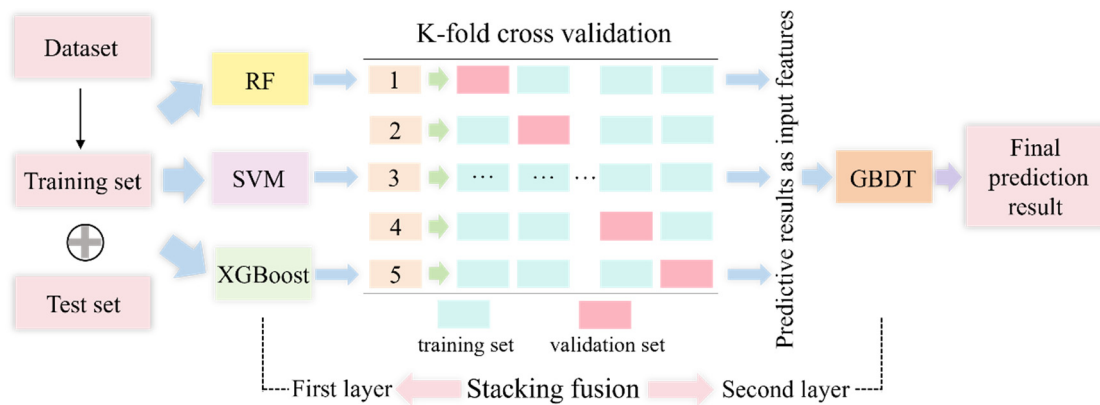


Figure 1. Stacking Ensemble Learning Diagram

4. Analysis of Stacking Model Prediction Results

4.1. Model Evaluation Metrics

In evaluating the performance of the predictive model, this paper employs three performance metrics—Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2)—to assess the model's predictive performance. The specific calculation formulas are as follows:

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

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

4.2. Model Prediction Results and Comparative Analysis

To intuitively compare the predictive performance of various models, the SSA-Stacking model was employed

alongside the standalone RF, SVM, and XGBoost models for coal temperature prediction. The predicted values from these models were then compared and analyzed against actual measured coal temperature data; the results obtained on the test set are presented in Figure 2.

In the validation of generalization performance on the test set, the RF model demonstrated the best generalization capability, yielding an MSE of 569.1167, an RMSE of 23.8562, and an R^2 of 0.9027, thereby achieving the highest prediction accuracy. The performance of the Stacking model and the XGBoost model on the test set was highly comparable—with R^2 values of 0.9019 and 0.8979, respectively—producing stable and reliable predictions; both models exhibited excellent generalization performance. In contrast, the SVM model performed the poorest on the test set, recording an MSE of 3753.7 and an R^2 of only 0.3582; its large prediction errors and low accuracy render it incapable of meeting the requirements for coal temperature prediction.

A comprehensive comparison reveals that the Stacking model achieves optimal fitting performance on the learning set, with an MSE of merely 0.3234, an RMSE of 0.5687, and an R^2 value reaching as high as 0.9999, demonstrating an exceptionally high degree of fit to the training data. On the test set, its generalization performance remains stable, with prediction accuracy essentially on par with that of the RF

model; it effectively integrates the respective strengths of its base learners—Random Forest, Support Vector Machines,

and XGBoost—thereby mitigating the predictive biases inherent in single models.

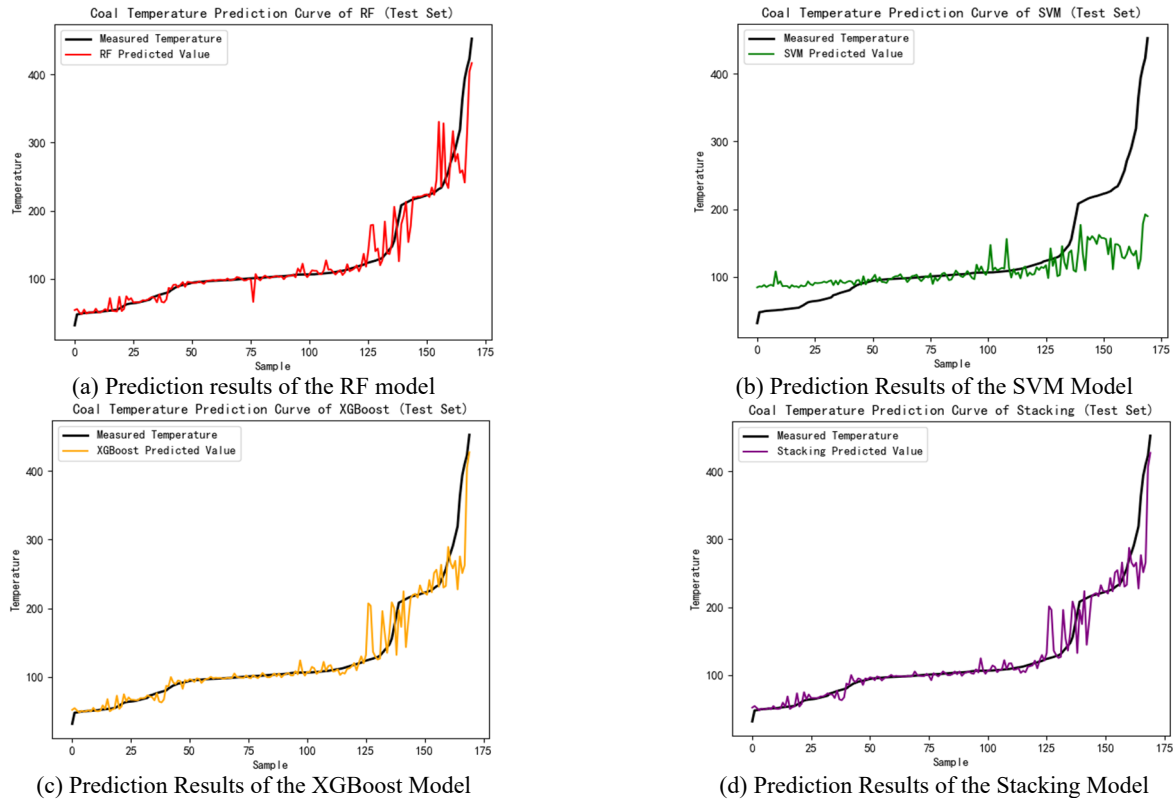


Figure 2. Model Prediction Results

The XGBoost model exhibits outstanding fitting capabilities, though its generalization performance falls slightly short of that of the RF and Stacking models. The RF model demonstrates the strongest generalization capabilities and possesses significant practical utility, whereas the SVM model yields suboptimal predictive results within the specific data context of this study. The results indicate that the Stacking model constructed in this paper strikes a balance between exceptional fitting accuracy and robust generalization capability, enabling the precise prediction of coal spontaneous combustion temperatures and providing reliable support for the early warning of coal spontaneous combustion hazards.

5. Conclusion

Addressing the challenge of accurately predicting the spontaneous combustion temperature of water-immersed and air-dried coal, this paper focuses on the selection of early warning indicators and the construction of intelligent predictive models. Through Grey Relational Analysis, the core early warning indicators for coal spontaneous combustion are identified; subsequently, a Stacking ensemble learning model—utilizing RF, SVM, and XGBoost as base learners—is constructed and validated against individual models. The main research conclusions are as follows:

1) During the spontaneous combustion process of water-immersed and air-dried coal, CO and CO₂ effectively reflect the early self-heating state of the coal mass, while C₂H₄ and C₂H₆ serve as key indicators for identifying the rapid oxidation stage. The introduction of the alkene-to-alkane ratio (C₂H₄/C₂H₆) effectively mitigates interference caused by air leakage; the resulting refined indicator system comprehensively characterizes the spontaneous combustion

features of the coal mass across its various oxidation stages, thereby providing reliable input support for predictive modeling.

2) During the spontaneous combustion process of water-immersed and air-dried coal, CO and CO₂ effectively reflect the early self-heating state of the coal mass, while C₂H₄ and C₂H₆ serve as key indicators for identifying the rapid oxidation stage. The introduction of the alkene-to-alkane ratio (C₂H₄/C₂H₆) effectively mitigates interference caused by air leakage; the resulting refined indicator system comprehensively characterizes the spontaneous combustion features of the coal mass across its various oxidation stages, thereby providing reliable input support for predictive modeling.

3) The constructed Stacking ensemble model effectively integrates the strengths of its constituent base learners, demonstrating excellent fitting performance on the training set with an MSE of merely 0.3234 and an R² of 0.9999. On the test set, it maintains stable generalization performance, yielding an R² of 0.9019 and an RMSE of 23.9473; its predictive accuracy is on par with the RF model and superior to the XGBoost model. By successfully balancing both fitting precision and generalization capability, the model enables the accurate prediction of coal spontaneous combustion temperatures.

4) The Stacking two-layer ensemble learning framework is well-suited to prediction scenarios involving the multi-indicator coupling and nonlinear characteristics of coal spontaneous combustion. Compared to single models, it demonstrates superior predictive accuracy and stability, thereby providing an effective technical approach for the intelligent early warning of coal spontaneous combustion hazards. It serves as a reliable support system for the early

warning of spontaneous combustion within goafs of shallow-buried, closely spaced coal seams, and also offers conceptual insights for the construction of prediction models for similar types of disasters.

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