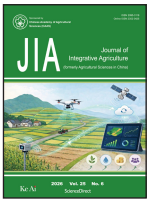
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RESEARCH ARTICLE

Machine learning-driven prediction of nitrogen loss in organic solid waste composting

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Highlights

- Machine learning algorithms were utilized to predict nitrogen loss during manure composting.
- The adaptive boosting model achieved an R^2 of 0.847 for nitrogen loss prediction.
- Model performance enhanced following Bayesian optimization of hyperparameters.
- Redundant features (e.g., scale and C/N) were eliminated to optimize input variables.
- Shapley additive explanation (SHAP) analysis revealed time stages and bulking agents as critical factors.

Abstract

Composting represents a crucial component of sustainable waste management, providing significant resource recovery and environmental advantages. However, nitrogen loss during composting remains a significant challenge, necessitating the development of a predictive model for nitrogen loss during the composting process. This investigation implemented five machine learning models, utilizing 307 data points encompassing composting strategies, physicochemical properties, and composting time stages, to predict nitrogen loss during organic solid waste composting. The findings demonstrated that the adaptive boosting (AdaBoost) algorithm achieved optimal performance with a coefficient of determination of 0.847 after eliminating redundant features (scale and C/N). Moreover, Shapley additive explanation analysis identified several key factors significantly influencing nitrogen losses during composting, including composting time stages, bulking agents, raw materials, and ammonium nitrogen levels. Notably, the initial phase of composting emerged as the most critical period for nitrogen loss. The utilization of sawdust, rice husk, and corn stalk as bulking agents enhanced nitrogen retention in compost. Furthermore, implementing static aeration for ventilation and applying chemical additives effectively reduced nitrogen losses during the composting process. These results provide a scientific foundation for identifying optimal composting conditions to minimize nitrogen loss, thereby offering practical guidance for effective composting operations.

Keywords: machine learning, composting, adaptive boosting, nitrogen loss, feature selection

1. Introduction

The rapid urbanization and population growth are driving a significant increase in the generation of complex solid waste, particularly organic solid waste. Projections indicate that by 2025, urban areas in Asia will generate approximately 1.8 million tons of organic solid waste daily (Arnold and Dennis 2017). Inadequate management of this waste could result in substantial negative impacts on society, the economy,

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and the environment, highlighting the need for increased attention and action (Yang *et al.* 2024; Yuan *et al.* 2024). Composting, a widely adopted technology globally, effectively converts organic waste into valuable resources, reducing landfill dependence while enabling cost-efficient production of organic amendments for agricultural use (Muhammad *et al.* 2023; Nordahl *et al.* 2023). However, the composting process can result in substantial nitrogen loss through the emission of nitrogen gas, ammonia gas and nitrous oxide, diminishing compost quality and efficacy while causing environmental contamination and reducing composting's sustainability benefits. Notably, ammonia's pungent odor negatively impacts the surrounding environment, while nitrous oxide, a potent greenhouse gas, exhibits a global warming potential approximately 265 times greater than carbon dioxide (Shukla *et al.* 2019). Furthermore, nitrous oxide concentrations have reached unprecedented levels not observed in at least 800,000 years (Core Writing Team *et al.* 2023). Consequently, enhanced research and management practices for mitigating nitrogen loss during composting are essential.

Nitrogen loss during composting is influenced by multiple factors, including compost raw materials, ventilation method, additives, compost temperature, moisture content, pH, carbon-to-nitrogen ratio (C/N), total nitrogen content (TN), and ammonium nitrogen concentrations, among others (Nguyen *et al.* 2022; Mo *et al.* 2023). Research has extensively documented that managing these variables can reduce nitrogen loss during composting (Hoang *et al.* 2022; Chen A *et al.* 2023). However, developing effective integrated optimal composting methods for nitrogen loss reduction through single-factor experiments remains challenging. Previous studies have employed various methodologies, such as orthogonal experiments and meta-analyses, to elucidate the complex relationships between specific factors and nitrogen loss (Chen X M *et al.* 2023; Liu Y *et al.* 2023; Tang *et al.* 2023; Wu *et al.* 2023). Nevertheless, these methods are typically time-consuming and often inadequate for capturing the intricate non-linear relationships and high-dimensional interactions inherent in composting processes.

In contrast to conventional statistical analysis, machine learning (ML) can identify complex patterns within high-dimensional data through statistical learning and optimization techniques (Zeguendry *et al.* 2023), establishing connections between parameters and research objectives to develop predictive models. The increasing availability of data and advancement in computing technology has expanded ML applications in environmental risk assessment and prediction. For example, ML has successfully predicted biochar efficiency in immobilizing heavy metals in soil environments, achieving a coefficient of determination (R^2) of 0.92 (Palansooriya *et al.* 2022). ML has also demonstrated significant value in advancing composting technologies. ML-based predictions of compost maturity have been implemented, with maturity levels significantly enhanced through composting parameter optimization (Ding *et al.* 2022; Shi *et al.* 2025). Furthermore, Wang *et al.* (2024) successfully employed ML to predict ammonia emissions and their contribution to global warming during composting. Despite these applications demonstrating ML's effectiveness in environmental studies and composting, research utilizing ML to predict nitrogen loss during composting remains limited.

This study employed ML based on 15 variables to evaluate their influence on nitrogen loss during composting. Initially, five ML models were implemented: random forest (RF), support vector regression (SVR), multi-layer perceptron (MLP), gradient boosting decision tree (GBDT), and adaptive boosting (AdaBoost). RF, GBDT, and AdaBoost utilized integer encoding, while SVR and MLP employed one-hot encoding, with encoding strategies selected to optimize each model's data adaptation and prediction capabilities (Soofi *et al.* 2023; Uddin *et al.* 2023). The models' prediction accuracy was evaluated using root mean square error (RMSE) and R^2, with the best-performing model selected for subsequent analysis. Subsequently, Pearson correlation analysis and Shapley additive explanation (SHAP) were utilized to determine the impact and key factors of input features on nitrogen loss. Finally, the optimized model was validated using recently collected data to predict nitrogen loss, thereby assessing its applicability to novel data. These findings offer potential for predicting and reducing nitrogen loss during composting while providing valuable guidance for optimizing composting practices.

2. Materials and methods

2.1. Data collection and transformation

The detailed methodology for ML exploration related to nitrogen loss prediction during composting is illustrated in Fig. 1. A comprehensive literature review was conducted using Web of Science and Google Scholar, examining studies published between 2003 and 2023 using the Boolean string ("composting" or "composting test") and ("nitrogen loss" or "nitrogen reduction").

The literature review revealed that multiple factors influence nitrogen loss during composting. Composting substrates, including raw materials, additives, and bulking agents, affect nitrogen transformation processes and retention by influencing TN, C/N, aerobic conditions, and microbial composition (Chen X M *et al.* 2023; Huang *et al.* 2023; Piao *et al.* 2023). Furthermore, nitrification, denitrification, and related nitrogen transformation and loss processes are significantly influenced by compost properties such as pH, temperature, ammonium nitrogen, nitrate nitrogen, and moisture content (Adegoke and Ku 2023; Yan *et al.* 2023; Jin *et al.* 2025). Data regarding these influencing factors and nitrogen loss were extracted from literature tables and text, or retrieved from figures using Plot Digitizer (v. 2.6.11). This process yielded a dataset of 178 raw entries (Appendix A). To analyze nitrogen loss and its influencing factors across different time intervals during composting, the raw data were transformed to represent nitrogen loss between specific time points within the composting process. This approach effectively captures distinct phases of the composting period. The chronological sequence of time stages was maintained to ensure data consistency. Physicochemical properties were represented by average values between the "start date"

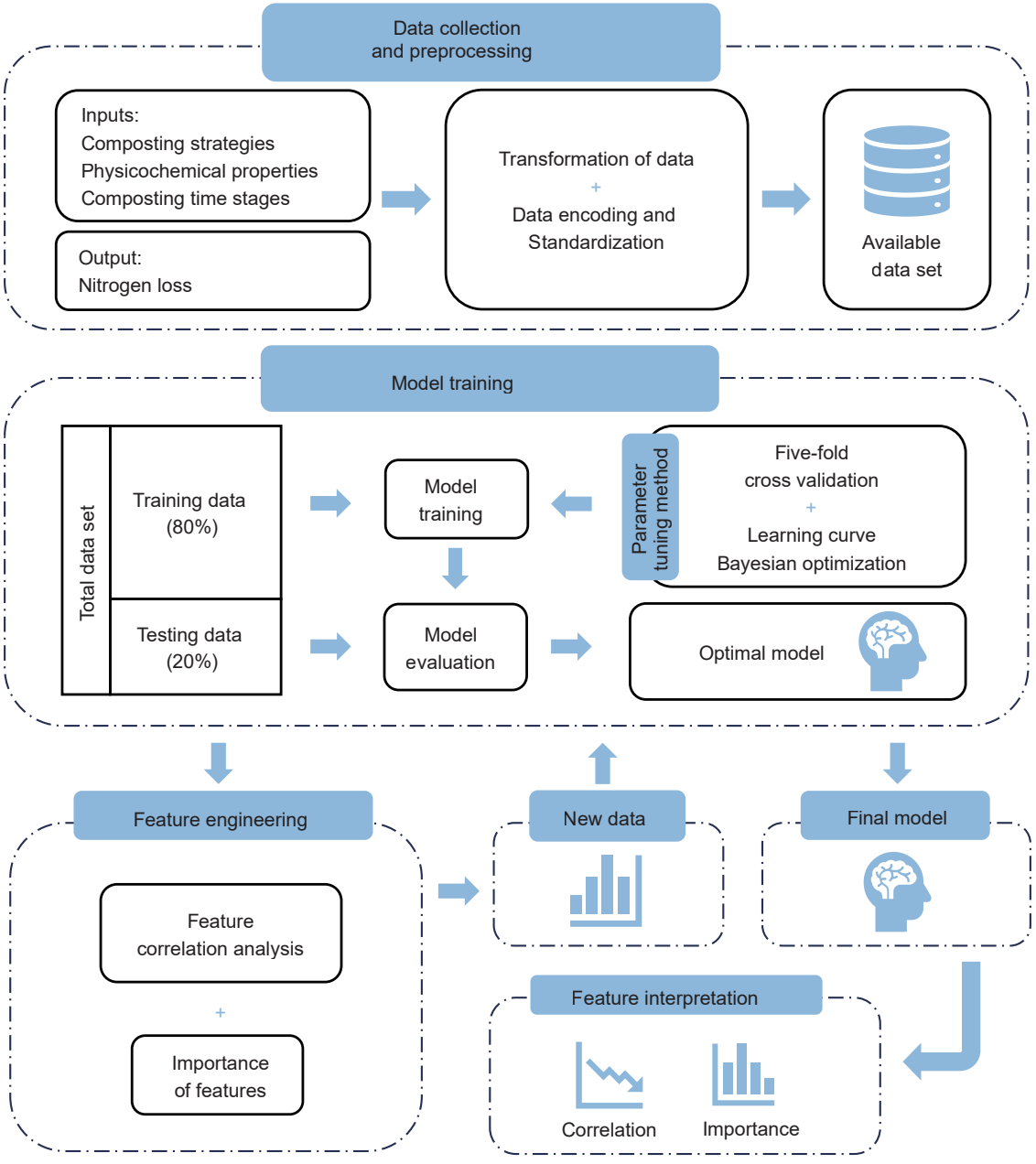


Fig. 1 Flowchart detailing the strategies of the machine learning framework to determine nitrogen loss during the composting process.

and "finish date" for analysis purposes. Additionally, the temperature difference between these dates was calculated to quantify temperature variations. The final transformed dataset comprised 307 entries (Appendix B), featuring one output variable (nitrogen loss) and 15 input variables, including composting strategies (ventilation method, scale, raw material, bulking agent and additive), composting time stages (start date and finish date), and physicochemical properties (maximum temperature date, temperature difference, pH, TN, ammonium nitrogen, nitrate nitrogen, C/N, moisture content) (Appendix C).

2.2. Model selection and data preprocessing

This study employed five models, primarily categorized into tree-based models (e.g., RF, AdaBoost and GBDT), support vector machine (e.g., SVR), and neural network model (e.g., MLP). These models demonstrate robust performance across various applications (Guo *et al.* 2024; Li Z L *et al.* 2024; Liu B *et al.* 2024). Among the tree-based models, RF is an ensemble method that combines multiple decision trees, reducing sensitivity to outliers and mitigating overfitting (Huang *et al.* 2022; Palansooriya *et al.* 2022). AdaBoost iteratively enhances weak learners by adjusting sample weights, focusing on misclassified instances. This adaptive weighting mechanism inherently reduces overfitting to the training dataset, ensuring more robust predictions (Liu *et al.* 2022). GBDT employs gradient descent to optimize the loss function, achieving superior performance (Jiang *et al.*

2024). Unlike tree-based models that construct decision rules for prediction, SVR determines the optimal regression hyperplane by minimizing prediction errors, performing effectively with small sample sizes and high-dimensional data (Pan *et al.* 2024). MLP exhibits strong nonlinear modeling capabilities, enabling complex feature representation learning from raw input data. Its flexible architecture adapts to diverse data characteristics (Anand *et al.* 2024). Given these unique attributes and broad applicability, RF, GBDT, AdaBoost, SVR, and MLP are expected to achieve superior prediction results in this investigation.

The obtained dataset was subsequently utilized to develop different types of ML models (Fig. 2-A–C). Categorical text data on composting strategies required conversion to numerical format before ML model training (Li Z L *et al.* 2024). Tree-based models (RF, GBDT and AdaBoost) implemented integer encoding (Fig. 2-D), mapping each category to a unique integer (Kim and Yoon 2023). This approach proves suitable as tree-based models utilize splitting processes that do not assume ordinal relationships between categories (Uddin *et al.* 2023). For SVR and MLP models, one-hot encoding transformed categories into binary vectors (Fig. 2-F) (Nishimura *et al.* 2022). This method prevents misinterpretation of ordinal relationships that label encoding might introduce, ensuring accurate feature interpretation (Soofi *et al.* 2023). A violin plot illustrated the statistical distribution and outliers of variables related to composting time stages and physicochemical properties of compost (Fig. 2-E). Continuous variables underwent normalization using Python to ensure similar scale and approximate normal distribution, enhancing ML model training for rapid convergence (Von *et al.* 2023).

2.3. Model development and evaluation

To achieve optimal model performance and ensure sufficient testing data, the dataset was randomly divided into an 8:2 ratio for training and testing sets (Mendez *et al.* 2023; Von *et al.* 2023). Using the 80% training dataset, hyperparameters were optimized through a combination of five-fold cross-validation learning curves and tree-structured parzen estimators (TPE). Learning curves provided initial adjustments, while TPE refined optimal hyperparameter selection (Li X *et al.* 2024; Wang B *et al.* 2024). As ML algorithms possess distinct hyperparameters, the tuning process focused on algorithm-specific parameters (Appendix D). RF optimization addressed the number of trees, max_depth, and max_features. AdaBoost tuning focused on the number of weak learners and learning rate. GBDT parameters included weak learners, learning rate, max_depth, and subsample ratio. SVR optimization involved epsilon (ε), kernel function, and penalty parameter. MLP convergence was enhanced by optimizing architecture through adjustments

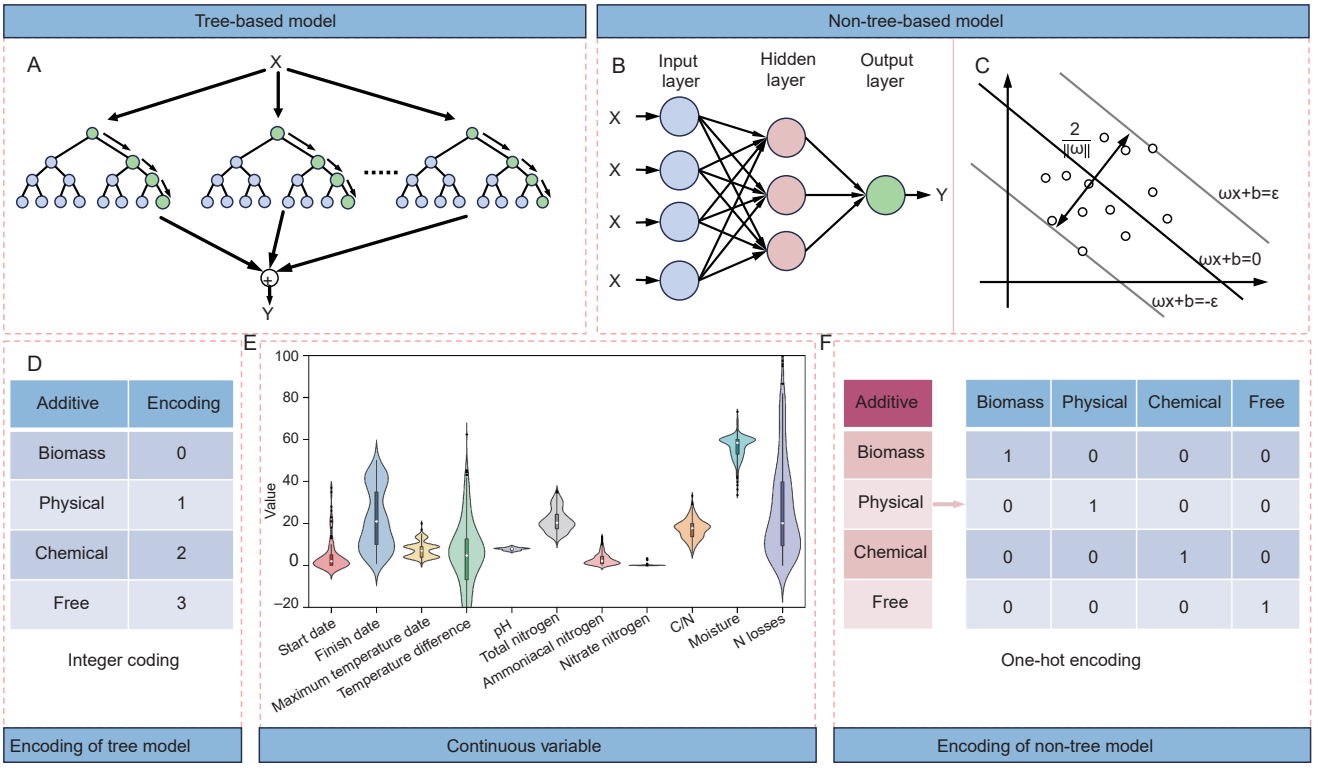


Fig. 2 Preprocessing of the dataset based on different machine learning models. A, schematic diagram of tree-based models including random forest (RF), gradient boosting decision tree (GBDT) and adaptive boosting (AdaBoost). B, schematic diagram of multi-layer perceptron (MLP). C, schematic diagram of support vector regression (SVR). D, example of integer encoding of nominal variable data, mapping each category to a unique integer. E, violin plot with illustrating the statistical distribution of variables related to composting time stages and the physicochemical properties of compost. F, example of one-hot encoding of nominal variable data, converting categories into binary vectors.

to hidden layers and neurons per layer.

Following these hyperparameter tuning methods, each model's parameters were optimized. Model performance regarding fitting accuracy and predictive precision was evaluated using the 20% test dataset according to R^2 and RMSE metrics (Huang *et al.* 2024). R^2 and RMSE values were calculated using eqs. (1) and (2), respectively:

$$R^2=1-\frac{\sum_{i=1}^{n}(y_p^i-y_a^i)^2}{\sum_{i=1}^{n}(y_a^i-y_m)^2} \quad (1)$$

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(y_a^i-y_p^i)^2}{n}} \quad (2)$$

where y_p^i represents the predicted value of the model output, y_a^i denotes the actual value collected from the literature, y_m indicates the mean of all predicted values of the model, and n represents the number of samples in the training or test datasets.

2.4. ML-based feature engineering and performance analysis of the optimized model

To enhance and streamline the optimal model's performance, Pearson correlation coefficient (PCC) was utilized to evaluate the relationships among features (Xue *et al.* 2024). A feature importance analysis was performed using the developed model to determine the influence of input features on the output variable (Feng *et al.* 2021). Through the integration of feature importance and inter-feature correlations, where correlation coefficient is denoted as r, critical features were identified while less significant features highly correlated with others ($|r|\geq0.8$) were removed (Shen *et al.* 2024). Subsequently, the model underwent retraining and retesting using the refined dataset from feature engineering. During this process, hyperparameters remained unchanged, with modifications limited to input features. Enhanced predictive performance of the updated model indicated successful feature selection, while decreased performance would require hyperparameter adjustment. In this study, the optimized AdaBoost model demonstrated improved performance.

The finalized AdaBoost model was employed to examine the significance and relevance of each input feature regarding nitrogen loss during composting. The analysis utilized SHAP analysis (Wang *et al.* 2023), a widely adopted feature analysis method (Wang *et al.* 2023; Luo *et al.* 2024). This method's computational foundation lies in cooperative game theory, primarily aiming to quantify individual feature contributions to the overall outcome. The process involves calculating each feature's marginal contributions when combined with all possible subsets of remaining features. These weighted average marginal contributions are then aggregated to determine each feature's Shapley value, representing its contribution to model prediction accuracy.

2.5. ML model validation

To assess the model's generalization capability with unseen data and confirm whether the optimized model provided more comprehensive and reliable evaluations, its predictive performance underwent further assessment using an additional dataset following interpretative analysis. The selection of sample points emphasized data integrity and quality to maintain consistency with the training dataset. The newly collected data incorporated the basic compost characteristics present in the training data, ensuring sufficient information for model validation. This new dataset comprises recent literature published after 2024 and includes results from studies made available after eliminating two redundant features during feature selection (Li *et al.* 2018; Zeng *et al.* 2018; Liu Z Z *et al.* 2024; Zhang *et al.* 2024; Xue *et al.* 2025; Yu *et al.* 2025). Ultimately, eighteen new sample points were collected to validate the model's predictive capability for nitrogen loss during composting (Appendix E).

3. Results and discussion

3.1. Model construction and performance comparison

Following data preprocessing, five ML algorithms (RF, SVR, MLP, GBDT, and AdaBoost) were utilized to predict nitrogen loss during composting based on 15 input features. Hyperparameters for each model were optimized using learning curves and Bayesian optimization with five-fold cross-validation to minimize prediction error, thereby reducing overfitting due to suboptimal dataset splits (Mendez *et al.* 2023). The performance of these models is shown in Fig. 3. For the SVR model, the training R^2 and RMSE values were 0.913 and 0.067, respectively, while the testing values were 0.743 and 0.114, respectively (Fig. 3-A). The MLP achieved an R^2 score of 0.916 on the training set and 0.825 on the testing set (Fig. 3-B). Regarding training R^2, both models demonstrated similar performance. However, nitrogen loss during composting is influenced by multiple complex factors with highly non-linear relationships. This complexity potentially explains the lower testing R^2 score for SVR compared to MLP. Specifically, MLP exhibits superior performance in capturing complex non-linear relationships through its multi-layered architecture and non-linear activation functions (Liu B G *et al.* 2024). While SVR can handle non-linear data, its effectiveness relies on appropriate kernel function selection, which may not capture data nuances as effectively as MLP's layered structure (Li *et al.* 2023; Esmaeili-Falak and Benemaran 2024). Furthermore, composting process datasets often contain significant noise and outliers, challenging model generalization. MLP provides greater architectural flexibility and benefits from regularization techniques including dropout, weight decay and early stopping, which help prevent overfitting and improve generalization to unseen data (Anand *et al.* 2024). The results indicate MLP achieved higher testing R^2 than SVR, while SVR exhibited more pronounced overfitting.

The three tree-based models demonstrated superior performance in predicting nitrogen loss during composting, with their robustness to outliers enabling them to surpass SVR and MLP (Liu B G *et al.* 2024). Both RF and GBDT achieved a training R^2 of 0.971, with testing R^2 of 0.831 and 0.829, respectively (Fig. 3-C and D), indicating comparable predictive performance on the test dataset. As shown in Fig. 3-E, the AdaBoost model achieved higher training and testing R^2 values (0.987 and 0.838, respectively) and lower

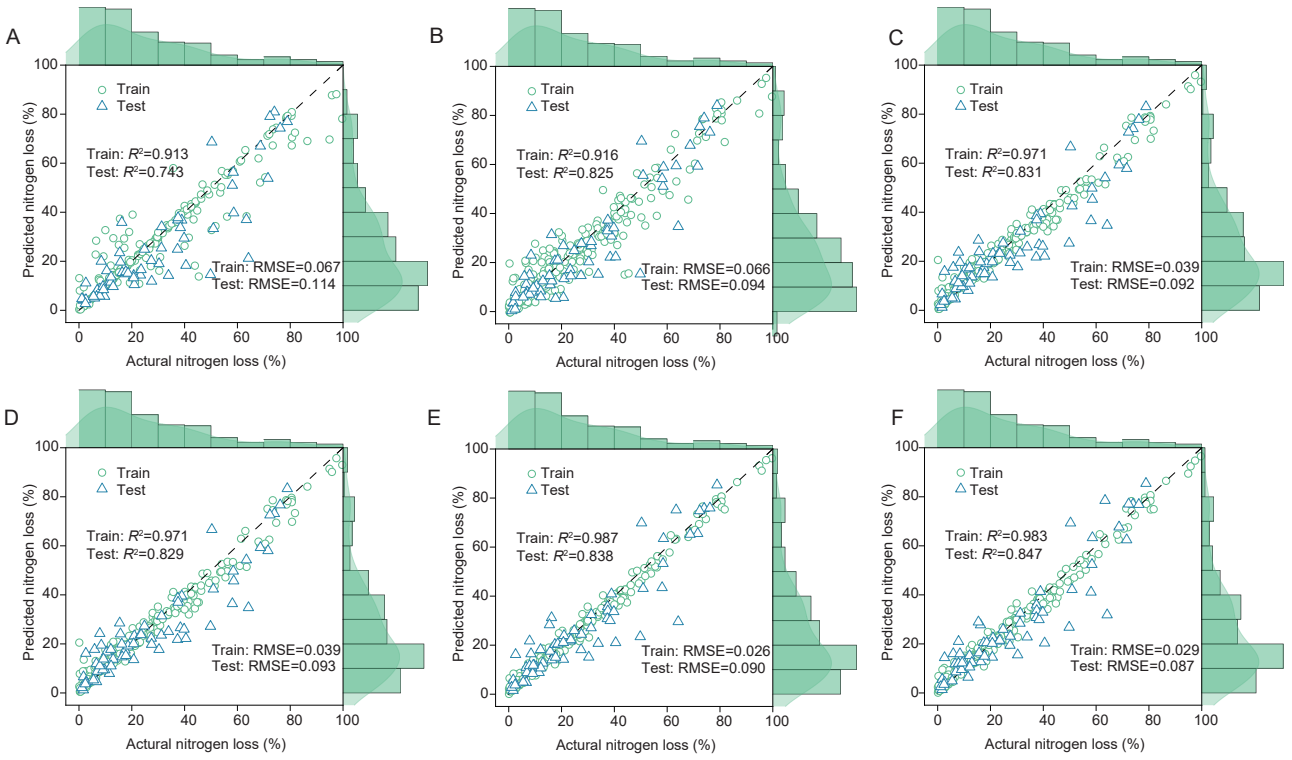


Fig. 3 Predictive performance of different machine learning models. A, support vector regression (SVR). B, multi-layer perceptron (MLP). C, random forest (RF). D, gradient boosting decision tree (GBDT). E, adaptive boosting (AdaBoost). F, updated AdaBoost. RMSE, root-mean-square error; R^2, coefficient of determination.

RMSE values (0.039 and 0.093), outperforming the other four models (Fig. 3-E). Furthermore, to assess the average predictive performance across different subsets and ensure generalization ability, a comparison of cross-validation scores was performed. As presented in Appendix F, the AdaBoost model's cross-validation score reached 0.778, exceeding that of the other models. This enhanced performance can be attributed to AdaBoost's ability to dynamically adjust sample weights based on previous weak learners' errors, focusing more on misclassified instances in subsequent iterations (Cai *et al.* 2023). These findings demonstrate that the optimally tuned AdaBoost model was most effective for predicting nitrogen loss in composting.

3.2. Feature analysis and redundant feature identification

While AdaBoost demonstrates promising prediction accuracy for nitrogen loss during composting, incorporating less significant features alongside numerous input features may reduce the model's generalization capacity (Palansooriya *et al.* 2022; Zhao *et al.* 2024). Through combining feature importance with feature correlations, less important features can be identified and eliminated to simplify model structure and enhance prediction performance (Jiao *et al.* 2024). Fig. 4-A illustrates the correlations between different features based on PCC. The correlation heatmap indicates a strong correlation (ca. 0.837) between composting scale and raw material type. This correlation likely stems from lab-scale setups, encoded with higher numerical values during data processing, being more precisely controlled and monitored, resulting in lower nitrogen losses (Manea *et al.* 2024; Ucaroglu and Ozbek 2025). Similarly, raw materials such as sewage sludge, pig manure, and chicken manure — encoded with higher numerical values — demonstrate comparable nitrogen losses, as confirmed by subsequent SHAP analysis. Furthermore, PCC reveals a strong negative correlation (ca. –0.818) between TN and C/N. This correlation exists because high-nitrogen raw materials, particularly livestock manure, typically exhibit lower C/N ratios (Chen K S *et al.* 2023). This finding aligns with previous research identifying a strong negative correlation between C/N and TN (Li *et al.* 2023). For ML models, such high correlation suggests that substantial variance in one feature can be explained by another, indicating information redundancy (Shen *et al.* 2024). Therefore, less important features can be removed based on their relative importance. As shown in Fig. 4-B, scale and C/N demonstrated relatively lower importance (importance score≤4.0) on nitrogen loss during composting compared to raw material and TN, respectively. Consequently, scale and C/N were identified as redundant and removed. This approach may simplify the model and address potential multicollinearity issues, thereby improving model stability and generalization (Shen *et al.* 2024). The remaining important features for predicting nitrogen loss during composting were retained for model updating.

3.3. Model update and final feature exploration

After removing the scale and C/N features, a dataset comprising 13 features was utilized to retrain the AdaBoost

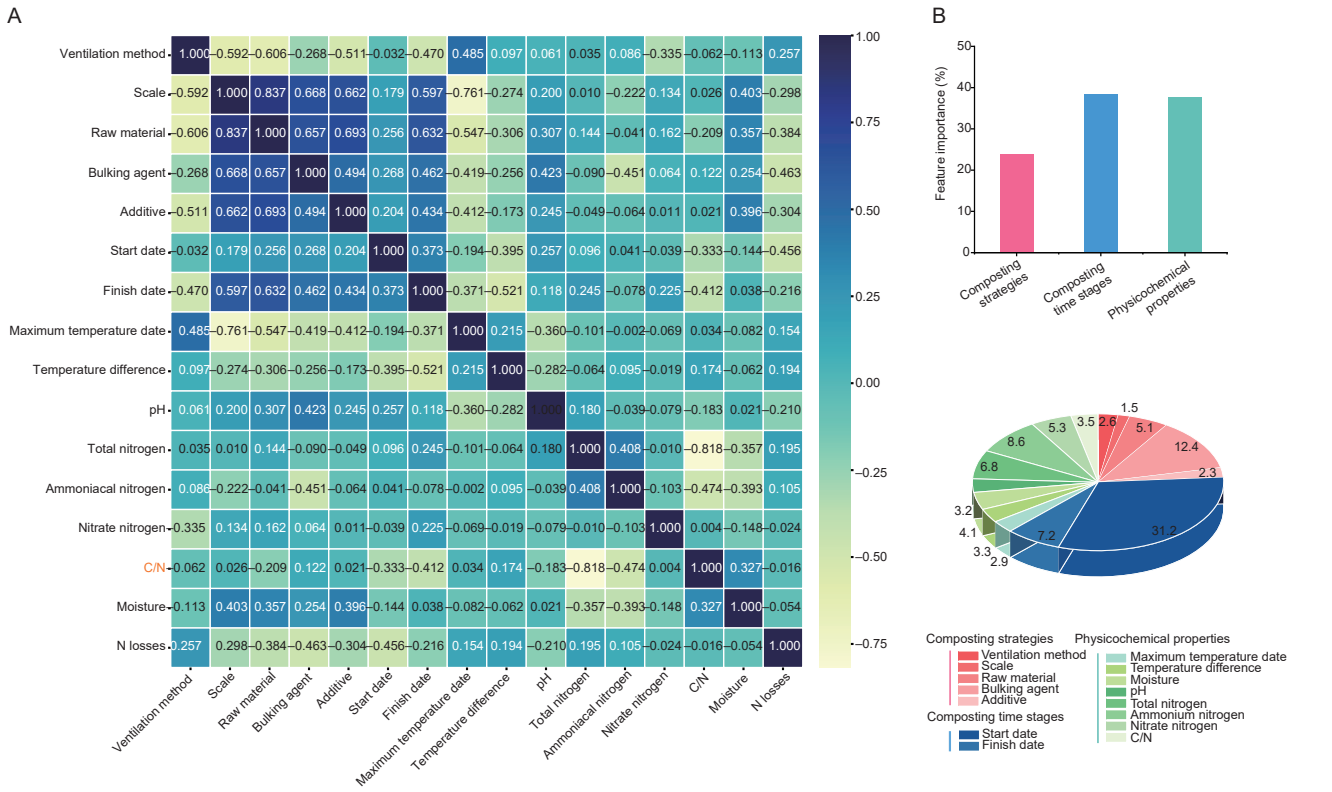


Fig. 4 Input feature analysis. A, Pearson correlation coefficient between compost parameters and nitrogen loss. B, the importance of individual features to the overall prediction result based on the AdaBoost model. The same color scheme represents the same type of input features.

model. Fig. 3-F demonstrates the prediction accuracy of the updated AdaBoost model. The new R^2 values for training and testing datasets reached 0.983 and 0.847, respectively, with corresponding RMSE values of 0.029 and 0.087. The updated model exhibited superior training and testing R^2 values and lower RMSE values compared to the original model. Moreover, despite maintaining identical hyperparameters and model complexity, the updated AdaBoost model achieved an enhanced cross-validation score of 0.812, indicating improved predictive accuracy and reliability for unseen data (Aldrees *et al.* 2024). The performance improvement was anticipated, as the removed features likely introduced redundancy in the original model, potentially compromising its accuracy and generalization capability (Farek and Benaidja 2023). Although the difference between training and testing R^2 reached 0.136, suggesting some degree of overfitting, this discrepancy remains relatively modest given the highly satisfactory testing R^2 of 0.847 (Yuan *et al.* 2021; Shi *et al.* 2023; Zhou *et al.* 2023). However, attempts to remove additional less important features, such as temperature difference and moisture, resulted in notable performance decline. This indicates that these features, despite their lower importance scores, remain crucial for maintaining model predictive accuracy. These findings confirm that the feature selection process effectively enhanced model performance, achieving satisfactory results using the 13 significant features.

Based on the updated AdaBoost model, SHAP analysis was conducted to examine the relationships between input features and nitrogen loss during composting, and the significance of each feature for predicting nitrogen loss was evaluated (Fig. 5). As demonstrated in Fig. 5, the start date of the composting process emerged as the most influential factor affecting nitrogen loss. The distribution of points for the start date revealed that SHAP values corresponding to earlier start dates were predominantly positive and notably high, indicating that nitrogen loss occurs primarily during the initial composting stages (Fig. 5-B). This observation was reinforced by the fact that, despite larger finish date values, their impact on nitrogen loss remained minimal. This finding corroborates previous studies, where NH_3 and NO_2 emissions occurred predominantly within the first seven days of composting (Hwang *et al.* 2020; Qiu *et al.* 2021; Liu C W *et al.* 2023). Following start date, bulking agent and raw material emerged as critical determinants for nitrogen loss during composting. Notably, as shown in Fig. 6, the influence of each subcategory of composting strategies, categorical variables, on nitrogen loss prediction revealed an unexpected pattern. Chicken manure, pig manure, and sewage sludge, which typically exhibit higher nitrogen content and lower C/N ratios compared to other raw materials, counterintuitively resulted in lower nitrogen losses. This phenomenon may be attributed to the addition of common bulking agents during composting, such as sawdust, rice husk and corn stalk, which demonstrated greater importance than raw materials (Fig. 5) and could mitigate nitrogen loss during composting (Fig. 6).

These three bulking agents enhanced nitrogen retention within the composting process potentially due to their high lignocellulose content and acidic properties, which can reduce the compost pile pH, thereby decreasing ammonium nitrogen volatilization (Tannouri *et al.* 2023). This effect has been validated in previous research (Huang *et al.* 2004; Leconte *et al.* 2009). Moreover, as high-carbon materials, they effectively balance the C/N ratio, which proves crucial for maintaining microbial activity and enhancing nitrogen fixation within microbial biomass, thus further reducing nitrogen loss (Akdeniz 2019; Manga *et al.* 2022; Wang F *et al.* 2024). Conversely, brewery waste and coffee husk as bulking agents demonstrated higher nitrogen loss, potentially due to their elevated pH levels, higher nitrogen content, and lower C/N ratios (Tannouri *et al.* 2023). This underscores the essential role of bulking agent selection in minimizing nitrogen loss during composting.

The form and concentration of nitrogen significantly influence nitrogen loss during the composting process. As shown in Fig. 5, ammonium nitrogen exhibited a positive correlation with nitrogen loss. This relationship aligns with previous research (Bao *et al.* 2022; Nguyen *et al.* 2022),

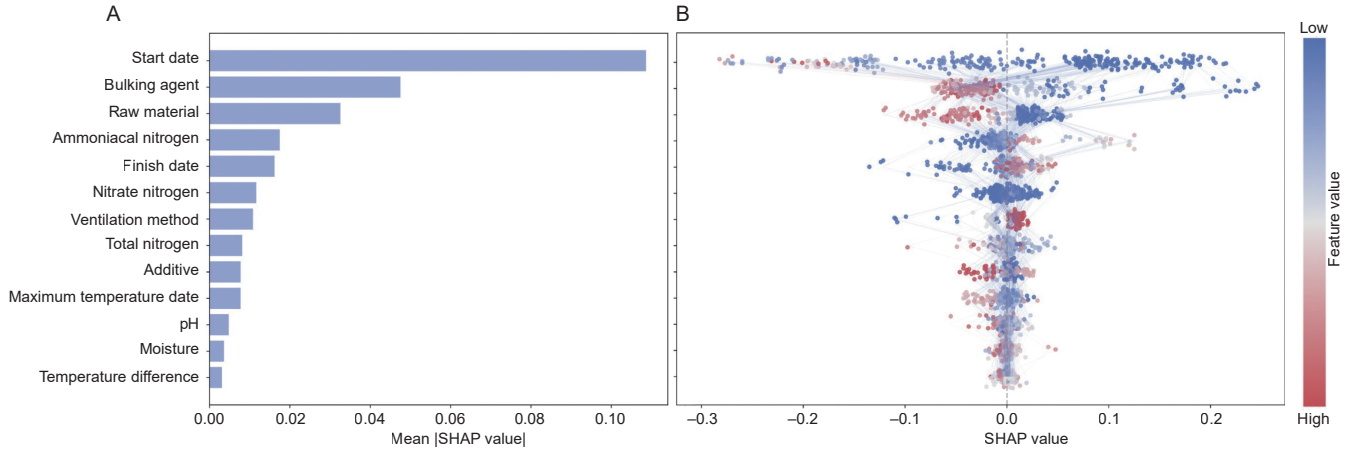
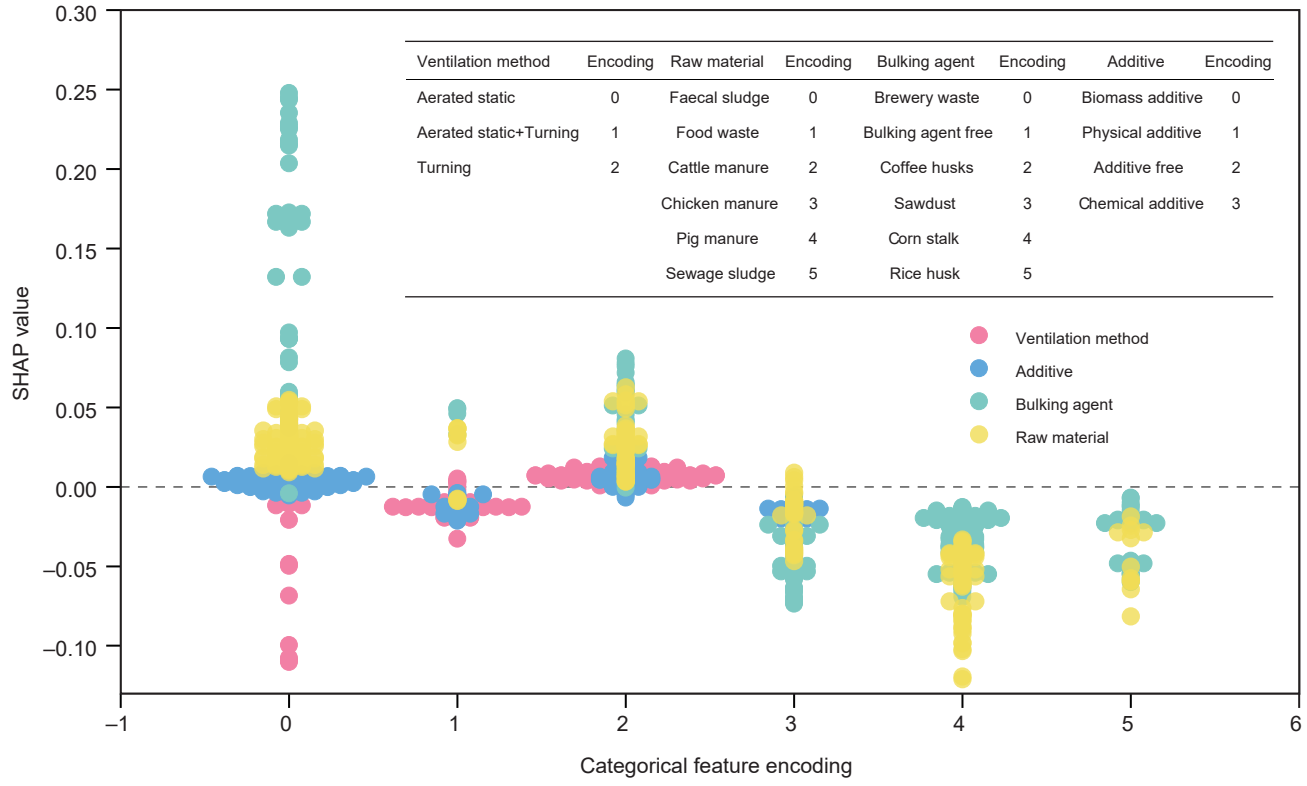


Fig. 5 Effects of input characteristics on nitrogen loss during composting. A, the importance of each feature regarding nitrogen loss during composting. B, the specific shapley additive explanation (SHAP) value for each data point of different features.



Ventilation method	Encoding	Raw material	Encoding	Bulking agent	Encoding	Additive	Encoding
Aerated static	0	Faecal sludge	0	Brewery waste	0	Biomass additive	0
Aerated static+Turning	1	Food waste	1	Bulking agent free	1	Physical additive	1
Turning	2	Cattle manure	2	Coffee husks	2	Additive free	2
		Chicken manure	3	Sawdust	3	Chemical additive	3
		Pig manure	4	Corn stalk	4		
		Sewage sludge	5	Rice husk	5		

Fig. 6 Shapley additive explanation (SHAP) values for the impact of subcategories of categorical variables on nitrogen loss in composting. The integer encoding of the classification feature subcategories is shown in the table in the top right.

where nitrogen loss associated with high ammonium nitrogen content primarily occurs through two mechanisms: NH_3 volatilization and nitrification. According to Bao *et al.* (2022), ammonium nitrogen readily converts to ammonia under elevated pH and temperature conditions, subsequently volatilizing into the atmosphere (Bao *et al.* 2022). Furthermore, ammonium nitrogen undergoes oxidation to nitrate through nitrifying bacteria in aerobic conditions. The resultant nitrate can contribute to additional nitrogen loss through leaching or denitrification in anaerobic zones (Hoang *et al.* 2022; Liu B G *et al.* 2024). Regarding nitrate nitrogen, elevated levels in compost correlate with increased nitrogen loss, likely due to enhanced denitrification under anaerobic conditions (Yan *et al.* 2022; Tian *et al.* 2024). Research by Liang *et al.* (2024) indicates that during cooling to maturity stages, the abundance of dominant denitrifying bacterial genera showed a positive correlation with nitrate nitrogen concentrations. High nitrate nitrogen concentrations can stimulate bacterial proliferation, thereby enhancing nitrate nitrogen reduction and increasing N_2O and N_2 production. Consequently, effective nitrogen loss mitigation during composting requires proper management of ammonium and nitrate nitrogen concentrations, pH regulation, and temperature and oxygen level control to reduce NH_3 volatilization and denitrification (Tannouri *et al.* 2023).

Based on these findings, future research should prioritize the optimization of key parameters to effectively reduce nitrogen loss during composting. Microbial inoculants were employed to accelerate heating rates and shorten the thermophilic phase, while bulking agents were utilized to optimize pH and C/N ratios, thereby reducing nitrogen loss. Additionally, static aeration was applied to enhance compost stability, and chemical additives were incorporated to inhibit nitrogen volatilization. Despite these advancements, further research should focus on elucidating the complex biochemical interactions and multifactorial elements influencing nitrogen loss during composting. Such investigations will provide more precise guidance for optimizing composting practices and minimizing nitrogen loss, ultimately improving the sustainability and efficiency of organic waste management.

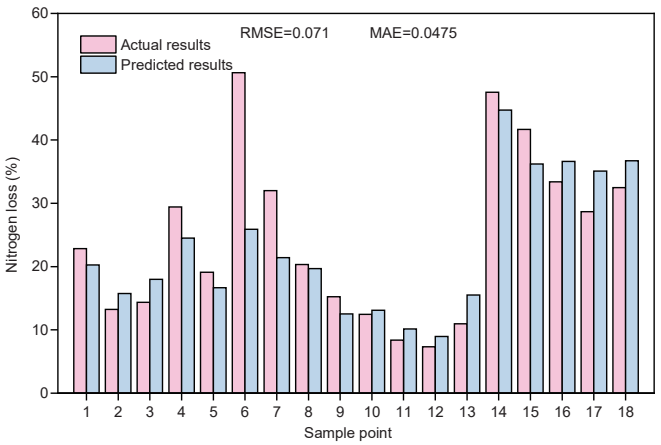


Fig. 7 Comparison of model predictions and actual data of nitrogen loss. RMSE, root-mean-square error; MAE, mean-absolute error.

3.4. Validation of the model and future challenges

To assess the applicability of the developed model, its predictive performance was evaluated using 18 newly collected datasets from six independent studies (Li *et al.* 2018; Zeng *et al.* 2018; Liu Z Z *et al.* 2024; Zhang *et al.* 2024; Xue *et al.* 2025; Yu *et al.* 2025). Each dataset contained 13 input features along with corresponding nitrogen loss values (Appendix E), providing a comprehensive representation of nitrogen loss dynamics throughout the composting process. The predicted results demonstrate that the AdaBoost model performs effectively in predicting nitrogen loss, with a RMSE of 0.071 and a mean absolute error (MAE) of 0.0475 (Fig. 7). However, the predictions for the sixth and seventh data points deviate significantly from the actual values, resulting in a higher RMSE for the new dataset compared to the RMSE of the AdaBoost model. Given that RMSE is particularly sensitive to outliers, the discrepancy likely stems from the sixth and seventh data points corresponding to sludge composting, where the model exhibited substantial prediction errors. This suggests that the limited sludge composting data in the training set may have impaired the model's generalization capability. After excluding these data points, the recalculated RMSE and MAE values of 0.0351 and 0.0314, respectively, closely approximate the AdaBoost model's RMSE of 0.029, indicating high precision in predicting nitrogen loss for chicken and pig manure composting. The MAE of 0.0314 further confirms that the predicted values differ from actual values by only 0.0314 on average in these scenarios. Future research should expand the dataset to include more sludge composting data, thereby enhancing the model's generalizability for sludge composting scenarios.

The present study utilized readily available composting data to develop predictive models. However, several critical factors, including microbial community composition, oxygen levels, and operational management strategies, were not incorporated due to limited data availability in the literature. Future research should systematically investigate the influence of these parameters on nitrogen loss during composting to enhance model precision and robustness. Furthermore, addressing model inaccuracies requires strategic refinements, including expert-driven error analysis, dataset expansion, and advanced feature selection techniques. These improvements will enhance model generalization, reduce prediction errors, and facilitate more reliable nitrogen loss predictions in composting systems.

4. Conclusion

This study utilized ML models to predict nitrogen loss during the composting process. The Adaptive Boosting algorithm produced the best results (R^2=0.847), demonstrating the significant value of this approach in evaluating and optimizing the composting process. The SHAP analysis highlighted that time stages of composting, type of bulking agent, raw materials used, and levels of ammonium nitrogen are crucial factors influencing nitrogen losses. Notably, the majority of nitrogen loss occurs during the initial phase of composting.

To better retain nitrogen in the compost, it is recommended to use bulking agents such as sawdust, rice husk, and corn stalk. Static aeration and chemical additives are more conducive to reducing nitrogen losses during composting. Additionally, the model's strong predictive performance on unknown data, validated through rigorous testing, underscores its reliability and generalizability. This research not only offers valuable insights into optimizing composting operations and enhancing nitrogen retention but also provides new approaches to improve the efficiency and sustainability of compost management practices.

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Declaration of competing interest

The authors declare that they have no conflict of interest.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used Qianwen-3 to assist in improving the clarity and readability of the language. All content generated was carefully reviewed and revised by the authors as necessary, and the authors take full responsibility for the final content of the article.

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