Exploration of the scientific development of AI-assisted pyrolysis of waste plastics（Part A）

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Abstract: The pyrolysis of waste plastics, as a kind of environmentally friendly and efficient waste treatment method, has received widespread attention. This paper expounds the development strategy of the basic theoretical system for AI waste plastics pyrolysis; explores the main functional analysis and key technology implementation strategies of the AI waste plastics pyrolysis model; explores the design of the AI waste plastics pyrolysis system; expounds and analyzes the application cases of AI waste plastics pyrolysis; discusses the future development trends and challenges of AI waste plastics pyrolysis technology, pointing out that how to achieve the optimal environmentally friendly waste plastics pyrolysis has become a key issue that needs to be urgently addressed. This paper provides a reference for intelligent solutions for waste plastics pyrolysis.

Key words: AI; waste plastics; pyrolysis; scientific development

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In recent years, with the rapid development of AI and its widespread application in various fields, the pyrolysis of waste plastics empowered by AI has gradually emerged, demonstrating tremendous potential and prospects. The pyrolysis technology of waste plastics empowered by AI optimizes the pyrolysis process through intelligent means, improves pyrolysis efficiency, reduces energy consumption, and achieves efficient resource utilization of waste materials. It is expected to provide a more environmentally friendly, efficient, and sustainable green solution to address the environmental problems of waste plastics. This not only enhances the intelligent level of pyrolysis but also promotes the dual improvement of environmental protection and economic benefits, providing a sustainable green solution to the problem of plastic pollution.

This article expounds on the development strategy of the basic theoretical system for AI waste plastic pyrolysis; explores the main functional analysis and key technology implementation strategies of the AI waste plastic pyrolysis model; explores the design of the AI waste plastic pyrolysis system; elaborates and analyzes the application cases of AI waste plastic pyrolysis; discusses the future development trends and challenges of AI waste plastic pyrolysis technology, pointing out that how to achieve the optimal environmentally friendly waste plastic pyrolysis has become a key issue that needs to be urgently addressed. This article provides a reference for intelligent solutions for waste plastic pyrolysis.

1 Development strategy for the basic theoretical system of AI waste plastic pyrolysis

The AI theoretical system has been introduced into the field of waste plastic pyrolysis. Based on the scientific development of environmentally friendly green pyrolysis of waste plastics, an AI-based fundamental theoretical system

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for waste plastic pyrolysis has been developed and integrated, providing theoretical support for AI-assisted waste plastic pyrolysis and achieving and enhancing the level of intelligence in waste plastic pyrolysis.

The fundamental theoretical system of AI-assisted pyrolysis of waste plastics is a scientific framework that integrates knowledge from multiple disciplines, including artificial intelligence, chemical engineering, environmental science, and materials science.

With the development of AI waste plastic pyrolysis, the theory of AI waste plastic pyrolysis is also evolving and developing in practical applications. Researchers have employed modern scientific methods such as scientific experimental design, data analysis techniques, machine learning algorithms, and machine learning models to explore the theory of AI waste plastic pyrolysis. The exploration of the basic theory of AI waste plastic pyrolysis mainly revolves around the following aspects:

1.1 Development strategy for the basic theory of mathematical models for pyrolysis processes

Through theoretical computational chemistry and molecular dynamics simulations, we aim to gain a deep understanding of the cracking mechanisms of plastic molecules under different temperatures, pressures, and oxygen concentrations, including radical chain reactions and thermodynamic equilibria. We will develop and optimize mathematical models for the pyrolysis process, such as reaction kinetics models and heat and mass transfer models, to predict the product distribution and yield under various conditions.

1.2 Development of basic theory for pyrolysis process optimization

By collecting key parameters during the pyrolysis process, such as temperature, pressure, reaction time, feedstock type, and product composition, outliers and missing values are removed and stored in an efficient data system. Based on the physicochemical principles of the pyrolysis process, key features that have a direct impact on target optimization are selected or constructed. Statistical methods or machine learning algorithms are used to screen the features that have the greatest impact on optimization results. Appropriate machine learning or deep learning models are selected based on the nature of the problem. Cross-validation techniques are used to ensure the generalization ability of the model and avoid overfitting. Model parameters are adjusted through methods such as grid search, random search, or Bayesian optimization to improve prediction accuracy. Data is collected in real-time and compared with model predictions. Real-time feedback is used to adjust process parameters and continuously optimize the pyrolysis process. Interdisciplinary innovation is carried out by combining knowledge from multiple fields such as chemistry, mechanics, and electrical engineering. New materials, sensors, control systems, etc. are explored and applied to enhance the intelligence level of the pyrolysis process.

1.3 Development strategy for basic theories of model fitting and prediction

By collecting a large amount of experimental data, including pyrolysis temperature, pressure, feedstock properties, product characteristics, etc., key features that have a direct impact on the pyrolysis process are selected, mathematical models are established, and appropriate machine learning or deep learning models are selected for training. The collected dataset is used to train the selected models, and key parameters such as product distribution, yield, and energy consumption under different conditions are predicted. The models are continuously adjusted and optimized in combination with practical application backgrounds.

1.4 Development strategy for basic theories of feature selection and dimensionality reduction techniques

By selecting the feature subset that contributes the most to the model's predictive ability from the original feature set, combined with data cleaning, handling missing values, and other dimensionality reduction techniques, machine learning can identify the factors that have the greatest impact on the pyrolysis process. This helps simplify the model, enhance interpretability and practicality, effectively improve the predictive accuracy and efficiency of the AI waste plastic pyrolysis system, and reduce the consumption of computational resources

1.5 Development strategy for basic theories of online learning and adaptive adjustment

Through machine learning algorithms, key parameters of the pyrolysis process are adjusted online in real-time based on current data and model predictions. The online learning algorithm enables the model to learn from data updates after each pyrolysis process, eliminating the need to train the entire model from scratch. The model can quickly adjust its parameters to adapt to changes. In the actual pyrolysis process, environmental conditions, raw material composition, and other factors may change. The machine learning model can adapt to these changes through continuous learning and self-adjustment, maintaining high performance and stability. This technology combines the adaptive learning capabilities of artificial intelligence with the principles of pyrolysis processes in chemical engineering, aiming to continuously optimize pyrolysis process parameters through real-time data feedback, maximize resource utilization, and minimize environmental impact.

1.6 Development strategy for basic theories of ensemble learning and multi-model fusion

By developing a diverse set of models, conducting sampling with replacement on the training data, and weighted averaging the prediction results of all models, we can evaluate the importance of each model to the features. Through careful design and optimization, ensemble learning and multi-model fusion can play a powerful role in prediction and optimization in complex scenarios such as waste plastic pyrolysis, while improving the robustness and efficiency of decision-making. By combining the advantages of multiple machine learning models and utilizing ensemble learning methods, we can enhance prediction accuracy and robustness, better handling the complex and variable pyrolysis process.

1.7 Development strategy for basic theories of process optimization and control

By collecting key parameters during the pyrolysis process of waste plastics, we utilize statistical analysis and machine learning algorithms to screen the features that have the greatest impact on the pyrolysis process and create new features. We select appropriate machine learning models based on the complexity of the problem, develop models to accommodate real-time data streams, continuously update model parameters, optimize the pyrolysis process, dynamically adjust pyrolysis conditions based on real-time data and the results of predictive models, and ensure that the optimization and control development of the AI waste plastics pyrolysis process is a continuous iterative process that requires close collaboration among interdisciplinary teams as well as tracking and application of the latest technologies. The AI model can learn optimal operating conditions through historical data and predict outputs under different parameter combinations, thereby achieving automation and refined control of the process.

1.8 Development strategy for basic theories of prediction and modeling

By collecting relevant data on the pyrolysis process of waste plastics, statistical analysis or machine learning methods (such as recursive feature elimination, feature importance evaluation) are used to select the features that have the greatest impact on the pyrolysis process. Based on the nature of the problem, an appropriate machine learning model or deep learning model is selected. The performance of the model on the validation set and test set is evaluated, and appropriate metrics are used to judge the generalization ability of the model. The trained model is applied to the actual pyrolysis process of waste plastics to predict key parameters (such as yield, product type, energy consumption, etc.), and operational parameters are adjusted based on the prediction results to optimize the pyrolysis process. Prediction models are developed to predict key parameters and product characteristics during the pyrolysis process, such as oil yield, gas generation, and carbon black production. These models can be based on statistical learning, deep learning, or hybrid learning methods, and predict results under different conditions by training a large amount of experimental data.

1.9 Development strategy for basic theory of by-product analysis and classification

By collecting all relevant information about the pyrolysis process of waste plastics, including but not limited to the chemical composition and physical properties of the pyrolysis products, pyrolysis conditions (such as temperature, pressure, time, etc.), and other parameters that may affect the product characteristics. Data preprocessing includes cleaning data, removing outliers, standardizing numerical ranges, etc., to facilitate subsequent analysis and classification. Select an appropriate machine learning or deep learning model to classify the by-products. Evaluate model performance using methods such as cross-validation to select the best model. Evaluation metrics typically include accuracy, recall, F1 score, confusion matrix, etc. Depending on the evaluation results, it may be necessary to adjust model parameters or try different feature combinations. Through integrated learning methods, such as online learning or incremental learning, the model can continuously optimize itself based on new data. The classification results output by the model should be interpretable and used to guide practical operations.

1.10 Development strategy for basic theories of environmental impact assessment

By collecting environmental impact data related to waste plastic pyrolysis, we establish a model framework for environmental impact assessment. We select an appropriate AI model to predict and assess environmental impacts, train the model using historical datasets, and verify its accuracy and generalization ability through methods such as cross-validation and leave-one-out. This ensures that the model can provide reliable predictions across different datasets. The trained model is applied to actual waste plastic pyrolysis processes to assess environmental impacts under various conditions. The model can predict direct and indirect environmental impacts under different pyrolysis parameters, helping decision-makers optimize the pyrolysis process and reduce environmental burden. With technological advancements and the accumulation of new data, the model is continuously improved and expanded to incorporate more influencing factors, enhancing the accuracy and comprehensiveness of the assessment. The AI model can assess the environmental impacts of the pyrolysis process, such as greenhouse gas emissions and pollutant releases. Through predictive modeling, the environmental impacts under different operating conditions can be quantified, guiding optimization strategies and reducing negative environmental impacts.

1.11 Development strategy for basic theory of resource recovery rate prediction

By collecting historical data on the physicochemical properties, pyrolysis conditions, product types, and recovery rates of waste plastics, as well as any factors that may affect the recovery rate, statistical methods or machine learning algorithms are used to determine which features are most important for predicting the recovery rate. New features, such as temperature-time interaction features, are created, or new patterns are discovered through methods such as cluster analysis. Appropriate models are selected based on the nature of the problem and the characteristics of the data, and model parameters are verified and adjusted to optimize model performance. The predictive model is integrated with the pyrolysis process control system to achieve integrated optimization. The performance of the predictive system is continuously monitored, and feedback data is collected to evaluate the long-term effectiveness of the model. The model is updated and optimized based on new data and feedback to adapt to changes in the process and environmental conditions.

Develop an AI system capable of predicting and optimizing the resource recovery rate during the pyrolysis process of waste plastics, thereby enhancing resource utilization efficiency and reducing environmental pollution.

1.12 Development strategy for basic theory of equipment maintenance and fault prediction

By collecting historical operational data and real-time operating status of equipment, select features that have a significant impact on equipment fault prediction and create new features. Connect the real-time collected data with the prediction model to achieve real-time fault prediction. Integrate the prediction system with existing equipment management systems and workflow systems to ensure smooth data flow. Deploy the prediction system in the actual environment and continuously monitor its performance and effectiveness. Regularly evaluate the accuracy and efficiency of the prediction system and optimize it based on the evaluation results.

1.13 Development strategy of basic theories of integration and collaboration

By integrating various AI technologies into every aspect of the entire waste plastic pyrolysis process, efficient and environmentally friendly resource recovery and processing can be achieved. Firstly, an integrated data platform needs to be established, which is capable of collecting, storing, and processing data from different sources. Develop AI-based scheduling and optimization algorithms. Build a prediction and decision support system. Develop a visual user interface. Establish a continuous learning mechanism to enable the system to learn from each operation and continuously optimize its prediction and decision-making capabilities. In the face of constantly changing market and environmental conditions, the system automatically adjusts its strategies and parameters.

1.14 Development strategy for basic theories of real-time monitoring and quality control

Through real-time processing and analysis of collected data, the real-time monitoring system is integrated with the quality control process to achieve a closed-loop control system. By comparing the monitoring data with the set target values through a feedback loop, process parameters are automatically adjusted to achieve optimal operating conditions. Through real-time monitoring and AI analysis, product quality during the pyrolysis process can be monitored, and process parameters can be adjusted in a timely manner to ensure the stability and high quality of output.

2 Main functional analysis and key technology implementation strategy of AI waste plastic pyrolysis model

The pyrolysis technology of waste plastics, empowered by AI, is advancing towards the goal of higher efficiency, cleaner operation, and maximized resource recovery and utilization. Firstly, deep learning algorithms are applied to optimize the control of the pyrolysis process. By monitoring and predicting pyrolysis conditions in real-time, precise regulation of reaction parameters is achieved, thereby enhancing pyrolysis efficiency and product quality. Secondly, reinforcement learning technology demonstrates great potential in simulating the complex dynamic behaviors of the pyrolysis process. By constructing a virtual experimental platform, optimization strategies are continuously adjusted to achieve the best pyrolysis results. Furthermore, integrating artificial intelligence with the Internet of Things (IoT) technology enables remote monitoring and intelligent maintenance of pyrolysis equipment, reducing operational costs and enhancing equipment reliability.

AI waste plastic pyrolysis technology is developed around improving efficiency, optimizing processes, enhancing decision-making capabilities, and prediction.

2.1 Main analysis and key technical implementation strategies of linear regression model and logistic regression model

The application of linear regression and logistic regression models in the pyrolysis of waste plastics is primarily manifested in two aspects: prediction and classification, specifically targeting numerical prediction and categorical prediction tasks, respectively.

2.1.1 Analysis of main functions and implementation strategies for key technologies of linear regression model

Main function: The regression model is primarily used for predicting continuous variables, such as the yield, energy consumption, and temperature changes during the pyrolysis process of waste plastics.

Key technology implementation strategy:

(1) Data collection: Collect various parameters during the pyrolysis process of waste plastics, such as temperature, pressure, time, type of raw material, yield of pyrolysis products, etc.

(2) Feature selection: Select features that have a significant impact on the prediction target as input variables.

(3) Model Training: Train a linear regression model using historical data to find the optimal parameters (weights and intercept) that minimize the error between the predicted and actual results.

(4) Model evaluation: Evaluate the predictive performance of the model through methods such as cross-validation to ensure that the model exhibits good predictive ability even on unseen data.

(5) Application and optimization: Apply the model to real-time data to predict yields, energy consumption, etc. under different conditions. Adjust the pyrolysis process parameters based on the prediction results to optimize pyrolysis efficiency and resource recovery rate.

2.1.2 Main functional analysis and key technical implementation strategies of logistic regression model

Main function: The logistic regression model is primarily used for classification tasks, such as predicting whether waste plastics are suitable for pyrolysis, and the types of products produced after pyrolysis of different types of waste plastics.

Key technology implementation strategy: several key technical steps for application:

(1) Data collection: Collect the physicochemical properties of waste plastics, the types of products before and

after pyrolysis, and the pyrolysis conditions.

(2) Feature engineering: Based on the problem definition, select or create features that enable the differentiation of different product categories.

(3) Model Training: Train a logistic regression model using historical data to learn the relationship between input features and target categories.

(4) Model evaluation: Evaluate the classification performance of the model through indicators such as accuracy, recall rate, and F1 score.

(5) Application and optimization: Apply the model to new waste plastic samples to predict the types of products after pyrolysis, guiding the selection and optimization of pyrolysis processes.

2.1.3 Selection strategy for key technology implementation

By rationally applying linear regression and logistic regression models, the efficiency of the waste plastic pyrolysis process, resource utilization, and environmental benefits can be improved.

In practical applications, the scikit-learn library in Python can be utilized to implement these two models. For instance, LinearRegression can be employed for linear regression, while LogisticRegression can be used for logistic regression. Furthermore, to enhance the predictive performance of the model, tasks such as feature selection, feature scaling, and model parameter tuning are typically required.

Choose an appropriate model based on the specific nature of the problem. Linear regression is suitable for predicting continuous variables, while logistic regression is suitable for binary or multi-class classification problems. Steps such as data cleaning, feature engineering, standardization, or normalization are crucial to the performance of the model.

Use appropriate evaluation metrics and cross-validation methods to ensure the generalization ability of the model. In practical applications, the real-time performance of the model needs to be considered, and online learning or incremental learning methods may be required.

The linear regression model is suitable for handling small-scale datasets, especially when the relationships between features are relatively simple and linearly separable. The logistic regression model can be used to predict the type or quality of pyrolysis products under specific conditions.

2.2 Functional analysis and key technology implementation strategy of support vector machine (SVM) model

Main function: A kind of very powerful supervised learning algorithm, which excels particularly in classification and regression problems. The core idea of SVM is to construct a decision boundary by maximizing the interval between data points, thereby improving the accuracy of classification. SVM can be used to predict the composition of products from the pyrolysis process under different temperatures and reaction times. In waste plastic pyrolysis technology, SVM can be used to distinguish between different types of plastic materials, or to optimize pyrolysis conditions to maximize the yield of specific products.

Key Technical Implementation Strategies: Select a kernel function suitable for linearly separable data, a polynomial kernel that captures nonlinear relationships by combining additional features, a radial basis function (RBF) kernel suitable for nonlinearly separable data and capable of handling high-dimensional spaces, and a Sigmoid kernel similar to the activation function in neural networks. Control the fault tolerance of the model, use K-fold cross-validation to evaluate the model's generalization ability, employ optimization algorithms (such as the SMO algorithm) to solve the optimization problem of SVM, select the features that contribute most to model performance through statistical methods or recursive feature elimination (RFE), and use methods such as principal component analysis (PCA) and singular value decomposition (SVD) to extract new features from the original features for the model. Deploy the trained model to the production environment for real-time prediction, and evaluate the actual performance of the model through A/B testing.

2.3 Main functional analysis and technical implementation strategies of decision tree and random forest models

Main functions: Both decision trees and random forests provide visual tools and features to help users understand the decision-making process of the model, which have significant application value in classification and regression tasks. Decision trees are used to understand how different parameters in the pyrolysis process individually or collectively affect the final result. Random forests, on the other hand, improve prediction accuracy by integrating multiple decision trees to predict key parameters of the pyrolysis process, such as temperature and pressure, in order to optimize pyrolysis efficiency and product quality. Models such as decision trees and random forests are used to identify key factors affecting pyrolysis efficiency, such as the type, composition, and impurity content of waste plastics, as well as the characteristics of pyrolysis equipment, thereby guiding the design of more efficient pyrolysis systems.

Key technology implementation strategy:

Select a technical implementation strategy for the decision tree that involves choosing features with strong influence on the target variable. Use classic decision tree algorithms such as ID3, C4.5, and CART, or utilize the DecisionTreeClassifier or DecisionTreeRegressor from the sklearn library. Set parameters such as the depth of the decision tree, minimum sample size, and splitting criteria (such as information gain and Gini index) to optimize model performance. Train the model, evaluate its generalization ability through cross-validation, avoid overfitting, and assess model performance.

Technical implementation strategy of Random Forest. Utilize an ensemble learning framework, such as the RandomForestClassifier or RandomForestRegressor from the scikit-learn library. Adjust parameters, including the number of decision trees, maximum depth of each tree, and feature subset size. Train the Random Forest model using training set data. Random Forest enhances model stability by integrating multiple decision trees. Optimize model performance by adjusting Random Forest parameters, such as increasing the number of trees and adjusting the feature subset size. Train the model, evaluate its generalization ability through cross-validation, avoid overfitting, and assess model performance. Decision trees can be used to understand how different parameters in the pyrolysis process individually or collectively affect the final result. Random Forest, on the other hand, provides more stable predictions and enhances prediction accuracy by integrating multiple decision trees.

2.4 Analysis of main functions and implementation strategies for key technologies of neural network models

Main functions: Applied to various scenarios such as image recognition, natural language processing, and recommendation systems, it is used to simulate complex pyrolysis chemical reaction pathways, predict the generation probability of various by-products during the pyrolysis process, and provide a basis for process optimization. It can handle complex nonlinear relationships, learn feature representations through multi-layer structures, and is suitable for large-scale and complex datasets.

Neural networks encompass feedforward neural networks, recurrent neural networks (RNNs), and long short-term memory networks (LSTMs), which are utilized to capture intricate relationships and patterns.

Key technical implementation strategy: Select an appropriate neural network architecture. For image data, operations such as rotation, scaling, and flipping can be performed to increase the diversity of training data. Apply data standardization/normalization techniques to ensure that all features are on a similar scale, which is beneficial for model training. Select an appropriate optimizer for model training, set an appropriate loss function, use a learning rate decay strategy, apply regularization techniques, choose an appropriate batch size, and balance training speed and model performance. Monitor model performance in real-time, adjust model parameters or retrain the model according to actual conditions. Pay attention to the latest developments in the field of neural networks and introduce new technologies in a timely manner.

2.5 Analysis of the main functions and implementation strategies of key technologies for machine learning, reinforcement learning, and deep learning models

Main functions: Machine learning is a kind of algorithm that enables computers to automatically learn patterns from data and use these patterns for prediction or decision-making. It improves the efficiency and product quality of the pyrolysis process by constructing predictive models, handling complex data relationships, capturing nonlinear and high-dimensional features during the pyrolysis process, and achieving in-depth understanding and optimization of the pyrolysis reaction mechanism. Reinforcement learning is an algorithm that learns how to take actions in a given environment to maximize a certain cumulative reward through interaction with the environment. It emphasizes trial-and-error learning and self-improvement through reward and punishment signals, making it particularly suitable for complex systems that need to adapt to constantly changing conditions. Deep learning, especially convolutional neural networks (CNN) and recurrent neural networks (RNN), can identify complex patterns and time series changes in the pyrolysis process, and is particularly effective for predicting the relationship between key parameters such as temperature and residence time and product characteristics.

Key Technology Implementation Strategy: Machine learning, reinforcement learning, and deep learning are crucial components in the field of artificial intelligence, each with its unique characteristics and application scenarios. The selection of each model should be based on the specific needs of the waste plastic pyrolysis process, data characteristics, computational resources, as well as the interpretability and generalization ability of the model, to ensure optimal predictive accuracy and decision support. When implementing any machine learning technology, it is essential to pay attention to data quality and the model's generalization ability, ensuring that the model performs well on unseen data. By combining the strengths of machine learning, reinforcement learning, and deep learning, hybrid models can be designed for specific problems, such as using deep learning for feature extraction and then using reinforcement learning for strategy optimization.

2.6 Main functional analysis and key technical implementation strategies of the performance evaluation model

Main functions: During the pyrolysis process of waste plastics, AI performance evaluation primarily focuses on predicting the yield and quality of pyrolysis products, as well as assessing the accuracy, stability, generalization ability, and practical feasibility of optimizing pyrolysis process parameters.

Key Technology Implementation Strategy: Set specific performance metrics based on evaluation objectives, such as response time, throughput, concurrent user count, resource utilization, latency, etc. Conduct tests according to the predetermined test plan, record data, and observe the dynamic behavior of the system. Based on the test results, propose optimization suggestions, which may include code optimization, algorithm adjustment, resource scheduling, system architecture improvement, etc., and retest to verify the optimization effect. Systematically evaluate and enhance the performance of technical products to ensure their reliability and efficiency in practical applications.

2.7 Main functional analysis and key technical implementation strategies of data preprocessing and feature engineering models

Main functions: When developing a machine learning model for the pyrolysis process of waste plastics using AI, data preprocessing and feature engineering are crucial steps. By utilizing data augmentation techniques to generate more training samples, the generalization ability of the model can be improved.

Data preprocessing and feature engineering are crucial steps in constructing an effective model, ensuring the quality and applicability of data, and enhancing the performance of AI models in the pyrolysis process of waste plastics.

Key technology implementation strategy: Identify and handle missing and outlier values in the data. This can be done through deletion, filling, or interpolation methods. Remove noise and interference information from the data to enhance its purity.

2.8 Main functional analysis and key technical implementation strategies of data collection and cleaning model

Main functions: Obtain high-quality datasets and perform necessary preprocessing to eliminate noise, missing values, and outliers. Improve data accessibility. Through meticulous data collection and cleaning efforts, a solid foundation can be provided for the subsequent construction of machine learning models, thereby enhancing the accuracy and practicality of model predictions for waste plastic pyrolysis processes.

Key technology implementation strategy: During the data collection process, it is essential to ensure the comprehensiveness and representativeness of the data, encompassing different types of waste plastics, various pyrolysis conditions, and diverse factors that may influence the pyrolysis process. Data cleaning involves identifying and addressing inconsistencies, errors, or incomplete information within the data. The data is then formatted and standardized to meet subsequent data analysis and modeling requirements.

2.9 Main functional analysis and key technical implementation strategies of feature selection and extraction model

Main functions: Reduce the number of features in the dataset, enhance the interpretability of the model, and decrease the consumption of computational resources. Selecting or extracting the most relevant features can improve the model's prediction accuracy and the algorithm's operational efficiency.

Key technology implementation strategy: In the feature selection and extraction stage, it is necessary to conduct an in-depth analysis of the original data first, identifying the features most relevant to the pyrolysis process of waste plastics and the ultimate goals (such as product yield, quality, or pyrolysis efficiency). Feature engineering is the process of creating, selecting, and transforming features.

2.10 Main functional analysis and key technology implementation strategies of the integrated model of intelligent control system

Main functions: The intelligent control system optimizes and automates the pyrolysis process of waste plastics, thereby enhancing overall operational efficiency and competitiveness.

Key technology implementation: Clearly define the goals of integration, such as improving production efficiency, optimizing processes, reducing failure rates, or enhancing user experience. Conduct a comprehensive investigation of existing systems to understand their functions, performance, interfaces, data flows, etc., and identify potential integration points and challenges. Write detailed requirement documents, including integration goals, expected effects, required functions, interface requirements, etc. Design a unified standard interface to ensure smooth communication and data exchange between different systems. Select or develop integration tools based on the characteristics and integration requirements of the system. Design a data integration strategy to ensure that data from different systems can be uniformly managed and accessed. Continuously monitor system performance, adjust configurations based on actual operating conditions, and optimize system performance. By adopting advanced sensor technology and real-time data processing algorithms, precise monitoring and dynamic adjustment of key parameters such as temperature, pressure, and gas composition in the pyrolysis reactor are achieved. Regularly evaluate and update the system architecture to maintain the progressiveness and adaptability of the system.

(To be continued)