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Intelligent Grain, Oil and Food Processing Equipment: AI-Based Fault Diagnosis and Predictive Maintenance

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***Abstract*-The rapid development of AI technology has made its application in the grain, oil and food processing industry more and more extensive, especially in equipment fault diagnosis and predictive maintenance shows great potential. The traditional maintenance of food processing equipment often relies on empirical judgment and regular maintenance, which has the disadvantages of lagging response, high maintenance cost and long downtime. AI-based fault diagnosis and predictive maintenance technology, however, collects equipment operation data in real time through an integrated sensor network, and analyzes the data characteristics using machine learning algorithms to realize real-time monitoring of equipment status and fault prediction. This paper introduces the basic principles of AI in fault diagnosis, including key steps such as data collection and processing, feature extraction, model building and prediction result evaluation. In addition, this paper analyzes how AI can identify potential failure modes and formulate maintenance plans in advance by analyzing equipment operation data, thus effectively reducing unplanned downtime and maintenance costs. AI-based fault diagnosis and predictive maintenance technology has revolutionized the grain, oil and food processing industry, which not only improves production efficiency and guarantees product quality, but also significantly reduces maintenance costs. The research results of this paper have practical value for promoting the intelligent upgrading of the grain, oil and food processing industry.**

Keywords-AI-Based; Fault Diagnosis; Predictive Maintenance; Processing Equipment

I. INTRODUCTION

In the grain, oil and food processing industry, the stable operation and efficient maintenance of equipment is a key factor to ensure product quality and production efficiency. However, with the expansion of production scale and the improvement of automation, the diagnosis and maintenance of equipment failure has become a complex and arduous task. Traditional maintenance methods often rely on manual inspection and empirical judgment, which have problems such as lagging response, low efficiency and high cost. Therefore, it is particularly important to explore a more intelligent and efficient equipment fault diagnosis and predictive maintenance method. In recent years, related scholars have carried out relevant research in data-driven fault diagnosis, the application of machine learning in predictive maintenance, the exploration of deep learning in fault diagnosis, multi-source information fusion technology, the construction of real-time monitoring system, fault diagnosis and predictive maintenance based on cloud platforms, and interdisciplinary fusion, respectively.

Zhang, J et al. collects equipment operation data by installing sensors, and mines and analyzes the data using machine learning algorithms to identify equipment failure modes and abnormal states. This method can realize real-time monitoring and early warning of equipment failures and improve the accuracy and timeliness of fault diagnosis [1]. However, in practical applications, the problems of poor data quality and reliability occur from time to time due to sensor failures, data transmission errors. Li, X et al. By constructing a prediction model, the equipment operation data are learned and trained to predict the remaining life and potential failures of the equipment [2-3]. However, for grain, oil and food processing enterprises, collecting and processing a large amount of equipment operation data requires a large amount of human, material and financial resources.

Smith, A et al. began to try to apply it to equipment fault diagnosis. Deep learning models have powerful feature extraction and pattern recognition capabilities, which can extract useful fault features from complex equipment operation data and improve the accuracy and robustness of fault diagnosis [4]. However, at present, technicians in the grain, oil and food processing industry generally lack the knowledge and skills of AI technology. This causes enterprises to face problems in training and application of technicians when applying AI technology. Chen, M et al. integrate and analyze data from different sensors and monitoring systems to obtain more comprehensive information about equipment status [5-6]. However, in practical application, enterprises often neglect the importance of algorithm optimization and model updating. This leads to a gradual decline in the performance of AI technology and fails to meet the actual needs of enterprises.

Liu, Y et al. studied the construction method of real-time monitoring system. By integrating the parts of data acquisition module, data processing module and early warning module, real-time equipment operation data are collected and processed and analyzed [7]. However, there is a lack of unified standards and specifications in the field of fault diagnosis and predictive maintenance of grain, oil and food processing equipment, which leads to difficulties in data sharing and interoperability. Jones, C et al. uploads the equipment operation data to the cloud for processing and analysis in order to realize remote monitoring and fault diagnosis, and improve the convenience and efficiency of maintenance [8-9]. When utilizing AI technology for equipment troubleshooting and predictive maintenance, a large amount of equipment operation data needs to be collected and processed. How to safeguard the security and privacy protection of enterprise business data has become an urgent issue.

Although research in the field of fault diagnosis and predictive maintenance of grain, oil and food processing equipment has made some progress, there are still many shortcomings and challenges. In order to promote the innovation and development of this field, it is necessary to further strengthen the data quality management, reduce the cost of model training, enhance the training of technicians, and optimize the algorithms and models. The research in this paper demonstrates significant application advantages in comprehensive data management and analysis strategies, efficient and low-cost model training and optimization, and interdisciplinary integration and technological innovation. By introducing a data quality control mechanism, data bias due to sensor failures or data transmission errors is effectively reduced, thus improving the accuracy and robustness of AI models. Techniques such as migration learning and incremental learning are used to reduce the need for re-training on new data and reduce the overall cost.

In summary, the research in this paper fully integrates the knowledge and methods of multiple disciplines, such as mechanical engineering, computer science, and mathematics, to realize technological innovation through interdisciplinary fusion, and to construct a fault diagnosis and predictive maintenance model that is more in line with practical needs. This interdisciplinary integration approach makes the research in this paper more prospective and practical. In summary, the research results of this paper are more innovative, practical and generalizable, and are expected to provide strong support for the intelligent upgrading of the grain, oil and food processing industry.

II. Fault Diagnosis and Predictive Maintenance Models

A. Theoretical Research Modeling

The construction of AI-based fault diagnosis and predictive maintenance model includes several aspects such as data acquisition and preprocessing, fault feature extraction, fault diagnosis model construction, fault prediction model, and formulation of maintenance and optimization strategies. Among them, in the aspect of data acquisition and preprocessing, data is the basis of the AI model [10]. In grain, oil and food processing equipment, the data to be collected include, but are not limited to, equipment operating parameters, production environment parameters (e.g., humidity, temperature, etc.), and historical fault records. After data acquisition, pre-processing is required, including data cleaning, data standardization (unifying the scale) and data dimensionality reduction (reducing the computational complexity) to ensure that the data quality meets the model training requirements.

B. Data Preprocessing and Feature Extraction

The raw data collected often contains noise, outliers, and other disturbing factors that require preprocessing to improve data quality. The preprocessing steps include data cleaning, data standardization and data dimensionality reduction. Data cleaning can use sliding average, median filtering and other methods to remove noise; data standardization is often used Z-score standardization or Min-Max standardization method. Data dimensionality reduction can be realized by PCA, LDA and other methods.

Feature extraction is the extraction of information useful for fault diagnosis and prediction from preprocessed data. Commonly used feature extraction methods include time domain analysis, frequency domain analysis, time-frequency analysis and so on. For example, the time-domain signal can be converted into a frequency-domain signal by FFT, as shown in Equation 1 below, which in turn analyzes the vibration frequency characteristics of the equipment; it can also use wavelet transform and other methods to perform multi-scale analysis to extract the multi-level features of equipment faults.

$$\delta[x] = \sum_{i=0}^{n-1} k[i] e^{-j\frac{2\pi}{n}xi} \quad (1)$$

In which, $\delta[x]$ is the frequency domain signal, $k[i]$ is the time domain signal, n is the signal length, and j is the imaginary unit.

C. Fault Diagnosis Model

In terms of fault feature extraction, as a key part of fault diagnosis, machine learning algorithms such as PCA and ICA are utilized to perform feature extraction on the preprocessed data to identify feature variables that are closely related to equipment faults. These feature variables will be used as inputs for subsequent model training. In terms of constructing the fault diagnosis model construction based on the extracted fault features, commonly used machine learning algorithms include SVM, RF, DNN, and so on. These algorithms are able to learn patterns in the data to achieve accurate classification and identification of equipment faults. Among them, the calculation of SVM is shown in Equation 2 below:

$$g[x] = sign(\alpha \cdot x + \beta) \quad (2)$$

Where $sign(\cdot)$ is the sign function, if $\alpha \cdot x + \beta > 0$, then $g[x] = 1$, otherwise $g[x] = -1$. Random forest (RF) decision tree voting function is shown in equation 3 below:

$$Class[\theta] = arg\max_{i} \sum_{t \in T} Z\left(y_t(\theta) = i\right) \quad (3)$$

In which, T is the set of decision trees, $y_t(\theta)$ is the classification result of the t-th tree for sample θ, and Z is the indicator function.

D. Predictive Maintenance Model

Fault prediction models aim to predict possible future failures based on the current equipment state. Commonly used prediction methods include time series analysis, regression analysis and neural network models. Among them, neural network models are favored for their powerful nonlinear fitting ability. The ARIMA model is calculated as shown in equation 4 below:

$$\varphi[\omega] y_t = \vartheta(\omega) \gamma_\tau \quad (4)$$

In which, $\varphi[\omega]$and $\vartheta(\omega)$ are autoregressive and moving average polynomials, respectively, ω is a backward shift operator, and γ_τ is a white noise sequence. Based on the fault diagnosis and prediction results, maintenance and optimization strategies are formulated. For the faults that have occurred, timely repair measures are taken; for the predicted potential faults, maintenance plans are formulated in advance to avoid the occurrence of faults. Meanwhile, the accuracy and efficiency of fault diagnosis and prediction are improved by continuously optimizing the algorithm and model.

III. AI-Based System Architecture Design

A. Data Acquisition and Preprocessing

Data acquisition is the basis of intelligent fault diagnosis and predictive maintenance. In grain, oil and food processing equipment, the operating data of the equipment is acquired in real time by installing various sensors. These data include key parameters such as temperature, pressure, vibration, current and voltage of the equipment, as well as environmental information such as ambient temperature and humidity and noise. Data acquisition methods include sensor monitoring, manual inspection and remote monitoring.

Raw data often contain noise, outliers and missing values, and need to be pre-processed to improve data quality. The preprocessing steps include data cleaning, data conversion, data integration, and feature extraction. Through preprocessing, raw data can be transformed into high-quality data suitable for processing by machine learning models. The data acquisition process architecture of the AI-based system is shown in Figure 1 below, which demonstrates the overall process of data acquisition, including sensor installation, data acquisition, data transmission, and data storage.

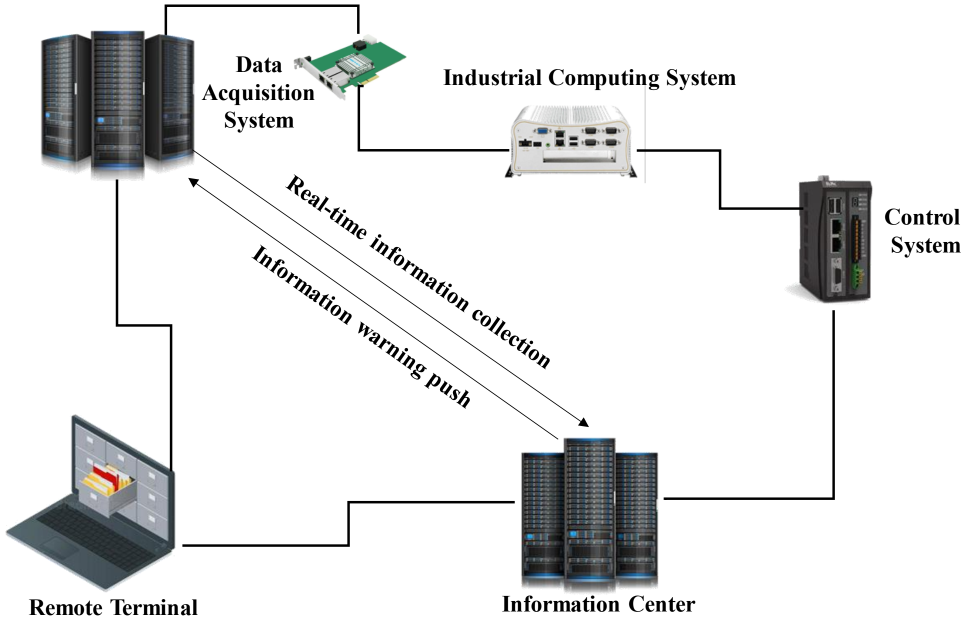

Figure 1 The AI-based data acquisition process system architecture

The data preprocessing process of the AI-based system is shown in Figure 2 below, which describes in detail the process of data preprocessing, including steps such as data cleaning, data transformation, data integration and feature extraction.

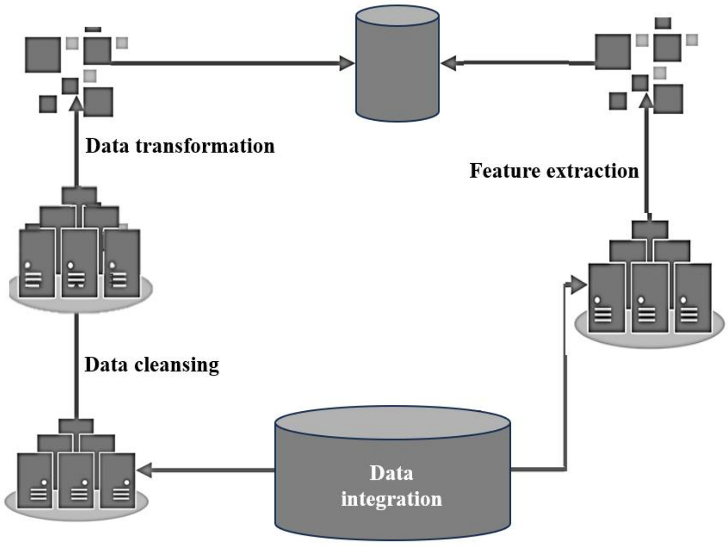

Figure 2 The data preprocessing process of the AI-based system

Feature selection is a key step in constructing an efficient prediction model. In the fault diagnosis of grain, oil and food processing equipment, it is necessary to select fault-related features from a large amount of raw data and exclude irrelevant or redundant features. Feature selection can be realized by statistical methods, correlation analysis, principal component analysis and other techniques. In addition, in order to reduce the computational complexity and improve the model effect, feature dimensionality reduction processing is needed to reduce the feature dimension. The real-time monitoring system is the core component of intelligent fault diagnosis and predictive maintenance. Through real-time data collection and model prediction, the system can detect equipment abnormalities or potential failures in a timely manner and issue an early warning to notify relevant personnel. The early warning information includes the type of failure, failure level, and expected development trend, so that maintenance personnel can take timely measures to repair.

B. System Architecture Design Process

The design process of the AI-based intelligent grain, oil and food processing equipment fault diagnosis and predictive maintenance system architecture includes many modules as shown in Figure 3 below. Among them, the requirement analysis module is used to clarify the specific requirements of fault diagnosis and predictive maintenance of grain, oil and food processing equipment, including the type of equipment to be monitored, key parameters, fault types, etc. Through the requirement analysis, the functional and performance requirements of the system are determined. Based on the results of the requirement analysis, design the overall architecture of the system. The system architecture includes a data acquisition layer, a data processing layer, a model prediction layer, a real-time monitoring and warning layer, and a user interface layer. Data transmission and interaction between the layers are carried out through interfaces.

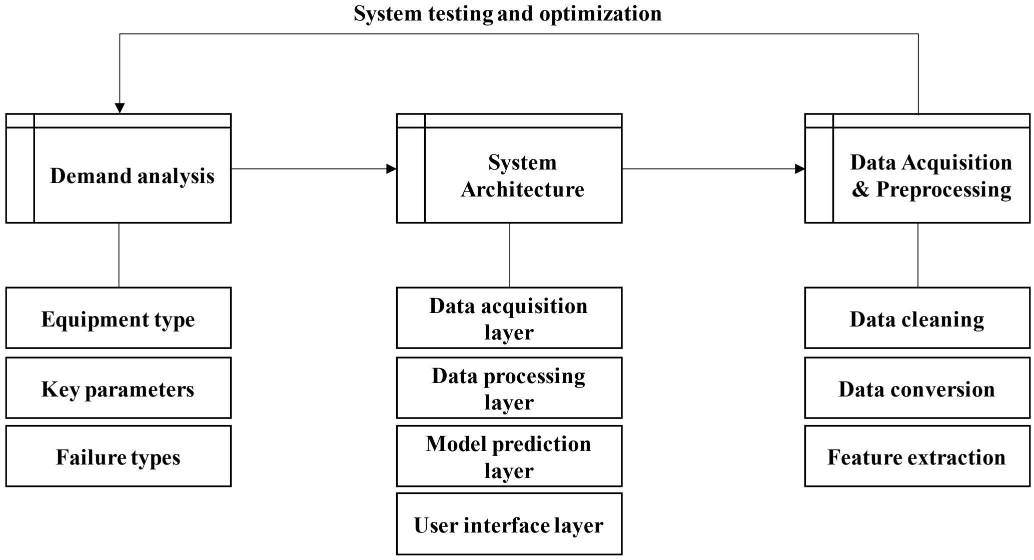

Figure 3 The system architecture design process

In addition, the data acquisition and preprocessing module installs sensors and acquires real-time equipment operation data according to the designed data acquisition scheme. The collected raw data are preprocessed, including data cleaning, conversion, integration and feature extraction to improve data quality. The model selection and training module selects appropriate machine learning algorithms based on data characteristics and task requirements, and uses historical data to train the model. By adjusting the model parameters and optimizing the algorithm, the prediction accuracy and generalization ability of the model are improved. The real-time monitoring and warning module inputs new data into the trained model for real-time fault prediction. When equipment abnormalities or potential failures are predicted, the system issues an early warning to notify relevant personnel. The system testing and optimization module conducts comprehensive testing of the system, including functional testing, performance testing and stability testing. Based on the test results, the system is optimized to improve the reliability and stability of the system.

IV. Fault Diagnosis and Predictive Maintenance System Application

A. Equipment Data Acquisition and Pre-Processing

Traditional fault diagnosis of grain, oil and food processing equipment relies on manual inspection and regular maintenance, which is not only inefficient, but also easy to miss potential faults. The AI-based intelligent system collects a variety of status data such as temperature, pressure, vibration, etc. of the equipment in real time through sensor networks and IoT technology. These data undergo preprocessing steps such as cleaning, denoising and normalization to provide a high-quality data source for subsequent model training. A comparison of the data collection efficiency of AI-based intelligent grain, oil and food processing equipment fault diagnosis and predictive maintenance with that of the traditional approach is shown in Figure 4 below.

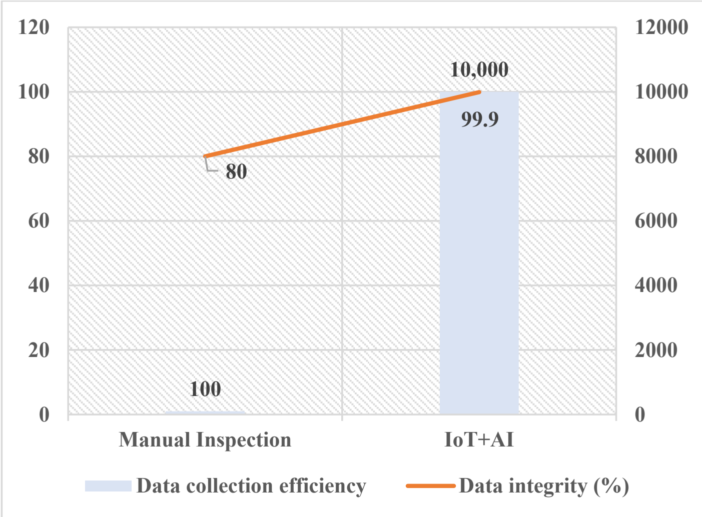

Figure 4 Comparison of the data collection efficiency of AI-based system

In addition, massive amounts of device data need to be stored and managed efficiently and securely. The AI-based system utilizes cloud storage and big data technology to achieve real-time uploading, classified storage, and rapid retrieval of data. This not only improves the reliability of data storage, but also facilitates subsequent data analysis and model training.

B. Model Training and Optimization

In terms of model selection, AI-based intelligent systems usually use machine learning and deep learning algorithms, such as support vector machine (SVM), neural network (NN) and convolutional neural network (CNN). These algorithms construct high-precision fault diagnosis and prediction models by training on historical fault data. Once the models are trained, continuous optimization is required to improve their accuracy and generalization. The AI-based system continuously optimizes the model parameters and structure to adapt to the dynamic changes in equipment status through cross-validation, hyper-parameter tuning and incremental learning. A comparison of the accuracy, training practices, and precision improvement effects of the different models is shown in Table 1 below.

Table 1 Results of Students' Completion and Innovation Enhancement

Models	Training time (hours)	Accuracy (%)	Degree of Improvement (%)
SVM	24	85	19
CNN	72	72	11
RNN	56	79	10
KNN	77	80	13
NN	48	90	22
DT	38	88	15

C. Interdisciplinary Integration of Practice

The degree of automation of grain, oil and food processing equipment is constantly increasing, and the integration of AI technology further improves the intelligent level of equipment. Through the real-time monitoring and analysis of equipment status by AI algorithms, the system is able to automatically adjust equipment parameters, predict potential failures and warn in advance, realizing the intelligent operation and maintenance of equipment. IoT technology provides a rich data source for the AI system, while the AI algorithm conducts in-depth mining and analysis of IoT data, realizing the accurate perception and prediction of equipment status. The integration of the two not only improves the efficiency of equipment operation and maintenance, but also reduces the probability of failure.

D. Technician Training Practice

The AI-based intelligent grain, oil and food processing equipment fault diagnosis and predictive maintenance system puts forward higher requirements for technicians. Enterprises need to organize professional training courses, including AI basics, machine learning algorithms, IoT technology, equipment operation and maintenance management and other content. Training methods can be online video teaching, offline practical exercises and case studies. Evaluate the training effect of technicians through regular skill tests and practical assessments. At the same time, establish a feedback mechanism for technicians to understand their learning needs and difficulties in a timely manner, and continuously optimize the training content and methods. Table 2 below shows the feedback data on the increased competence of technicians trained in the AI-based intelligent fault diagnosis and predictive maintenance system for grain, oil and food processing equipment.

Table 2 The Improvement Effect of Technicians' Skill Mastery

Competency indicators	Pre-training	Post-training	Degree of Improvement
AI comprehension rate	≤50%	≥80%	≥30%
Fault diagnosis accuracy rate	≤70%	≥90%	≥20%
Fault prediction accuracy rate	≤40%	≥75%	≥30%
Accuracy of data analysis	≤60%	≥85%	≥25%
Fault processing efficiency	≥2h	≤1h	≥50%
Competency indicators	≤50%	≥80%	≥30%

As can be seen from Table 2, the comprehensive skills of the relevant personnel in terms of basic understanding of AI technology, fault diagnosis accuracy, fault prediction ability, data analysis ability, fault handling efficiency, preventive maintenance awareness and implementation ability, and cross-domain knowledge fusion ability, etc., have been greatly improved through training.

E.Standardization, Normalization and Data Security Protection

The application of AI-based intelligent grain, oil and food processing equipment fault diagnosis and predictive maintenance system requires the development of corresponding standards and specifications. These standards include data acquisition standards, model training standards, fault warning standards, maintenance operation standards, etc., to ensure the stability and reliability of the system. On the basis of standardized development, enterprises need to strengthen the implementation of standardization. Through the development of detailed operation manuals and operating instructions, standardize the operating procedures and operating standards of technicians to improve the operational efficiency and safety of the system.

In addition, in terms of security and privacy protection, the data of grain, oil and food processing equipment involves the commercial secrets of enterprises and the private information of consumers, so strict data security measures must be taken. The AI-based system ensures data security and integrity through data encryption, access control, and regular auditing. Strict compliance with privacy protection regulations is required during data processing and model training. Enterprises should desensitize sensitive data to ensure that personal privacy is not leaked. At the same time, a privacy protection mechanism is established to regulate and audit the entire process of data processing and use.

V. CONCLUSIONS

This thesis addresses the challenges of equipment fault diagnosis and predictive maintenance in the grain, oil and food processing industry, and thoroughly researches an intelligent AI-based fault diagnosis and predictive maintenance system for grain, oil and food processing equipment. By introducing advanced algorithms such as machine learning and deep learning, it not only improves the accuracy and efficiency of fault diagnosis, but also reduces the dependence on manual experience, providing more reliable and efficient fault diagnosis solutions for grain, oil and food processing enterprises. At the same time, the system is also able to carry out in-depth mining and analysis of the collected data, discover potential problems and optimization space in equipment operation, and provide a scientific basis for enterprise equipment management and maintenance. In summary, the AI-based intelligent grain, oil and food processing equipment fault diagnosis and predictive maintenance system excels in improving the accuracy of fault diagnosis, reducing the failure rate, and improving production efficiency and economic benefits. With the continuous development and application of AI technology, the system will play a more important role in the grain, oil and food processing industry and promote the intelligent and efficient development of the industry.

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