

## *Retraction*

# **Retracted: Census and Inventory Method of Pollution Sources Based on Big Data Technology under Machine Learning**

### **Wireless Communications and Mobile Computing**

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### **References**

- [1] N. Liu, X. Sun, J. Mi, and S. Zhang, "Census and Inventory Method of Pollution Sources Based on Big Data Technology under Machine Learning," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 3706065, 7 pages, 2022.

## Research Article

# Census and Inventory Method of Pollution Sources Based on Big Data Technology under Machine Learning

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In order to strengthen the supervision and management of environmental pollution and timely understand and record the basic information of potential environmental pollution of enterprises and institutions, this paper proposes a general survey and inventory method of pollution sources based on big data technology under machine learning. Firstly, this paper evaluates and screens the data provided by government departments, constructs a machine learning classification model, and uses a variety of classification algorithms to compare and analyze according to the basic idea of machine learning to deal with practical problems. Then, the calibration data set constructed is used as the training set to predict and classify the national industrial and commercial data, provincial industrial and commercial data, and municipal industrial and commercial data provided by government departments. The experimental results show that the naive Bayesian classification algorithm is the best algorithm, and the F1 values of each data set are increased by 32.92%, 21.42%, and 14.91%, respectively. The classified prediction of the screened Internet data shows that the accuracy of the final Internet supplementary data is 17.26%, which is similar to the industrial and commercial data of the city. The availability of the machine learning model established in this paper is proven.

## 1. Introduction

For a long time since the reform and opening up, China has been blindly pursuing rapid economic development and rarely taking environmental protection measures. Almost all localities have followed the social and economic development model of “pollution before treatment,” which has caused great damage to the natural environment. For a time, there were negative reports on environmental health caused by serious poisoning caused by various pollutants and health disease events in many places across the country [1]. Later, all walks of life in China began to pay attention to the issue of environmental sustainable development and realized that “green water and green mountains are golden mountains and silver mountains.” Although China’s environmental protection work started late, it has achieved initial results with the joint efforts of the Chinese government and enterprises.

Generally speaking, the construction of China’s environmental information system can be roughly divided

into three development stages: the 1980s experienced a decade of exploration, the 1990s gradually moved towards maturity, and the early 21st century began to move towards marketization. In the stage of exploration and development, the research of information system focuses on the research of systematic theories and methods [2], and a series of preliminary construction work has been carried out at the national level and the local government level. In the later mature stage, the development technology of China’s environmental information system is gradually maturing. The research in this stage is combined with the actual development to further improve the functions of the environmental information system [3]. China’s environmental monitoring system and environmental protection industry and production enterprises complement each other. On the one hand, environmental information system can provide experimental data and experimental platform for environmental protection-related research and analysis. On the other hand, environmental protection-related research and analysis continue

to promote the development and continuous improvement of an environmental information system.

## 2. Literature Review

With the development of environmental protection in China, many environmental protection-related data have been accumulated, such as ground monitoring data, remote sensing monitoring data, and geographic information data. These data resources are distributed in different government departments such as environmental protection, water conservancy, agriculture, forestry, and meteorology. In terms of the application of big data in the field of environmental protection, Wj et al. put forward the method of using machine learning technology to integrate satellite data into the model, conduct objective analysis of big data, and conduct cross research with ground monitoring data, which can fill in and correct ground detection data, real-time detect pollution source changes, and more accurately predict air quality changes [4]. Guan et al. studied and established a big data platform for information service integration for the early warning direction of meteorological and geological disasters in China's petroleum industry [5]. Ge et al. used the HDFS technology in Hadoop, combined with ground detection data and remote sensing meteorological data transformed by ARL, to establish a big data platform for air pollution prevention and control in a certain region [6]. Miszczak et al. conduct a general survey of results of pollution sources and analysis of pollution sources in a city and put forward pollution prevention and control measures [7]. Bloetscher et al. identified beverage manufacturing, papermaking and paper products, food manufacturing, and agricultural and sideline food processing industries as typical industries to reduce oxygen demand pollution through the summary, analysis, and research on the census data of pollution sources and focused on the generation, emission, and treatment of five-day biochemical oxygen demand in four industries [8]. Liu et al. analyzed the production, emission characteristics, and pollution status of pollutants in Jingjiang City, Jiangsu Province, by using the census data of pollution sources and social statistical data and pointed out that while industrial pollution is paid attention to, domestic pollution and agricultural pollution cannot be ignored [9]. Wen et al. analyzed the main environmental problems within the jurisdiction according to the results of the general survey of pollution sources in a city and put forward corresponding countermeasures and suggestions in combination with local conditions [10].

The purpose of this paper is to build a model that can effectively use the business scope of an enterprise to predict whether an enterprise belongs to the scope of pollution source census and to correct the departmental data by using the massive business scope data provided by government departments and the actual household survey results of pollution sources. Combine the prediction model to judge the screened Internet big data, and explore the availability of Internet big data for the supplement of basic unit directory. Then, the paper summarizes the methods that can improve

the efficiency of compiling the list of basic units in the general survey and inventory stage of pollution sources.

## 3. Research Methods

### 3.1. Data Sources and Research Methods

*3.1.1. Data Source.* The data used in this study include government department data and public data.

The data sources of government departments mainly come from the information management systems of industrial and commercial departments at national, provincial, and municipal levels.

Public data refers to the Internet data obtained by the third-party team, which focuses on industries and regions for the census of pollution sources and uses web crawlers to publicly collect. The collected enterprise data sources include enterprise category interest point data based on public map services, Internet web page public data, and data obtained through commercial channels, involving Tianyancha, Alibaba, Qichacha, Liepin.com, Zhilian Recruitment, and atubo yellow pages, and nearly 240000 enterprise data have been obtained.

### 3.1.2. Research Methods

*(1) Big Data Availability Analysis Method.* In recent years, with the rapid development of information technology, the scale of data has also exploded. Big data has been widespread in all walks of life, and these data have become an important wealth of the information society. However, such a large number of data sets are prone to data quality problems. Therefore, exploring the availability of big data has become a difficult problem for us. It is generally believed that a correctly available big data set should have at least the following five properties: consistency, accuracy, integrity, timeliness, and entity identity [11].

In the general research process, the collected data shall be summarized and sorted according to the fixed principles to form a research database. Analyze the availability of the original data from the above five dimensions to realize the classification, collation, and pretreatment of the obtained data, so as to provide data support for subsequent research.

*(2) Machine Learning: Natural Language Processing.* Machine learning is the core of artificial intelligence and one of the main ways of big data analysis. Its application is widely distributed in various artificial intelligence fields. It mainly uses induction rather than deduction [12]. As an important technical foundation of artificial intelligence, computers not only have the ability to quickly process data through algorithms but also have the ability to predict and classify problems after training. Under the trend of increasing data volume, they have great development potential.

Natural language processing (NLP) is a technology and application that processes languages and words by using computers [13]. In recent years, with the arrival of the big data era, the rapid improvement of machine computing

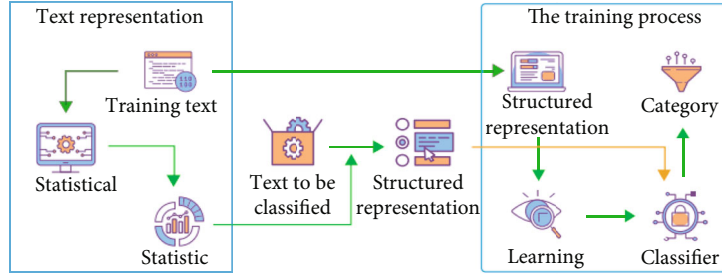


FIGURE 1: Text classification system based on statistics.

power and the wide application of machine learning algorithms have brought new breakthroughs in the application of natural language processing.

In the text classification problem, the machine learning method based on statistics is widely used. The general idea is to extract some documents evenly from all the documents, mark the category, and take this as the training set and then find the relationship between words and categories in the training set. Make use of mathematical expressions to explain the above summarized links and guide classification prediction. Because this method has a good theoretical basis, it is easy to obtain satisfactory classification results. As shown in Figure 1, it is the schematic diagram of the text classification system based on statistics [14].

The TF-IDF algorithm is essentially a statistical method. It uses the number of words appearing in the document as the evaluation standard of importance. If a word appears very frequently in an article (TF is high) and less frequently in other articles (IDF is high), it is considered that the word can better represent the article and is suitable for classification. Therefore, we can take the word frequency as the evaluation method to describe the importance of words to the specified document and the reverse file frequency as the evaluation method to judge the importance of words relative to all document sets and combine the above two to select features.

Suppose that for the word  $t_i$  in a document  $d_i$ , the word frequency of  $t_i$  can be expressed as follows [15]:

$$TF_{ij} = \frac{n_{ij}}{\sum_k n_{k,j}}, \quad (1)$$

where  $n_i$  and  $j$  represent the number of times the word  $t_i$  appears in document  $d_i$ , and the denominator represents the total number of times all words appear in document  $d_i$ .

The IDF of a word, as shown in formula (2), can be obtained by dividing the total number of files by the number of files containing the word and taking the logarithm.

$$IDF_{ij} = \log \frac{|D|}{|\{j : t_i \in d_j\}| + 1}. \quad (2)$$

$|D|$  represents the total number of all documents, and the content of the denominator represents the total number of documents containing the word  $t_i$ . In addition, in order to

prevent the denominator in the formula from being zero, we add 1 to the denominator.

Multiply TF and IDF as the value of the feature space coordinate system; that is, the TF-IDF value is as follows:

$$TF - IDF = TF_{ij} \times IDF_{ij}. \quad (3)$$

By using the algorithm of TF-IDF, we can obtain the importance of the target words in the document [16] and then complete the screening of words, so as to obtain the representative text feature items, which lays a foundation for the subsequent classification and prediction.

**3.2. Enterprise Industry Category Screening and Correction Method for Machine Learning.** Incorrect industry classification of enterprises will not only make it impossible to accurately establish a list of enterprises in key industries for pollution source census and greatly reduce the efficiency of preliminary census preparation but also increase the workload of census personnel in filling out the census registration form [17]. The human settlements and environment committee of a city hopes to make full use of the 3.18 million full-caliber industrial and commercial articles of a city to supplement the inventory of basic units as far as possible. It is undoubtedly extremely difficult to use manpower to manually judge the industry category according to the business scope. If the machine learning algorithm can be used to rematch and calibrate the industry categories of enterprises, the work efficiency will be greatly improved.

In order to correct the errors in the industry category of enterprises and avoid the omission of the data set submitted by the department, the study plans to explore the identification of the production and business scope of enterprises through the machine learning algorithm based on the national industrial and commercial data, provincial industrial and commercial data, and the full-caliber industrial and commercial data of a city provided by the human settlements and environment committee of a city, so as to screen and correct the enterprise industry and verify the feasibility of the method.

We hope to establish a machine learning model based on the above data and use the business scope field to predict the enterprise industry. The experimental process is shown in Figure 2. The enterprise industry classification prediction specifically adopts the following processes [18]: data collection and marking, document preprocessing, Chinese word segmentation, removal of stop words, structured representation

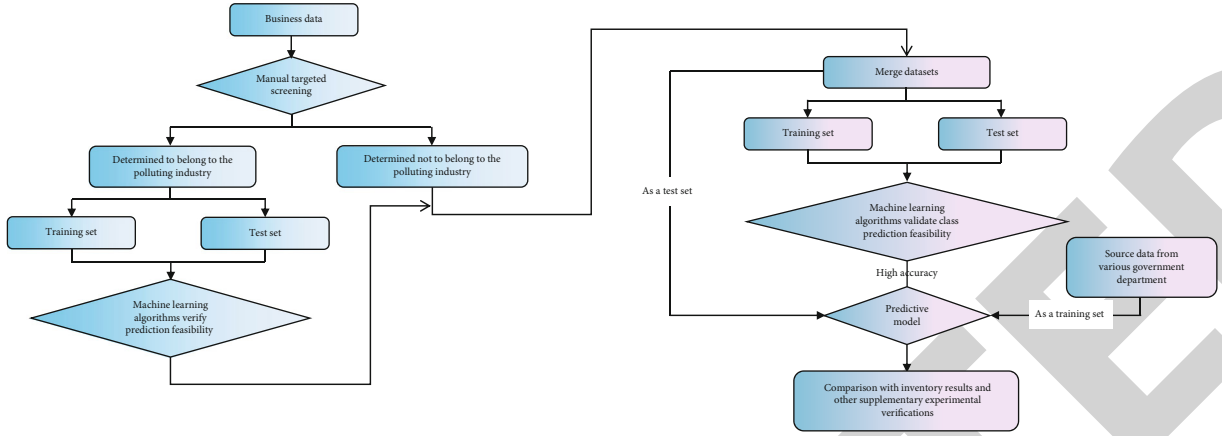


FIGURE 2: Flowchart of the industry classification prediction experiment.

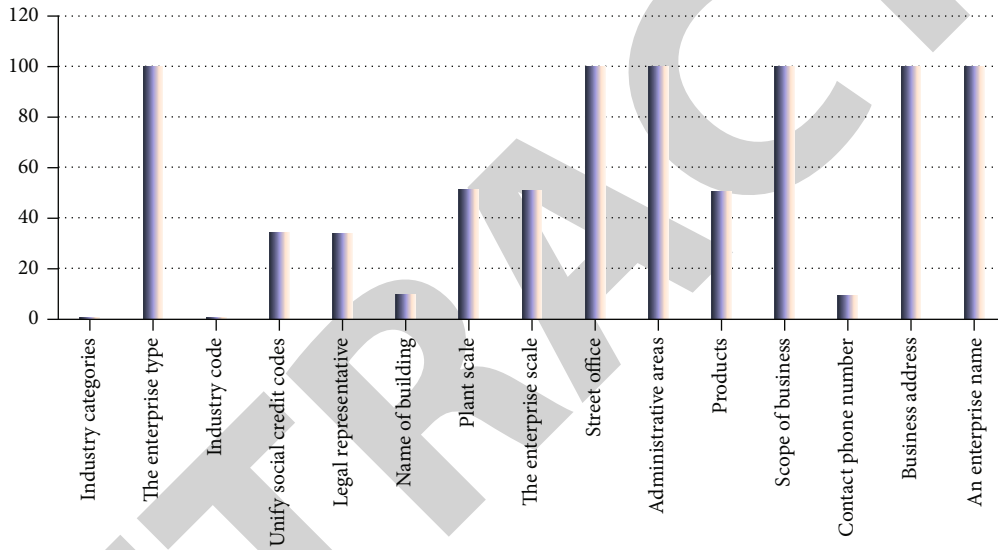


FIGURE 3: Statistics of the filling degree of each field of the Internet data source.

(construction of TF-IDF weighted word vector space), classification model selection, training and testing, performance evaluation, and model use.

**3.3. Internet Big Data Supplements the List of Basic Units.** For the data collected from Internet data sources [19], the method similar to the statistical analysis of department data is used to analyze and evaluate the quality of data sources. The evaluation results are shown in Figure 3. Take the summary data set of the Internet data source as the sample.

Using the constructed machine learning model, the verified accurate calibration data set is used as the training set, and the naive Bayesian classification algorithm with good verified performance is used to carry out the experiment. 500 data sets are randomly selected from the data set as the test set. The established machine learning model is used to predict the industry category of the enterprise. At the same time, according to the business scope of the enterprise, whether it belongs to the target industry of pollution source census is manually judged and marked. The results obtained are compared with the machine learning prediction results

TABLE 1: Evaluation of classification results of each algorithm.

Algorithm	Accuracy	Recall	F1 value
Naive Bayes	99.80%	99.80%	0.998
Decision tree	97.90%	97.90%	0.979
Logistic regression	90.90%	90.60%	0.907
KNN	79.80%	78.40%	0.791

to calculate the relevant evaluation parameters. At the same time, in order to avoid the experimental contingency, the data set was repeated three times. The accuracy rate, recall rate, and F1 value are still used as evaluation indicators for evaluation.

## 4. Result Analysis

**4.1. Analysis on the Results of Screening and Correction of Enterprise Industry Categories Based on Machine Learning.** The target industry data of 28 types of pollution sources have been calibrated for testing to determine the quality of

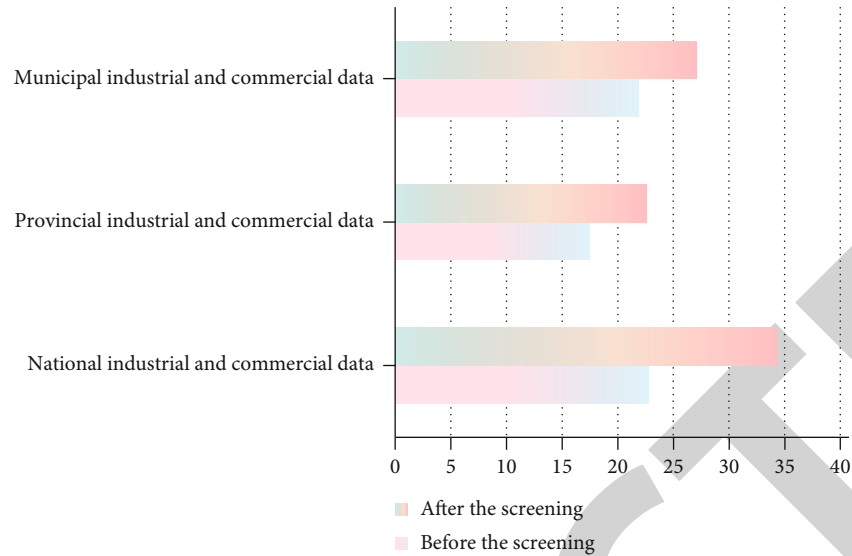


FIGURE 4: Comparison of accuracy rate of each data set after screening.

the artificially constructed data. Divide the 4690 constructed target industry data of pollution source census by industry, half as the training set and half as the test set, classify the internal 28 industries according to the above experimental steps, and use the naive Bayes classification algorithm, logistic regression classification algorithm, decision tree classification algorithm, and KNN ( $k$ -nearest) classification algorithm for prediction [20].

The results and comparison of industry category prediction models are shown in Table 1.

From the above results, it can be seen that this data set has a good representation effect for 28 different industries, and the accuracy of the naive Bayesian algorithm is the highest, with F1 value reaching 0.9980. Therefore, it is determined that the next part of the experiment can be carried out based on this data set.

In the current economic environment of rapid enterprise change, a large number of enterprises are closed down or relocated, resulting in a large number of classified forecast hits that cannot be checked and verified. Moreover, due to the limitations of actual working conditions, this household inventory is mainly a dragnet inventory within the scope of key industrial parks. At the same time, there are still a large number of problems existing in the actual work in the first general survey of pollution sources. It is difficult to be accurate and complete in the household inventory, and the inventory results will still be far from the actual situation. Based on the above reasons, the index of accuracy obtained by checking the household feedback test will be lower than the conventional cognition [21]. However, the accuracy rate is still much higher than that of the department data without screening. The comparison before and after screening is shown in Figure 4.

Before and after classification, the accuracy of each data source is less than 40%. When the accuracy and recall cannot be well considered, the F1 value is selected as the index of comprehensive evaluation. After classification and screening, the efficiency of the list has generally been improved to a

certain extent, and the F1 value has been increased by 32.92%, 21.42%, and 14.91%, respectively [22].

*4.2. Supplement Results of Internet Big Data to the Directory of Basic Units.* For the obtained Internet supplementary data, the actual feedback results of household inventory are still used for preliminary verification. After matching the feedback data, 2988 pieces of actually identified existing data are obtained; that is, the accuracy rate of Internet supplementary data is 17.26%. Since there is no original data comparison for this part of the data and the recall rate index cannot be calculated, this part only uses the accuracy rate for comparative evaluation. We can find that in the accuracy indicators, the Internet supplementary data is lower than the department data and is only similar to the municipal industrial and commercial data before screening in the department data [23]. The accuracy and comparison between the Internet big data supplementary data and the department data before and after screening are shown in Figure 5.

After screening and industry category judgment, the accuracy rate of the above Internet supplementary data is 17.26% after the initial test of the actual inventory and household feedback. The same as the content analyzed in Section 3, due to the actual conditions, the accuracy of the household inventory and feedback test is still low compared with that of the conventional cognition. At the same time, the usability of the model in the Internet source data will be in doubt. In view of this situation, it is planned to conduct a supplementary experiment, randomly select decimal data from the Internet data for inspection, conduct inspection through a manual review, judge the actual performance of the Internet supplementary data under the machine learning classification model, and explore the actual accuracy of the data set in combination with the Internet data screening principle to assist in verifying the availability of the machine learning model [24].

According to the above experimental process, the results of the Internet supplementary data supplementary experiment are shown in Table 2.

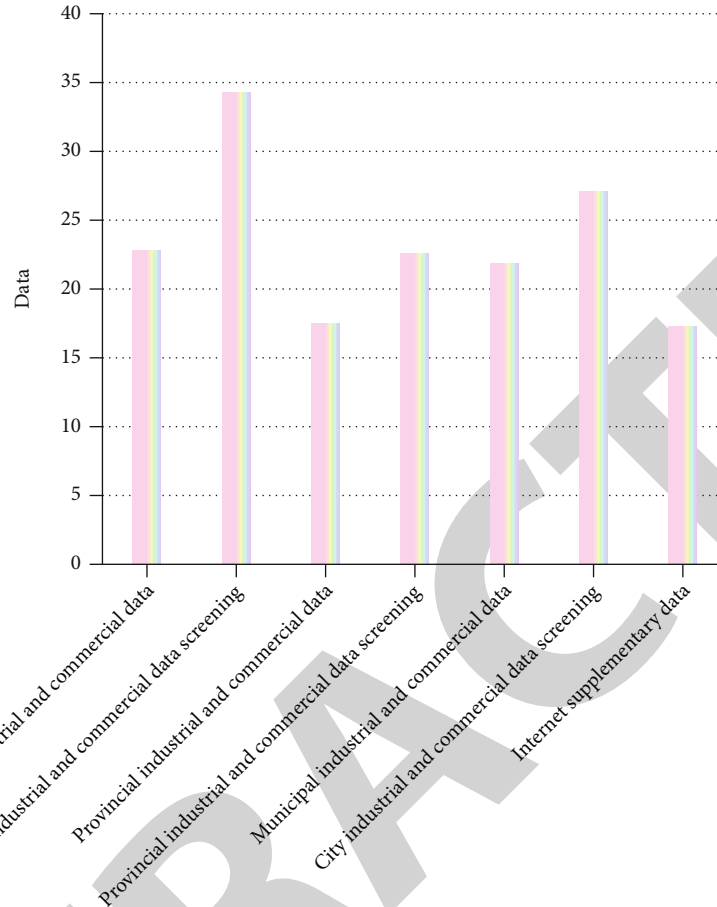


FIGURE 5: Comparison chart of data accuracy.

TABLE 2: Supplementary experimental results of Internet supplementary data.

	First experiment	Second experiment	Third experiment	Average value
Accuracy	76.67%	75.81%	78.64%	77.04%
Recall	82.24%	81.72%	82.39%	82.12%
F1 value	0.7936	0.7865	0.8047	0.7949

Through the above results, the average accuracy is 77.04%. Although each indicator is lower than the national and provincial industrial and commercial data, it is similar to the municipal industrial and commercial data. Therefore, it is concluded that the obtained Internet supplementary data are basically in line with the target industry scope of the pollution source census. At the same time, in combination with the screening principles developed through the availability of big data, the reliability of the obtained data has been basically guaranteed [25, 26].

## 5. Conclusion

After systematically studying the relevant regulations and requirements of China's pollution source census at the present stage and the existing problems, in order to improve the

efficiency of compiling the list of basic units in the pollution source census and inventory stage, this paper constructs a machine learning classification model, predicts the actual industry categories of enterprises through the business scope of enterprises, and realizes the correction and screening of the industry category fields in the data of government departments. Finally, it summarizes the optimization methods for the compilation of the list of basic units in the pollution source census and inventory stage, so as to improve the work efficiency in the inventory stage and save human and material resources.

## Data Availability

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

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## Acknowledgments

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