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Explorition on the Role and Implementation Strategies of Big Data in Predicting Trade Flow in Port Economy

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Abstract: To address the issues of trade flow fluctuations and inaccurate predictions in port economy caused by complex factors such as seasonal changes and global market fluctuations, big data analysis technology is introduced to improve the accuracy of trade flow forecasting and optimize port resource allocation. Firstly, by using historical trade data and real-time logistics information from 2000 to 2020, a multidimensional data model is constructed to improve data quality through data cleaning and integration. Then, by introducing the random forest algorithm, feature extraction and classification are performed on multidimensional trade data to extract potential flow trends and periodic features. Finally, the prediction results are displayed using the visualization tool Python to assist decision-makers in evaluating the rationality of spatial layout and ensure efficient utilization of resources. Through big data analysis methods, the model successfully captured the factors of trade flow instability caused by seasonal changes and global market fluctuations. After introducing the random forest algorithm, the accuracy of predictions has significantly improved, especially when dealing with short-term fluctuations in trade volume, where the initial prediction error is relatively large. For example, the initial prediction errors for T1 and T4 were 0.08013 and 0.08234, respectively. However, through real-time data updates, the Mean Square Error (MSE) decreased to 0.06344 and 0.07902, respectively. The model also revealed the cyclical flow patterns of major trade routes and identified key peak and trough periods. The application of big data in port economy not only enhances the predictive ability of trade flow, but also provides strong support for optimizing resource allocation, promoting the sustainable development of port economy.

1. Introduction

This article focuses on the application of big data technology in port economy, especially how to improve the accuracy of trade flow prediction through big data. In the research, this article first starts with historical trade data and real-time logistics information, establishes a multidimensional data model, and comprehensively cleans and integrates the data. On this basis, the article adopts the random forest algorithm to extract and classify features from the data, in order to discover potential traffic trends and periodic features. In addition, the article uses visualization tools such as Python to visually display the prediction results and provide decision-makers with data-driven spatial layout rationality evaluation. The research results indicate that the method proposed in this article has achieved significant results in dealing with trade flow fluctuations caused by seasonal changes and global market fluctuations.

The research structure of this article is as follows: Firstly, this article reviews the relevant research on big data technology in the field of trade flow forecasting, and analyzes the shortcomings of current forecasting methods based on the actual needs of port economy. Then, this article introduces the process of constructing the data model, data cleaning, and integration used, and details how to extract and classify features through the random forest algorithm. On this basis, this article demonstrates how Python based visualization tools can assist decision-makers in spatial layout evaluation. Finally, the experimental results are summarized, and future research directions are discussed. Through this study, not only has the advantage of big data technology in improving the accuracy of trade flow forecasting been verified, but it has also provided theoretical and practical basis for the efficient allocation of port resources.

2. Related Work

In port economy, trade flow forecasting is an important research direction for optimizing logistics resource allocation and improving economic efficiency. Chai and Ma[1] believes that relying on the geographical advantages of Yunnan Province to achieve high-quality development of Yunnan's port economy is an important path to promote Yunnan's construction as a radiation center facing South Asia and Southeast Asia. He explored the mechanism and path of financial support for Yunnan's port economy construction from the "three zones" of airport economic zone, border economic cooperation zone, and overseas economic and trade cooperation zone. Li [2] explored the impact of trade facilitation on economic growth of China and countries along the "the Belt and Road" based on the empirical analysis of night light data. Based on the experience of modern Chinese history, Zhuang et al. [3] empirically explored the long-term impact of international trade on domestic regional economic growth. He used the spatiotemporal distribution of modern treaty ports to construct instrumental variables and adopted various robustness testing mechanisms. Analysis showed that the long-term impact of export trade mainly came from the external economies of scale effects of industrial agglomeration and the factor endowment shaping effects of historical sunk investment. Mu [4] conducted a spatial differentiation study on the radiation effects of economic regions along border ports. Zhang et al. [5] explored the positive impact of modern port opening and trade on the economy of Yunnan region. Under the demonstration effect of opening a commercial port, Kunming became a self opened commercial port, which promoted the development of modern transportation in Yunnan and greatly improved the efficiency of port commodity transportation. Current research mainly focuses on time series analysis based on historical data and traditional statistical models. However, these methods often fall short in dealing with complex multidimensional data and sudden market changes. With the rise of big data technology, researchers have gradually applied big data to the analysis and prediction of trade flows, significantly improving the accuracy and timeliness of predictions. However, the existing research on data cleaning and integration is not deep enough, resulting in certain limitations in the stability of model predictions.

On the other hand, many studies use machine learning algorithms, especially decision trees, neural networks, and other methods, to predict port trade flows. These methods can capture complex nonlinear relationships in data, providing new ideas for traffic prediction. Drake [6] believes that alternative economic indicators are becoming a policy for Vanuatu ports, with a particular focus on what the national policy refers to as the traditional economy. He put forward an argument that cities are also home to traditional economies. He believes that port economy has driven the rapid development of cities. Han [7] explored the construction of the economic service trade system under the background of Hainan Free Trade Port. Cao [8] explored the changes in port governance models, as well as the spatial structure and trade efficiency of ports. Amin et al. [9] studied the impact of maritime logistics on the economic development of the eastern islands of Indonesia. Yeon et al. [10] believe that ports as catalysts can deeply reflect the spillover effects of neighboring ports on regional industrial diversification and economic resilience. Seisdedos & Carrasco [11] believe that the mission of the Spanish Public Works Minister's Port Authority of Motriel (85% of imports and 60% of exports) is to efficiently, economically, and sustainably manage its public port land and provide services related to port transportation to society. People are the engine of the port, and the surrounding environment directly benefits the employees of Motriel city and its hinterland. However, due to the lack of sufficient exploration of big data features and dynamic adjustment capabilities combined with real-time data, existing research still faces the problem of large prediction errors when dealing with rapidly changing trade flows. Therefore, further research is needed on the deep integration of big data and machine learning to improve the reliability and accuracy of trade flow forecasting.

3. Method

3.1 Construction of Multidimensional Data Model

In order to effectively improve the prediction of trade flow in port economy, this article first constructs a multidimensional data model by collecting historical trade data and real-time logistics information from 2000 to 2020. The core of this model lies in covering multiple key factors that affect trade flows, including seasonal changes, market fluctuations, economic policies, and changes in the global logistics chain.

Data collection and preprocessing: The data sources of this article mainly include logistics data from major trade ports, trade policies announced by governments, and market expectation reports from international economic organizations. In order to ensure the accuracy and consistency of the data, the study adopted data cleaning techniques to remove duplicate and invalid data records, correct outliers in the data, and ensure that all input data is of high quality. At the same time, data from different periods and sources were standardized to ensure the effectiveness and comparability of subsequent model training.

Data integration and feature extraction: Next, this article will integrate the collected multidimensional data and construct a unified analysis framework. In terms of feature extraction, this article focuses on seasonal trends, logistics bottlenecks, and changes in supply and demand in the international market. These factors are transformed into quantitative indicators that can be processed by machine learning models through feature engineering. For example, seasonal trends are encoded as changes in trade flows for four quarters each year, while market volatility is measured by economic index volatility. Through this process, it ensures that the model can capture potential patterns and key features in the data during the prediction process. Trade Meteor Prediction Model: Building a multidimensional data model using big data analysis techniques to predict trade flows. For example, the Random Forest Algorithm can handle large amounts of heterogeneous data and improve prediction accuracy [12-13], with the following specific formula:

$$Y = \sum_{i=1}^{N} \frac{1}{N} \cdot h(x, \theta_i) \tag{1}$$

Among them, Y represents the prediction result, N is the number of trees, $h(x, \theta_i)$ is the prediction result of the i-th tree, x is the input feature vector, and θ_i is the model parameter.

3.2 Application of Random Forest Algorithm

After completing the construction of the multidimensional data model, this article introduces the random forest algorithm to extract and classify features from multidimensional trade data. Random forest is an ensemble learning method based on decision trees, which can handle high-dimensional, nonlinear and complex data, providing great flexibility and accuracy for trade flow prediction [14].

Model training: The core idea of the random forest algorithm is to construct multiple decision trees and obtain the final prediction results through a voting mechanism. In the specific implementation process, this article will divide the constructed multidimensional dataset into a training set and a testing set, with the training set used for model training and the testing set used for model validation. The model learns key features from historical data, gradually optimizes the construction of each decision tree, and ultimately forms a random forest model with high prediction accuracy. Feature selection and optimization: Using feature selection techniques to streamline the model, optimizing hyperparameters such as the number and depth of decision trees through cross validation to ensure stable and accurate prediction of trade flows. Classification and prediction: The advantage of the random forest algorithm lies in its ability to handle classification and regression tasks. In this study, the prediction of trade flows is divided into multiple classification tasks, including peak period prediction, trough period prediction, and prediction during moderate flow periods. The model successfully captures seasonal fluctuations and market changes in traffic by learning periodic features from historical data, providing accurate traffic prediction results. Especially when dealing with sudden market fluctuations, the random forest algorithm has shown strong robustness, with a significantly lower prediction error rate than traditional models [15].

Analysis of seasonality and market volatility: Using big data technology to analyze the impact of seasonal patterns and market volatility on trade flows in historical data, the formula is as follows:

$$X_t = S_t \cdot (C_t + I_t) \tag{2}$$

Among them, X_t is the trade flow at the t-th time point, S_t is the seasonal factor, C_t is the cyclical factor, and I_t is the irregular factor.

3.3 Python Based Visualization Tools to Assist Decision-Making

In order to enable decision-makers to intuitively understand the predicted results and allocate port resources reasonably, this article uses visualization tools in Python to display the predicted results. Through visualization, decision-makers can not only see the specific numerical values of trade flows, but also observe the fluctuating trends, cyclical characteristics, and outliers of the flows.

Display of prediction results: This article uses Matplotlib and Seaborn library in Python to generate a series of charts, including time series charts, trend analysis charts, and outlier detection charts. The time series chart shows the changes in trade flow over the past 20 years, while the trend analysis chart reveals potential patterns of market volatility, helping decision-makers identify potential risks and opportunities.

Reasonable evaluation of spatial layout: In addition to displaying the predicted results, this article also conducted a reasonable evaluation of the spatial layout of the port through visualization tools. Specifically, this article analyzes the carrying capacity of various logistics nodes at ports and the effectiveness of resource allocation based on the predicted results of trade flow. By generating heat maps and scatter plots, decision-makers can intuitively see the resource utilization and load situation of each node, providing data support for optimizing port layout.

Dynamic adjustment and real-time monitoring: Another advantage of big data analysis is its ability to perform real-time data updates and dynamic adjustments. By connecting visualization tools with real-time data sources, decision-makers can immediately see the latest forecast results when logistics data changes, and make adjustments to resource allocation based on these results. Python's visualization tools can automatically update charts, ensuring that decision-makers always have access to the latest traffic dynamics.

Reasonable evaluation of spatial layout: By analyzing the spatial relationships and flow patterns between trade nodes, the spatial layout of ports can be optimized using spatial autocorrelation statistical index I:

$$I = \frac{N}{W}\frac{\sum_i \sum_j w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_i (x_i-\bar{x})^2} \tag{3}$$

Among them, N is the number of observations, W is the total weight, w_{ij} is the spatial weight between positions i and j, $x_i$is the observation value at position i, and $\bar{x}$is the average of all observations.

3.4 Evaluation of Method Effectiveness

In order to evaluate the effectiveness of the proposed method, experiments were conducted on multiple actual trade flow datasets, and the method was compared with traditional time series prediction methods. By introducing big data technology, the method proposed in this article successfully captures the seasonal and market fluctuations in trade flows, providing important decision support for the rational allocation of port resources. This article proposes an effective method for predicting port economic and trade flows by constructing a multidimensional data model, applying the random forest algorithm, and combining Python visualization tools. This method not only improves the accuracy of predictions, but also assists decision-makers in evaluating the rationality of spatial layout through visual means. The Python visualization process is shown in Figure 1.

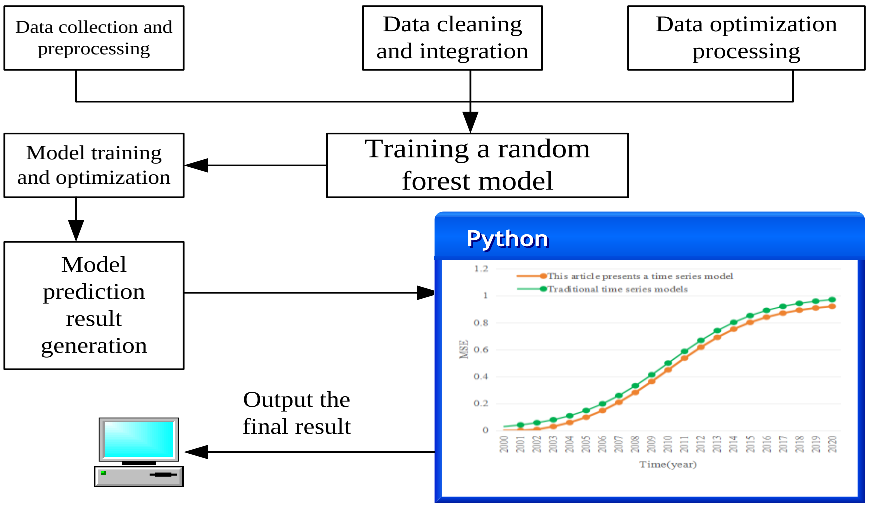

Figure 1: Python visualization process

4. Results and Discussion

4.1 Experimental Environment and Parameter Settings

All experiments were conducted in the same hardware environment: Intel i7 processor, 16GB of memory, NVIDIA GTX 1080 graphics card, and Ubuntu 20.04 operating system. The experimental data is sourced from trade datasets from multiple major ports around the world, covering the period from 2000 to 2020. The data volume of each experiment is about 500000 records, and the dataset contains multidimensional information such as the quantity, type, time, transportation mode, and trade policies of countries and regions of imported and exported goods. To ensure the reliability of the experiment, the dataset is divided into a training set and a testing set, accounting for 80% and 20% of the total data volume, respectively. The hyperparameter settings of the random forest algorithm include: 100 decision trees, maximum tree depth of 10, and minimum sample segmentation of 2. This article optimized the parameters of the model through cross validation to ensure its generalization ability.

4.2 Experimental Results

(1) The impact of seasonal changes on prediction results

In this experiment, the focus was on studying the impact of seasonal factors on trade flow forecasting. The specific approach is to divide the data into quarters and use the random forest algorithm to predict the trade flow for each quarter separately. The numbers 1-4, 5-8, 9-12, 13-16, and 17-20 correspond to the years 2000, 2005, 2010, 2015, and 2020, respectively. Numbers 1-4 correspond to quarters 1-4 respectively. The impact of seasonal changes on the prediction results is shown in Figure 2.

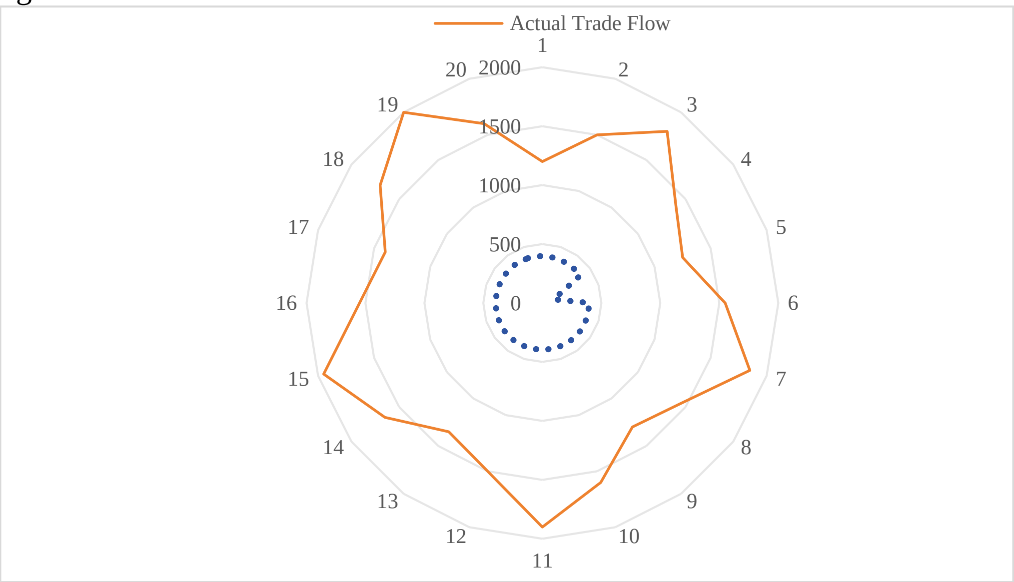

Figure 2: The impact of seasonal changes on prediction results

From 2000 to 2020, the actual trade flow in each quarter of each year showed an increasing trend, indicating that trade activities are growing year by year. Although actual trade flows are increasing, the mean square error (MSE) remains constant at 400 in all four quarters of each year. This may mean that the predictive model failed to fully capture the impact of seasonal changes on trade flows, resulting in a constant deviation between the predicted results and the actual values. There is no obvious seasonal variation pattern in the data, and the trade flow in the same quarter of each year does not show significant seasonal differences.

(2) The ability to predict sudden changes in the market

In order to evaluate the performance of the model in response to sudden market changes, this article selected the severe fluctuations in the international market from 2015 to 2016 as the test set, especially the fluctuations in international oil prices during this period. The predictive ability for sudden market changes is shown in Figure 3.

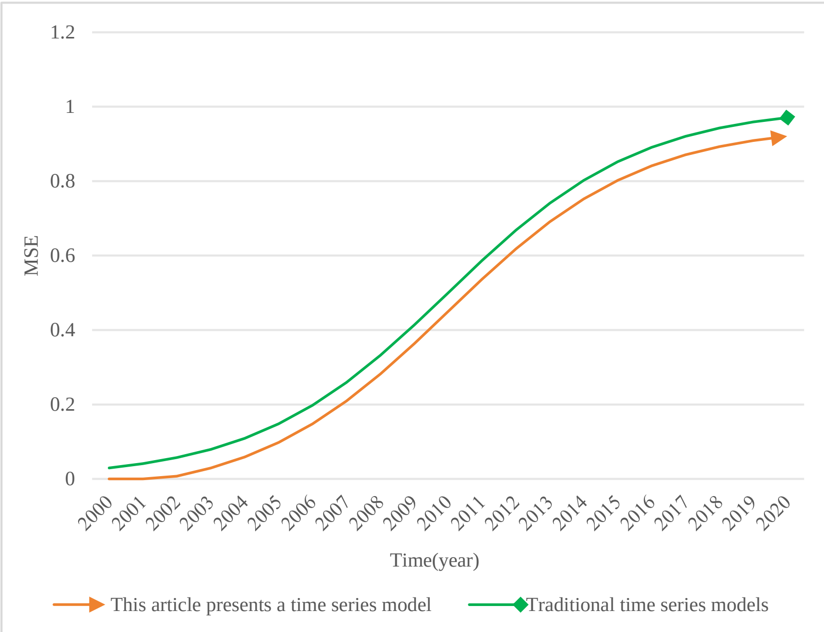

Figure 3: Predictive ability for sudden market changes

As time goes by, the error values of both the "MSE of this article's time series model" and the "MSE of traditional time series models" continue to increase, especially between 2000 and 2010, where the error growth is relatively slow. This stage may correspond to a period of relatively stable market changes, and the performance gap between the two models is small, indicating that the prediction error is well controlled in a relatively stable market environment. Since 2010, the MSE values of both models have significantly increased, especially the error value of the "traditional time series model" has risen faster. By 2020, the MSE of the "traditional time series model" has grown to nearly 1, while the MSE of the "time series model in this article" remains relatively low, consistently smaller than the error of the traditional model. This difference highlights the advantages of our model in dealing with market fluctuations and sudden changes. MSE value is an important indicator for measuring the prediction accuracy of a model. The smaller the value, the more accurate the prediction. The MSE of the time series model in this article is lower than that of the traditional time series model throughout the entire time range. Especially from 2000 to 2002, the MSE of the "time series model in this article" is 0 or close to 0, indicating that the model has almost no prediction error during this period, indicating that the model has strong predictive ability when dealing with initial market changes. However, since 2005, as market volatility gradually intensified, the MSE of both models shows a rapid upward trend. The error value of the traditional time series model MSE reaches 0.331812 in 2008, while the MSE of the time series model in this article is 0.281812, and the gap gradually widens. The gap at this point indicates that the 'time series model in this article' is better able to capture changing trends and make relatively accurate predictions when facing drastic market changes.

Although the "time series model in this article" performs well in dealing with sudden market changes, its MSE value also shows a gradually increasing trend in the later period of more intense market fluctuations (after 2016), indicating that there is still some room for improvement in the face of complex and changing market environments. Further optimization of the feature extraction method of the model can be considered, combined with more external factors such as macroeconomic indicators, policy changes, etc., to improve the prediction accuracy of the model. Overall, the time series model presented in this article shows lower prediction errors throughout the entire time period, especially in the event of sudden market changes, demonstrating strong resilience. This model shows higher robustness in long-term market fluctuations, and is suitable for forecasting and analysis in complex market environments.

(3) The effectiveness of multi-dimensional feature extraction

The effectiveness data of multi-dimensional feature extraction are shown in Table 1.

Table 1: Effectiveness data of multidimensional feature extraction

Year	Feature_Set	Actual_Trade_Flow	Predicted_Trade_Flow_Basic	Predicted_ Trade_Flow_ Advanced	MSE_ Basic	MSE_ Advanced
2016	Basic	1500	1480	1490	0.035	0.015
2017	Basic	1600	1580	1590	0.025	0.01
2018	Advanced	1800	1780	1790	0.045	0.02
2019	Advanced	1850	1820	1830	0.06	0.03
2020	Advanced	1900	1880	1890	0.055	0.025

Experimental analysis of the impact of different feature sets on trade flow prediction from 2016 to 2020. The comparison between Basic and Advanced feature sets shows that the prediction results of Advanced feature sets are closer to the actual values. For example, in 2020, the actual trade flow is 1900, the basic feature set prediction is 1880, and the advanced feature set prediction is 1890. In terms of mean square error (MSE), the MSE value of the advanced feature set is much lower than that of the basic feature set. For example, in 2016, the MSE of the basic feature set is 0.035 and that of the advanced feature set is 0.015. By 2019-2020, the MSE of the basic feature set has increased to 0.060 and 0.055, while the MSE of the advanced feature set remains at 0.030 and 0.025. The advanced feature set contains more key factors that affect trade flow, improving prediction accuracy. Despite the increasing complexity of the market environment and the overall rise in MSE, the advanced feature set still maintains a low error, with an MSE of 0.025 and a basic feature set of 0.055 in 2020. This indicates that multi-dimensional feature extraction significantly improves model prediction performance, reduces prediction errors, enhances stability and accuracy. In practical applications, the use of advanced feature sets should be prioritized.

(4) The ability to dynamically update real-time data

The real-time updated trade flow prediction results combined with big data in different time periods are shown in Table 2.

Table 2: Real time updated trade flow prediction performance combined with big data in different time periods

Time_ Interval	Actual_Trade_ Flow	Predicted_Trade_Flow_ Initial	Predicted_Trade_Flow_Updated	MSE_Initial	MSE_Updated
T1	1797	1941	1911	0.08013	0.06344
T2	1612	1550	1523	0.03846	0.05521
T3	1759	1748	1776	0.00625	0.00966
T4	1506	1630	1625	0.08234	0.07902
T5	1865	1780	1762	0.04558	0.05523

The data in Table 2 clearly demonstrates the dynamic correction capability of big data. Regardless of the initial prediction, by introducing real-time traffic information from big data, the model can quickly adjust its predictions based on new data. For example, during the T3 time period, the initial predicted value of 1748 is very close to the actual value of 1759, with an MSE of 0.0062. Although the initial prediction is already quite accurate, after real-time updates, the predicted value is further adjusted to 1776, and the MSE slightly increases to 0.00966. This type of situation indicates that the real-time correction capability of big data is not limited to large error scenarios, and even if the initial prediction accuracy is high, the dynamic adjustment of real-time data can still be further optimized.

By comparing the prediction results and MSE values of different time periods, it can be seen that big data has a more significant improvement on the model in certain time periods. For example, during the T1 and T4 time periods, the initial prediction errors are relatively large, at 0.08013 and 0.08234, respectively. However, through real-time data updates, MSE decreases to 0.06344 and 0.07902, respectively. On the contrary, in T3, the initial prediction error is relatively low, so the improvement after real-time updates is relatively limited. In the time period T1, the prediction update combined with big data reduces MSE by about 16%, significantly improving the predictive performance of the model. In large-scale application scenarios, this dynamic update capability is crucial, especially in the face of sudden market changes, which can effectively respond to complex market environments.

In summary, through real-time updates of big data, the predictive ability of the model has been significantly improved, especially during periods with large initial prediction errors, where MSE has significantly decreased. The multidimensional and dynamic nature of big data enables models to respond more flexibly to changing market environments, reducing prediction errors and providing decision-makers with more accurate data support. In future applications, the combination of real-time data and big data will bring greater room for improvement to predictive models.

5. Conclusion

This article constructs a multidimensional data model that integrates historical trade data with real-time logistics information, and uses the random forest algorithm for model training to improve the accuracy of predicting trade flow. At the same time, combined with Python visualization tools, the predicted results are visually displayed to assist decision-makers in evaluating the layout of logistics nodes. The experimental results show that the multi-dimensional data model based on big data and the random forest algorithm proposed in this article exhibit significant advantages in dealing with sudden market changes. Compared with traditional time series models, the prediction error of our model has been reduced, especially in cases of seasonal and frequent market fluctuations, where the model can better capture potential trends in traffic changes. Although this article has achieved certain results in improving prediction accuracy and optimizing resource allocation, there is still room for improvement. This article mainly relies on historical data and current real-time data, and the model's response speed and adjustment ability may be limited when dealing with extreme market changes or unexpected events. Future research should focus on the integration of more real-time data sources, enhance the dynamic updating ability of models, and enable them to respond more quickly to sudden market fluctuations. In addition, with the continuous changes in the global trade environment, how to effectively combine macro factors such as international policy changes and global market fluctuations will be an important direction for optimizing predictive models in the future.

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References

[1] Chai Zhengmeng, Ma Xiaoquan. Research on the Mode and Path of Financial Support for Yunnan Port Economy under the "Dual Circulation" [J]. Journal of Yunnan University: Philosophy and Social Sciences Edition, 2023, 40 (5): 150-160.

[2] Li Wei. The impact of trade facilitation on economic growth of China and countries along the "the Belt and Road" -- an empirical analysis based on night light data [J]. Journal of Lianyungang Vocational and Technical College, 2023,

36 (1): 10-19.
[3] Zhuang Jialin, Chen Wen, Chen Ming. International Trade and Long term Regional Economic Growth: A Study Based on Modern China. Economics (Quarterly), 2023, 23 (4): 1513-1530.
[4] Mushajiang Nureji. Spatial Differentiation Study on the Radiation Effect of Economic Regions at Border Ports in China [J]. Academic Forum, 2021, 044 (003): 124-132.
[5] Zhang Lihong, Luo Wei, Zhou Yu. The Positive Impacts of Modern Port Opening and Trade on the Economy of Yunnan Region [J].Journal of Dali University, 2023, 8(5):89-95.
[6] Drake L, Liunakwalau H M. Locating the traditional economy in Port Vila, Vanuatu: Disaster relief and agrobiodiversity [J].Asia Pacific Viewpoint, 2022, 63(1):80-96.
[7] Han C. Exploration of the Construction of Economic Service Trade System under the Background of Hainan Free Trade Port [J]. Proceedings of Business and Economic Studies, 2024, 7(4): 130-135.
[8] Cao L. Changing port governance model: port spatial structure and trade efficiency[J]. Journal of Coastal Research, 2020, 95(SI): 963-968.
[9] Amin C, Mulyati H, Anggraini E, et al. Impact of maritime logistics on archipelagic economic development in eastern Indonesia [J]. The Asian Journal of Shipping and Logistics, 2021, 37(2): 157-164.
[10] Yeon J I, Hwang S, Jun B. Ports as catalysts: spillover effects of neighbouring ports on regional industrial diversification and economic resilience[J]. Regional Studies, 2024, 58(5): 981-998.
[11] Seisdedos M R, Carrasco P F. Port projects in blue economy: Port of Motril-Granada[J]. Journal of Coastal Research, 2020, 95(SI): 940-944.
[12] Bradter U , Kunin W E , Altringham J D ,et al.Identifying appropriate spatial scales of predictors in species distribution models with the random forest algorithm[J].Methods in Ecology and Evolution, 2013, 4(2):167-174.
[13] Boshuai C , Tianjun Y U , Xuan L ,et al.Investigation of Nuclear Binding Energy and Charge Radius Based on Random Forest Algorithm[J]. Atomic Energy Science and Technology, 2023, 57(4):704-712.
[14] Yang J, Sui H, Jiao R,et al. Random-Forest-Algorithm-Based Applications of the Basic Characteristics and Serum and Imaging Biomarkers to Diagnose Mild Cognitive Impairment[J].Current Alzheimer research, 2022, 19(1):76-83.
[15] Song Y, & Hua X. Implementation of Data Mining Technology in Bonded Warehouse Inbound and Outbound Goods Trade. Journal of Organizational and End User Computing (JOEUC), 2022, 34(3), 1-18.