International Journal of Mathematical, Engineering and Management Sciences
Vol. 10, No. 1, 63-75, 2025
https://doi.org/10.33889/IJMEMS.2025.10.1.004

Ram Arti Publishers

Predicting the Total Export-import Volume of China's Economic Trade through Machine Learning

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(Received on March 14, 2024; Revised on August 30, 2024 & November 6, 2024; Accepted on November 29, 2024)

Abstract
By forecasting the total export-import volume of China's economic trade, valuable guidance can be provided for the formulation of relevant policies, thus holding significant practical importance. This paper first analyzed the current situation of the import and export of China's economic trade. Subsequently, key indicators such as gross domestic product (GDP) and producer price index (PPI) were selected. After eliminating irrelevant indicators through correlation coefficient calculation, seven remaining indicators were employed for research. Building upon the machine learning algorithm-support vector machine (SVM), an improved sparrow search algorithm (ISSA) was developed to optimize SVM parameters, forming the ISSA-SVM prediction method. Experimental validation was conducted using data from 2003 to 2022. The results revealed that the average time consumed by ISSA-SVM for forecasting was 1.742401 s, displaying a minimal difference compared to the SVM method. In terms of total volume prediction, the ISSA-SVM approach achieved a mean absolute percentage error of 0.02% and a root-mean-square error of 1068.25, surpassing logistic regression, back-propagation neural network (BPNN), and other methods. These outcomes verify the reliability of the ISSA-SVM method in total volume prediction, showcasing its practical applicability.

Keywords- Machine learning, China’s economy, Total export-import volume, Trade, Forecasting.

1. Introduction

The total export-import volume of trade activities serves as a key indicator reflecting a country's foreign economic trade level and is closely linked to its overall economic strength. China, along with numerous countries and regions, maintains close trade ties, consistently prioritizing the diversified development of foreign trade, thereby contributing to the global foreign trade market's growth (Wang, 2019). The development of foreign trade can promote regional economic growth (Zhao, 2021). Studying the prediction of the total export-import volume of China's economic trade is aimed at gaining a better understanding of future economic and trade trends, laying the groundwork for the development of governmental strategies, and supporting decision-making for investors and market participants. With the advancement of methods such as machine learning, many approaches have been applied in economic trade forecasting (Heinisch and Scheufele, 2019). Kumar et al. (2021) proposed a model based on multi-source unsupervised migration learning for predicting gross domestic product (GDP), demonstrating strong performance through experiments on data from six countries. Ortega-Bastida et al. (2021) employed a multimodal approach to forecast regional GDP by integrating past GDP values with information derived from GDP-related messages on the Twitter platform. This approach, combining a multitasking autoencoder and a multimodal transport network, enabled early regional GDP predictions. Xu et al. (2022) developed a model using a bi-directional gated recursive unit (GRU) and reinforcement learning (RL) for stock price prediction. By learning features from news texts, the method demonstrated state-of-the-art performance. Sui et al. (2021) designed a three-stage model to forecast trade demand in arctic sea routes, yielding high accuracy (R^2 = 0.937). At present, there have been numerous studies on the prediction of China's total import and export volume. However, there is still potential for further improvement in terms of accuracy in forecasting. There is relatively little research on the deep optimization of forecasting models. Therefore, in this paper, an

improved sparrow search algorithm (ISSA)-support vector machine (SVM) method was put forward to predict the total export-import volume of China's economic trade. The traditional SVM model was optimized in order to further enhance its predictive ability. Utilizing data from 2003 to 2022 as an example, the efficacy of the proposed method in total volume prediction was validated. The objective of this method is to improve the precision of predicting imports and exports in China's economic trade. This study provides reliable references for adjusting and formulating relevant trade policies in China, which is also beneficial for better assessing future trends in China's economic trade and promoting the development of import and export trade.

2. Analysis of the Total Export-import Volume of China's Economic Trade

2.1 Current Status

The total export-import volume of China's economic trade holds paramount significance both politically and economically, whose developmental trajectory is closely linked to the overall progress of the nation. It significantly contributes to the comprehensive strength of the country. Furthermore, the ongoing growth of import and export trade provides the nation with advantageous conditions, including advanced technology, enhanced liquidity, and increased development opportunities.

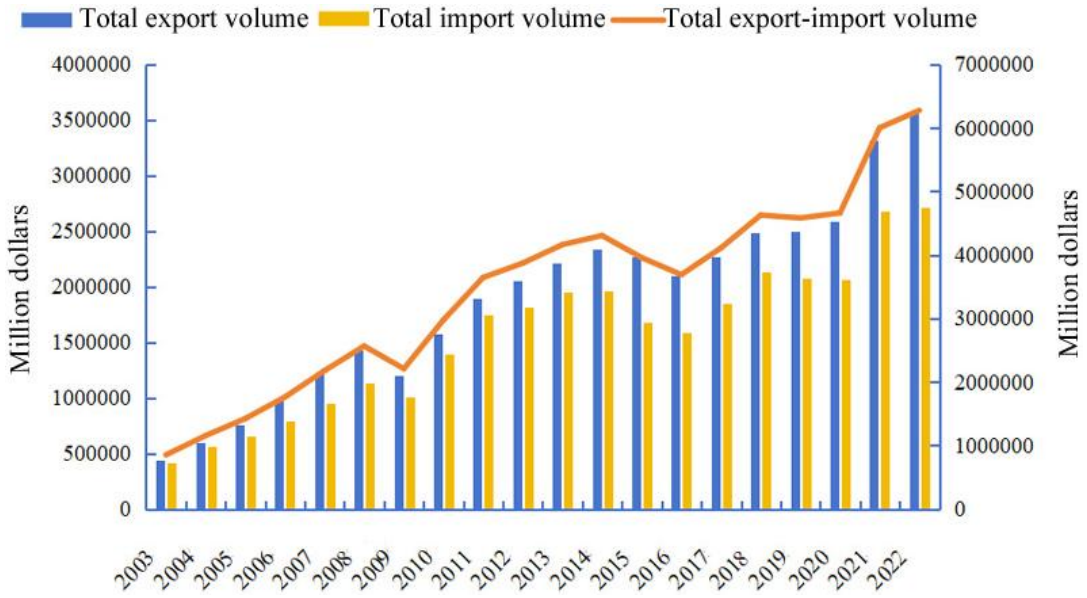

Figure 1. Changes in total export-import volume of China's trade between 2003 and 2022.

Figure 1 reveals that over the past two decades, the total export-import volume has predominantly exhibited an upward trend. The total volume of exports and imports has seen incremental growth, escalating from $850,990 million in 2003 to $6,270,110 million in 2022. Notably, there was a substantial decline in the total volume in 2009, correlating with the global financial crisis of 2008. However, after 2009, the foreign trade market rebounded, aided by adjustments in trade policies. The years 2015 and 2016 witnessed a downturn in China's import and export trade due to the influence of the global economy. Since 2019, the worldwide impact of the COVID-19 pandemic has further impeded China's import and export trade (Wei et al., 2021). The data illustrated in **Figure 1** indicates that the total export-import volume can be significantly influenced by various international and domestic factors.

In 2022, for example, China's top five import and export goods categorized in terms of volume (classified by Standard International Trade Classification) are shown in **Figures 2** and **3**.

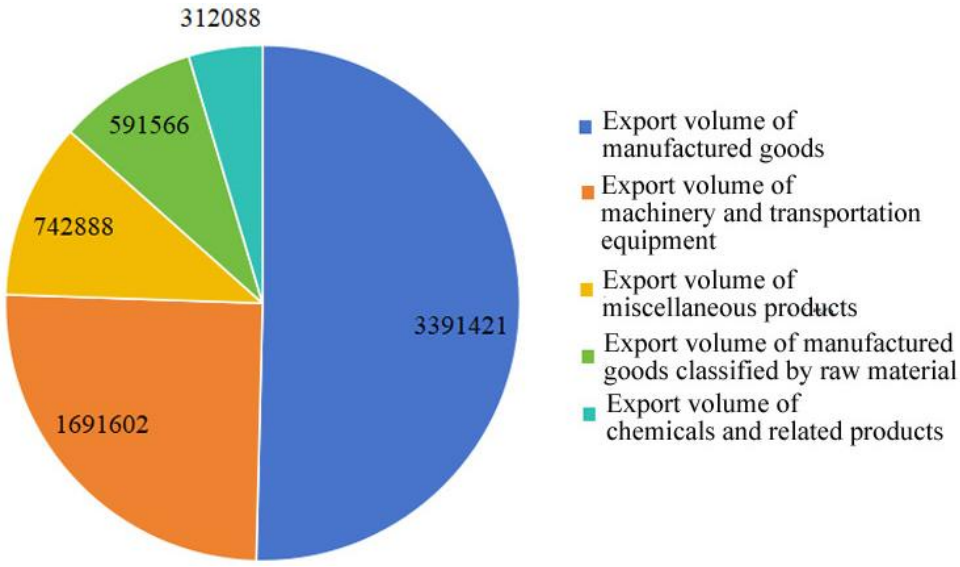

Figure 2. Top five exported goods in terms of volume in 2022 (unit: million dollars).

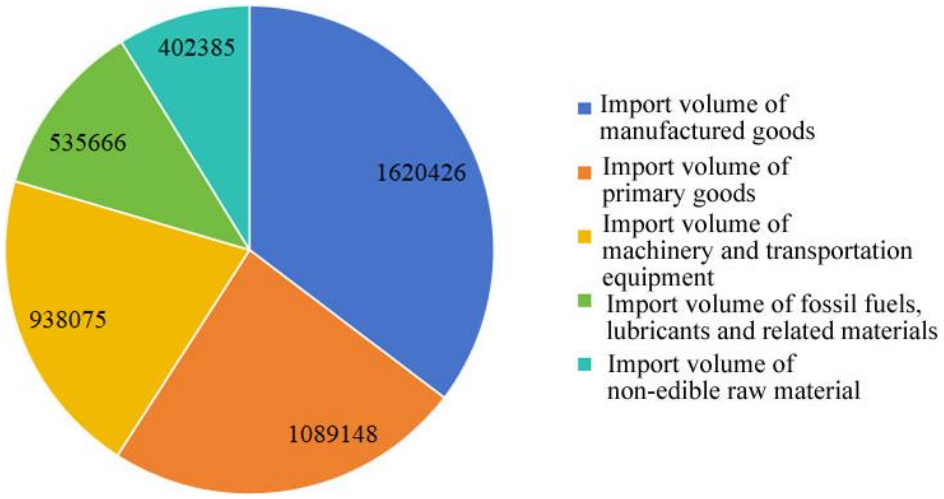

Figure 3. Top five imported goods in terms of volume in 2022 (unit: million dollars).

Figures 2 and **3** reveal that China's imports and exports predominantly revolved around manufactured goods. The export volume reached $3,391,421 million, while the import volume reached $1,620,426 million. Machinery and transportation equipment ranked second, demonstrating that China's foreign trade market is still dominated by the manufacturing industry currently.

In 2022, the total export-import volume between China and various countries (regions) is shown in **Figure 4**.

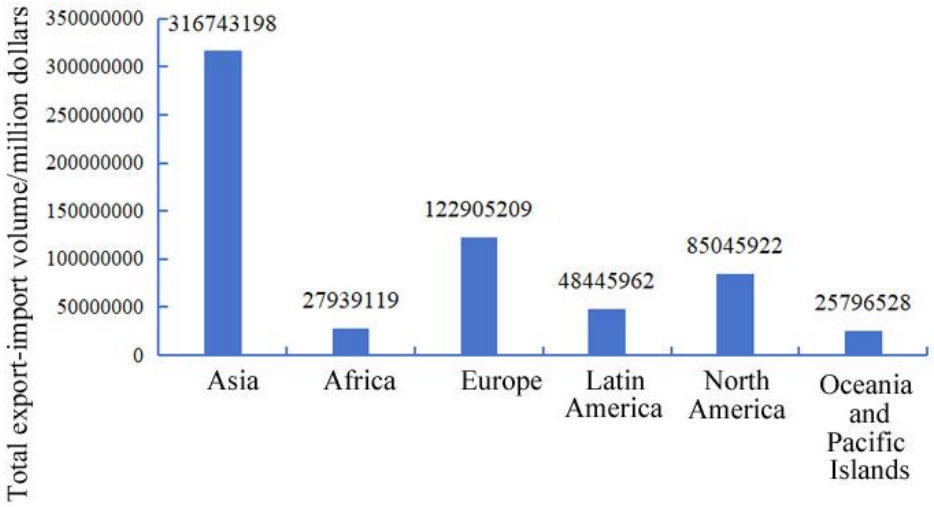

Figure 4. The total export-import volume between China and various countries (regions) in 2022.

As illustrated in **Figure 4**, China primarily focused on trade in Asia, with significant import and export volumes with countries such as Japan and Vietnam. Under the influence of the "Belt and Road" initiative, China has established strong cooperative relationships with many countries, contributing to the development of foreign trade.

2.2 Analysis of Influencing Indicators

According to the theory of economics, the total amount of imports and exports has some connection with both the political and economic environment. Combined with the current research, this paper chose seven indicators (**Table 1**) for analysis.

Table 1. Indicators affecting total export-import volume.

Serial number	Indicator
X1	GDP
X2	Consumer price index (CPI)
X3	Producer price index (PPI)
X4	Fixed-asset investment
X5	Total retail sales of consumer goods
X6	Total amount of foreign capital actually utilized
X7	Tariff rate
X8	Exchange rate
X9	Foreign exchange reserve
X10	Global economic growth rate

In **Table 1**, indicators such as GDP, CPI, PPI, and others serve as reflections of a country's overall economic level and development potential. The introduction of foreign investment is instrumental in bringing advanced technology and management practices, thereby strengthening the connection between foreign investment and foreign trade. Additionally, the tariff rate can offer insights into the prevailing policy environment to a certain extent. The exchange rate, foreign exchange reserve, and global economic growth rate can reflect the international economic environment. To gain further insights into the role of these indicators, the correlation between each indicator and the total amount of import and export was calculated using EViews (Unvana, 2021) with data sourced from the China Statistical Yearbook spanning from 2003 to 2022. **Table 2** presents the results obtained.

Table 2. Table of correlation coefficients for indicators.

Serial number	Correlation coefficient
X1	0.98
X2	0.08
X3	0.19
X4	0.93
X5	0.28
X6	0.81
X7	0.95
X8	0.86
X9	0.83
X10	0.75

According to **Table 2**, the correlation between X2 (CPI), X3 (PPI), X5 (total retail sales of consumer goods), and the total export-import volume is relatively low. Therefore, they are excluded from the subsequent total volume forecast. Among the remaining seven indicators, the correlation between X1 (GDP) and the total volume is highest, followed by X7 (tariff rate). The correlation between X4 (fixed-asset investment) and the total volume is also high, while the correlation between X10 (global economic growth rate) and the total volume is relatively weak.

3. Total Volume Prediction Method based on Support Vector Machine

In machine learning, SVM stands out as a widely employed method for diverse prediction tasks (Camastra et al., 2022). SVM demonstrates strong performance, particularly in addressing scenarios involving small sample sizes and nonlinear data (Fu and Tian, 2020). Its versatility makes it well-suited for prediction tasks related to total export-import volume, particularly in situations where there are insufficient samples and intricate influencing indicators.

The principle of SVM is to construct a hyperplane to classify different classes of samples. It is assumed that there is a collection of data $D = \{(x_i, y_i)_{i=1}^N\}$, $y_i = \{-1, +1\}$, where N denotes the total quantity of samples, $i = 1,2,\cdots, N$. In the case where the samples are not completely linearly divisible, the optimization problem of SVM is expressed as:

$$min \frac{\|w\|^2}{2} + C \sum_{i=1}^N \delta_i \quad (1)$$

$$s.t.\ y_i(wx_i + b) \geq 1 - \delta_i \quad (2)$$

where, w is a normal vector, b is a bias, δ is a slack variable, and C is a penalty factor.

Introducing a Lagrange multiplier transforms the above equation into a dual problem:

$$min \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N y_i y_j a_i a_j K(x_i, x_j) - \sum_{i=1}^N a_i \quad (3)$$

$$s.t.\ \sum_{i=1}^N y_i a_i = 0 \quad (4)$$

where, a is the Lagrange multiplier and $K(x_i, x_j)$ is a kernel function. The kernel functions commonly employed in SVM are:

(1) Linear kernel function: $K(x_i, x_j) = x_i \cdot x_j$;

(2) Radial basis function (RBF): $K(x_i, x_j) = exp\left(-\|x_i - x_j\|^2 / 2\sigma^2\right)$, where σ is the kernel parameter;

(3) Sigmoid kernel function: $K(x_i, x_j) = \tanh(\mu \cdot x_i \cdot x_j + \theta)$, $\mu > 0$, $\theta < 0$, which are parameters of the hyperbolic tangent function.

The RBF is acknowledged for its strong performance across different dimensions and scales (Zhu et al., 2019). Hence, in this paper, the RBF was selected to construct the SVM model for predicting the total volume. In an SVM, the size of penalty factor C influences the generalization ability, and the value of σ impacts the accuracy (Lian and He, 2022). A traditional SVM often employs grid search for parameter optimization (Valavan et al., 2021); however, its training time is relatively long, and it is susceptible to be trapped in local optimal solutions. To address this limitation and enhance the predictive performance of SVM on the total volume, this paper to optimize these two parameters using the sparrow search algorithm (SSA) (Xu et al., 2022).

SSA is based on the behaviors of sparrow search, which is more efficient and easier to implement than, for example, the particle swarm algorithm (PSO). A sparrow population containing N individuals search for food through three behaviors.

(i) The finder searches for food. At the k-th iteration, the position information of the i-th individual in the j-th dimension is $S_{i,j}$, then the position update of the finder is written as:

$$S_{i,j}^{k+1} = \begin{cases} S_{i,j}^{k} \cdot exp\left(-\frac{i}{\alpha \cdot k_{max}}\right), R < ST \\ S_{i,j}^{k} + QL, R \geq ST \end{cases} \quad (5)$$

where, α is a random number in (0, 1), R denotes the value of the warning issued by the vigilantes, $R \in (0, 1)$, ST is the early warning safety value, $ST \in (0.5, 1)$, Q is a random number following a normal distribution, and L denotes a 1×d matrix composed of all 1.

(ii) During foraging, the follower moves after the finder, and its position update can be written as:

$$S_{i,j}^{k+1} = \begin{cases} Q \cdot exp\left(\frac{S_w^k - S_{i,j}^k}{i^2}\right), i > \frac{n}{2} \\ S_b^{k+1} + \left|S_{i,j}^k - S_b^{k+1}\right| \cdot A \cdot L, otherwise \end{cases} \quad (6)$$

where, S_w^k stands for the worst individual at the k-th iteration, S_b^{k+1} stands for the optimal individual at the $k+1$-th iteration, and A is a matrix of $1 \times d$, whose element is assigned as a random value of either 1 or -1.

(iii) There are also 10-30% of individuals in the population that act as vigilantes, sending the alarm when a predator is detected, and their positional updates can be written as:

$$S_{i,j}^{k+1} = \begin{cases} S_b^{k+1} + \beta \cdot \left|S_{i,j}^k - S_b^k\right|, f_i > f_g \\ S_b^{k+1} + K \cdot \frac{1}{f_i - f_w + \varepsilon}, f_i = f_g \end{cases} \quad (7)$$

where, β is a random number, which obeys a normal distribution with a mean of 0 and a variance of 1, f_i denotes the current individual fitness, f_g represents the current maximum fitness, K is a random number in [-1, 1], f_w is the current minimum fitness, and ε is the minimum parameter preventing the denominator from being zero.

SSA has great randomness in initial population generation (Ouyang et al., 2021), so Tent mapping (Chen and Wang, 2020) is brought in to make the initial population more diverse:

$$X_{n+1} = \begin{cases} 2x_n, 0 \le x_n \le 0.5 \\ 2(1-x_n), 0.5 \le x_n \le 1 \end{cases} \quad (8)$$

Then, adaptive inertia weight ω_a is brought in during the position update process of the finder:

$$\omega_a = \omega_1(\omega_1 - \omega_2)\left(1 - \tan\frac{t\pi}{4t_{max}}\frac{t^2}{t_{max}^2}\right) \quad (9)$$

where, ω_1 and ω_2 are inertia tuning parameters, which are set as 0.9 and 0.4, respectively. Combined with ω_a, the position update formula of the finder is,

$$S_{i,j}^{k+1} = \begin{cases} \omega_a S_{i,j}^k \cdot exp\left(-\frac{i}{\alpha \cdot k_{max}}\right), R < ST \\ \omega_a S_{i,j}^k + QL, R \ge ST \end{cases} \quad (10)$$

The values of C and σ in SVM are optimized using the improved SSA (ISSA) to obtain an ISSA-SVM method for total volume prediction. The specific procedure is presented in **Figure 5**.

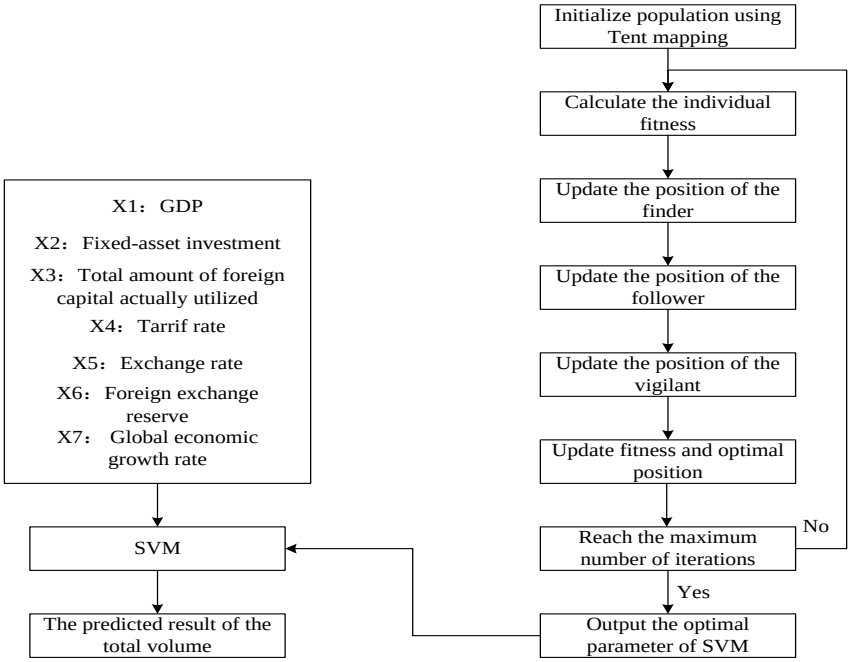

Figure 5. The ISSA-SVM method for total volume prediction.

4. Results and Analysis

4.1 Experimental Setup

Data taken from the China Statistical Yearbook over a 20-year period, from 2003 to 2022, were used. The data spanning from 2003 to 2017 was used as the training set, while the subsequent five-year data served as the test set. The data were normalized to avoid the influence of different data dimensions:

$$x' = \frac{x - min}{max - min} \quad (11)$$

The population size of the ISSA was set to 20, and the maximum number of iterations was 100. The ISSA was used to obtain the optimal C and σ, and they are input into the SVM to predict the total export-import volume. It is assumed that the actual value of the export-import volume in the t-th year is x_t and the predictive value is y_t. The following two indicators were used in the result evaluation.

(i) Mean absolute percentage error (MAPE) (Tomperi et al., 2022): it can reflect the error percentage of the prediction result:

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{x_t - y_t}{x_t}\right| \times 100\% \quad (12)$$

(ii) Root-mean-square error (RMSE) (Calasan et al., 2020): it can reflect the deviation between actual and predicted values:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left|\frac{x_t - y_t}{x_t}\right|^2} \quad (13)$$

4.2 Result Analysis

The effect of parameter optimization on the computational efficiency of the SVM method was analyzed by repeatedly running 20 predictions. The average time consumption is presented in **Figure 6**.

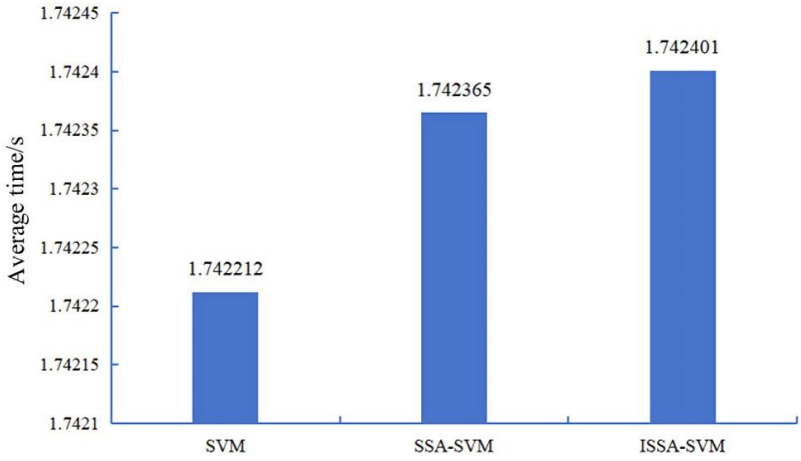

Figure 6. Comparison of average time.

As depicted in **Figure 6**, it is evident that when compared to the SVM method, both the SSA-SVM and ISSA-SVM methods exhibited a slight increase in computation time consumption after incorporating the parameter optimization method. However, the differences were extremely small. The SSA-SVM method only increased by 0.000153 s compared to the SVM method, and the ISSA-SVM method showed an increase of only 0.000189 s in comparison to the SVM method and 0.000036 s compared to the SSA-SVM method. These results indicated that the introduction of parameter optimization had a negligible impact on the computational efficiency of the SVM method.

The ISSA-SVM approach was compared with the other machine learning approaches, including:
(i) the logistic regression (LR) method (Vasu et al., 2022),
(ii) decision tree (DT) method (Javaid et al., 2023),

(iii) random forest (RF) method (Gu et al., 2023),
(iv) the back-propagation neural network (BPNN) method (Yin and Li, 2021),
(v) the genetic algorithm (GA)-SVM approach (Dinesh and Prabha, 2021),
(vi) the PSO-SVM approach (Deng et al., 2021),
(vii) the SSA-SVM method.

The results obtained through different approaches are presented in **Table 3**.

Table 3. The forecasting results of total export-import volume (unit: million dollars).

	2018	2019	2020	2021	2022
Actual value	4622440	4577890	4655910	5995790	6270110
LR	4712541	4652154	4785471	6125425	6398541
DT	4705418	4560153	4765248	6115268	6375421
RF	4692158	4647587	4732167	6105234	6352687
BPNN	4687541	4632514	4712541	6085214	6332514
SVM	4662514	4612541	4698521	6062514	6312548
GA-SVM	4652154	4601245	4685214	5962514	6301254
PSO-SVM	4632581	4569258	4642581	5978547	6265874
SSA-SVM	4627745	4572215	4650251	5990258	6265285
ISSA-SVM	4623514	4578995	4656952	5996865	6271154

Table 3 reveals a substantial disparity between the total volume prediction results of the LR, DT, RF, and BPNN approaches and the actual values. In contrast, the gap between the total volume prediction results obtained by the SVM approach and the actual values was comparatively smaller, indicating that among these machine learning methods, including LR, DT, RF, BPNN, and SVM, the SVM approach exhibited superior performance in predicting the total export-import volume. This result verified the reliability of using the SVM approach in relevant research. To further quantify the prediction effect, the MAPE and RMSE for different methods in total volume prediction were calculated, yielding the results in **Table 4**.

Table 4. Comparison of errors between different methods.

	MAPE	RMSE
LR	2.11%	112888.56
DT	1.76%	98561.52
RF	1.54%	76582.27
BPNN	1.26%	66813.03
SVM	0.87%	46637.73
GA-SVM	0.57%	29544.35
PSO-SVM	0.21%	11578.24
SSA-SVM	0.11%	5408.45
ISSA-SVM	0.02%	1068.25

The analysis of **Table 4** clearly shows that when comparing the MAPE values, the LR, DT, RF, and BPNN approaches exhibited values of 2.11%, 1.76%, 1.54%, and 1.26%, respectively, both exceeding 1%. In contrast, the SVM method achieved a considerably smaller MAPE of 0.87%, signifying superior performance compared to the LR, DT, RF, and BPNN methods. Similarly, in terms of RMSE, the SVM method outperformed the LR, DT, RF, and BPNN methods, providing further evidence of SVM's efficacy in total volume prediction. Comparing the impact of different optimization algorithms, the GA-SVM method achieved a MAPE of 0.57%, a 0.3% reduction in comparison to the SVM approach. Additionally, the RMSE of the GA-SVM method was 29,544.35, which showed a significant reduction compared to the SVM method and further verified the positive impact of parameter optimization on the predictive effectiveness of the SVM method.

Among the PSO-SVM, GA-SVM, and SSA-SVM approaches, the SSA-SVM approach stood out with a MAPE of 0.11% and an RMSE of 5,408.45, significantly smaller than those of the GA-SVM and PSO-SVM approaches. This result suggested that the SSA method had a superior effect than the GA and PSO methods in optimizing SVM parameters. Finally, when comparing the SSA-SVM method with the ISSA-SVM method, the latter achieved a MAPE of 0.02% and an RMSE of 1,068.25, which showed a decrease of 0.09% and 4,340.2 compared to the SSA-SVM method, respectively. These results highlighted the effectiveness of the enhancement in further improving the efficacy of the SVM method for forecasting the total export-import volume.

Moreover, the ISSA-SVM method was compared with two methods used for predicting total export-import volume in current research: 1. the improved ARIMA-GM (1, 1)-Markov chain combination model used in Long and Yan (2016); 2. the optimized long short-term memory (LSTM) model used in Zhang et. al (2019). The MAPE and RMSE of different methods for total volume prediction based on the same data are presented in **Table 5**.

Table 5. Comparison of errors with existing methods.

	Long and Yan (2016)	Zhang et al. (2019)	The proposed method
MAPE	6.39%	5.18%	4.12%
RMSE	75412.69	23562.67	5420.36

The proposed method still had the lowest MAPE and RMSE. The method proposed in Long and Yan (2016) had a MAPE of 6.39% for total volume prediction, which was 2.27% higher than the ISSA-SVM method, and its RMSE was also high. The method proposed in Zhang et. al (2019) had a MAPE of 5.18%, which was 1.06% higher than the ISSA-SVM method, and its RMSE was significantly higher at 23,562.67 compared to the ISSA-SVM method. These results demonstrated the advantages of the ISSA-SVM model over the models used in existing research.

5. Discussion

With the rapid advancement of information technology and innovative changes in transportation, the international economic connections have become even closer, leading to a significant increase in trade. For developing countries, the steady growth of import and export trade is beneficial for unleashing production capacity, increasing employment opportunities, as well as introducing advanced foreign products, technologies, and concepts. Therefore, predicting the total export-import volume of China's economic trade can help relevant departments better grasp the changing trends in export-import trade and take timely measures accordingly.

Among the selected indicators for predicting the total export-import volume in this article, GDP can directly reflect the current internal economic environment. Therefore, in correlation analysis, GDP has the highest correlation with the total import-export volume, reaching 0.98. Fixed-asset investment and the total amount of foreign capital actually utilized can both reflect the internal economic environment. The growth of fixed-asset investment implies an increase in production technology level, which can make exported products more competitive internationally. The total amount of foreign capital actually utilized represents foreign investment situation and has a positive effect on optimizing industrial structure and adjusting economic structure. Tariff rate is an important means to regulate national economic structure and increase fiscal revenue. Changes in tariff rates will cause adjustments in prices, trade, etc., directly reflecting import-export trade situation. Its correlation coefficient with the total import-export volume reaches 0.95, proving its importance. Foreign exchange reserves are an important tool for balancing international payments and serve

as the foundation of international trade. The growth of foreign exchange reserves has a significant impact on attracting foreign investment and stabilizing exchange rates. Meanwhile, global economic growth rate reflects the international economic environment; when global economic growth rate is high, global import and export trade becomes more active, providing more opportunities for foreign trade. Therefore, these two indicators also have a crucial influence on the total export-import volume.

Based on the above seven indicators, this paper designed an ISSA-SVM method. It achieved a MAPE of 4.12% and a RMSE of 5,420.36, which was not only lower than other machine learning methods such as LR and RF but also demonstrated better prediction accuracy compared to current prediction methods. Therefore, the ISSA-SVM method can be applied in practical predictions of China's economic trade imports and exports. In future work, consideration will be given to deploying the model in real-world environments for real-time monitoring and continuous surveillance of the total export-import volume, thereby enhancing management of international trade.

According to the research findings above, some suggestions and measures are proposed for the development of China's economic trade import and export sector.

(i) In light of the current import and export situation, it is recommended to strengthen trade cooperation with foreign countries, expand market access for foreign trade, and encourage more foreign investment in China.

(ii) To maintain long-term competitive advantages, it is necessary to pay attention to the quality of exported products and strictly control the quality of imported and exported products. Enterprises should optimize internal industry structure within enterprises and continuously pursue technological innovation.

(iii) In terms of cross-border e-commerce management, it is important to actively explore new areas in foreign trade based on its characteristics and development trends. By adjusting better systems and innovating services, better development conditions can be provided for cross-border e-commerce.

6. Conclusion

A novel ISSA-SVM method was proposed for predicting the total export-import volume of China's economic trade. Leveraging machine learning techniques, this method utilized data from 2003 to 2022, incorporating indicators such as GDP and fixed-asset investment. Experimental analysis revealed that the introduction of the parameter optimization method had minimal impact on the computational efficiency of SVM. Furthermore, when compared to machine learning methods like LR, the ISSA-SVM method demonstrated superior performance, exhibiting the lowest MAPE and RMSE in total volume prediction. This high prediction accuracy positions the ISSA-SVM approach as a promising tool for practical applications. In addition, in the future work, the deployment of the model in the real environment will be discussed more deeply to further improve the usability of the model.

Conflict of Interest

The author confirms that there is no conflict of interest to declare for this publication.

Acknowledgments

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The author would like to thank the editor and anonymous reviewers for their comments that help improve the quality of this work.

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