Modeling and Study of Pet Industry

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Abstract: This research focuses on the pet industry, aiming to systematically predict its development trends in China and globally and explore the core factors affecting pet food production and export. Through in - depth analysis of relevant data, a series of mathematical models are established. For China's pet industry, we analyze its development in the past five years, predict the number of cats and dogs in the next three years, and then comprehensively analyze the global pet industry's market demand. Additionally, we explore the relationships between pet food production and export in China, global demand, and international economic policies. The results provide valuable references for the sustainable development of the pet industry.

1. Introduction

In recent years, due to the improvement of people's living standards and consumption concept transformation, the pet industry has become a booming sector globally. Pets are not just companions but symbols of emotional and spiritual sustenance. In China, it has grown remarkably since the 1990s, with a rapidly expanding "pet economy" showing great potential. Meanwhile, the pet industry in Europe and the US is highly developed, dominating the global market. However, the Chinese pet industry faces challenges like policy changes, market demand fluctuations, and economic uncertainties[1].

Previous studies on the pet industry have multiple limitations. Zhang et al. simplifies the complex relationship between various factors and the pet industry's development. They assume a simple linear link between economic development and the pet market's growth, overlooking variables like pet - related infrastructure quality, professional pet - care service availability, and marketing effectiveness, thus incompletely understanding the industry's growth mechanisms[2]. Provensi et al. focuses on single - aspect analysis, such as only examining the impact of the change in the number of pet owners in isolation, neglecting interactions within the pet - industry ecosystem[3]. Moreover, Gawer and Phillips' studies fail to consider the dynamic evolution of the pet - industry landscape. With new products, changing consumer preferences, and e - commerce development, traditional static models in their studies can't adapt to long - term changes[4].

To fill the research gaps, this study innovates and improves. It integrates multiple data - analysis models like EWT, LSH_Attention, SA algorithm, Lasso regression, and random forest regression. EWT decomposes data, LSH_Attention optimizes the Informer model, and SA algorithm boosts prediction accuracy. Also, it focuses on the interaction of various factors to better understand the pet - industry ecosystem.

2. Methodology

2.1. Data Processing and Feature Selection

Data collection is the basis of this study. We collect comprehensive pet - industry data, including pet populations, economic indicators, and market data. Given the industry's long - term development and potential data issues, data cleaning is crucial. We use the UnivariateSpline interpolation method to handle missing values, ensuring data smoothness for time - series prediction[5].

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To build an effective predictive model, we first establish a set of metrics to describe factors influencing the pet industry. Then, feature selection is carried out to simplify the model and improve interpretability[6]. We conduct Spearman correlation analysis to explore relationships between indicators and pet - industry development, identifying key variables.

2.2. Model for Predicting the Number of Cats and Dogs in China

The key to predicting the number of cats and dogs in China is to build a scientific model using historical data. We preprocess the data through interpolation enhancement and feature standardization, and then apply the EWT - SA - Informer model.

The EWT decomposes pet - industry time - series data. It divides the Fourier spectrum of the signal into continuous intervals $\Lambda_n = [w_{n-1}, w_n], n = 1,2,\cdots,N(w_0 = 0, w_N = \pi)$, constructs wavelet filter groups for filtering, and reconstructs the signal. The reconstruction formula of signal $f(t)$ is:

$$f(t) = \sum_{k=0}^{N} W_f^e(k,t) * \varphi_{k+1}(t) \tag{1}$$

where $W_f^e(k,t)$ are the empirical wavelet coefficients. This process filters noise and extracts key features.

The Informer model, optimized by the LSH_Attention mechanism and SA algorithm, is used for prediction. The Informer model improves on the Transformer model to $(\mathrm{O(NlogN)})\left((\mathcal{J} = \arg max_{\mathrm{i}\in[1,\mathrm{N}]} \mathrm{N}_1 // \mathrm{Q_i k^T} //)\right)$, multi - scale modeling to capture short - and long - term patterns, and a sparse decoding mechanism $\left((\hat{\mathrm{Y}} = \mathrm{f_{Decoder}}(\mathrm{X_{important}}))\right)$ for better interpretability. The LSH_Attention mechanism further optimizes the sparsity process, and the SA algorithm globally optimizes the model's hyperparameters for higher accuracy[7].

2.3. Model for Analyzing Global Pet Industry Market Demand

For global pet - industry market - demand analysis, we expand the model input from single - country features to a joint - feature system of multiple countries (e.g., China, US, France, Germany). We adjust the input - feature matrix ($\mathrm{X} \in \mathrm{R}^{\mathrm{T}\times(\mathrm{N_{features}}\times\mathrm{N_{countries}})}$) and design a multi - task structure in the Informer model for multi - objective joint prediction.

In the encoder, each country's indicator matrix is input into a shared encoding module to generate temporal embedding representations:

$$H_i = \mathrm{Encoder}(X_i), \quad i = 1,2,3,4 \tag{2}$$

In the decoder, a multi - task structure with a shared - weight backbone network predicts the number of cats and dogs in multiple countries, and the output layer has independent heads for each country $\left((\hat{\mathrm{Y}} = \mathrm{Decoder}(\mathrm{H_{joint}}))\right)$.

Based on the objective function discussed above, this model is classified as a nonlinear programming problem, necessitating the use of heuristic optimization algorithms. The Slime Mould Algorithm (SMA) is an optimization algorithm that simulates the foraging behavior of slime mould in nature. It leverages the slime mould's food source tropism, oscillatory contraction behavior, and network adaptability in multi-food source environments to approximate optimal solutions through iterative position updates. The core mechanisms can be summarized into three rules: approaching food, surrounding food, and acquiring food.

To calculate global feed demand, we use the Monte Carlo simulation method combined with the predicted number of cats and dogs. The expected value of a random variable X in Monte Carlo simulation is calculated as :

$$E[X] = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{3}$$

We simulate the daily feed consumption of each cat and dog $\left((Feed_{cat,i} = \mu_{cat} + Z.\sigma_{cat}), (Feed_{cat,i} = \mu_{dog} + Z.\sigma_{dog}), (Z \sim N(0,1))\right)$, calculate the daily feed demand, repeat the simulation (e.g., 10000 times) to get the distribution, and then estimate the global total feed demand and its uncertainty range for the next three years[8].

2.4. Model for Analyzing Chinese Pet Food Production and Export Trends

To analyze China's pet - food production and export trends, we construct an indicator system with global feed consumption as the independent variable and China's pet - feed production and export values $\left((Y_{production,t}), (Y_{export,t})\right)$ as the dependent variables. The relationships are described by:

$$(Y_{production,t} = \beta_0 + \beta_1 X_{consumption,t} + \epsilon_t) and (Y_{export,t} = \alpha_0 + \alpha_1 X_{consumption,t} + \epsilon_t) \quad (4)$$

We use the Lasso regression model, which minimizes the loss function $L(\beta)$ to fit the relationship. It performs feature selection and prevents overfitting through L1 regularization[9].

$$L(\beta) = \sum_{i=1}^{n}\left(y_i - \sum_{j=0}^{p}\beta_j x_{ij}\right)^2 + \lambda\sum_{j=1}^{p}|\beta_j| \quad (5)$$

2.5. Model for Analyzing the Impact of International Economic Policies on the Pet Food Industry

To analyze the impact of international economic policies (e.g., tax rates) on China's pet - food industry, we construct an indicator system with tax rates of various countries as independent variables and China's pet - food production and export volumes as dependent variables.

We use the random - forest regression model. In the regression task, the final predicted value is:

$$\hat{Y} = \frac{1}{N}\sum_{i=1}^{N} f_i(X) \quad (6)$$

where N is the number of decision trees and $f_i(X)$ is the prediction result of the i - th decision tree. We analyze the results from feature importance, error analysis of production and export volumes, and the fitting effect of production and export volumes to reveal the impact of different countries' tax rates on China's pet - food industry[10].

3. Results and Discussion

3.1. Prediction Results of the Pet Industry in China

The EWT - SA - Informer model effectively forecasts the trends in the number of cats and dogs in China over the next three years. The results indicate that the number of cats will continue to experience a significant increase, while the number of dogs will tend to stabilize or might even slightly decline in certain situations. This prediction aligns with the current development trajectory of China's pet industry, where factors like urbanization and evolving lifestyles are contributing to the growing popularity of cats. As shown in Figure 1, the historical data and future predictions clearly display this trend. The growth of the cat population is depicted by a steadily rising curve, while the dog population shows signs of stabilization or a gentle downward slope in the predicted period.

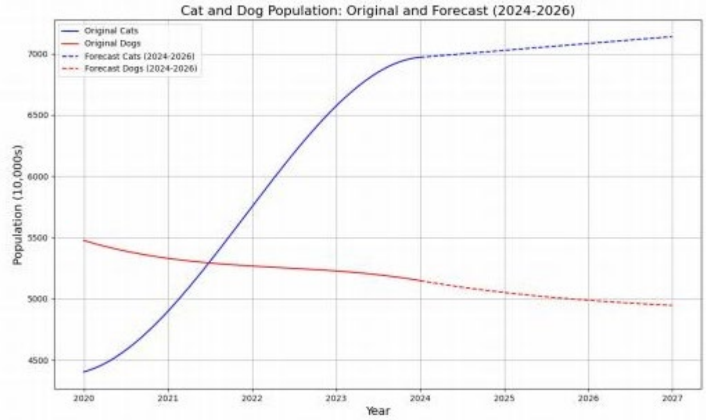

Figure 1 Historical Data and Future Projections of the Number of Cats and Dogs in the Chinese Pet Industry(2020 - 2026)

3.2. Analysis of Global Pet Industry Market Demand

By leveraging the predicted number of cats and dogs in multiple countries and conducting Monte Carlo simulations, we estimated the global pet - food consumption for the next three years. The analysis reveals substantial regional variations in market demand. Developed regions generally exhibit a higher demand for high - quality pet food, whereas developing regions are more inclined towards affordable pet products. This finding offers valuable insights for the global strategic layout of the pet - food market, as shown in Figure 2.

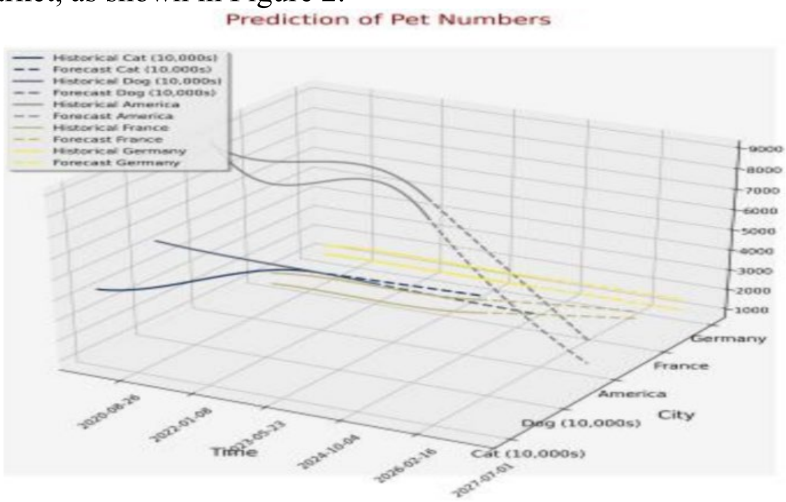

Figure 2 Analysis of Regional Differences in Global Pet Food Market Demands

3.3. Trends of Chinese Pet Food Production and Export

The Lasso regression model indicates that the growth trends of China's pet - food production and export are closely intertwined with global demand. As global pet - food consumption rises, China's pet - food production and export are likely to follow suit. However, factors such as international trade policies and market competition may introduce fluctuations. As shown in Figure 3, the historical and predicted data on China's pet - food production and export, in relation to global pet - food consumption, vividly illustrate this relationship. The figure showcases how changes in global demand are reflected in China's production and export trends, with some fluctuations due to external factors.

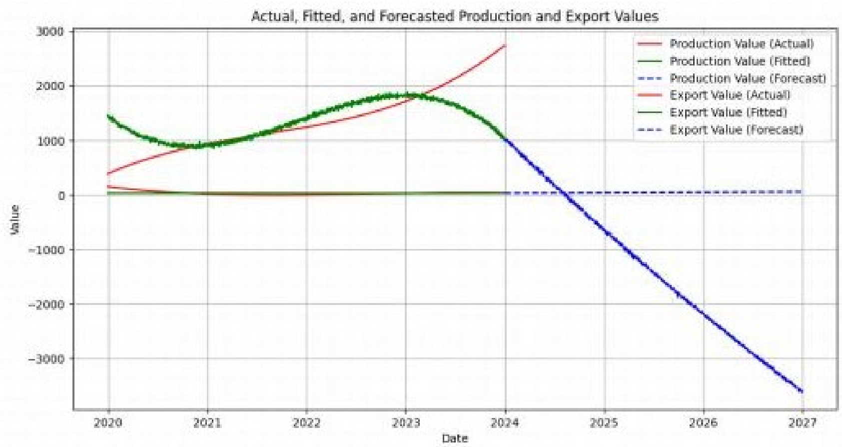

Figure 3 Trends of China's Pet Food Production and Export and Their Relationship with Global Demand

3.4. Impact of International Economic Policies on the Chinese Pet Food Industry

The random - forest regression model uncovers that the tax rates of major European countries, particularly Germany, have a notable impact on China's pet - food exports. In terms of production volume prediction, adjustments in Germany's tax rates can indirectly stimulate the growth of Chinese feed production by influencing European market demand. When it comes to export volume prediction, the impact of tax rates in the United States and China is relatively minor, suggesting that international market demand plays a more dominant role in determining China's pet - food exports. These results imply that China needs to closely monitor the tax - policy changes of major European countries and formulate appropriate strategies to better compete in the international market. As shown in Figure 4.

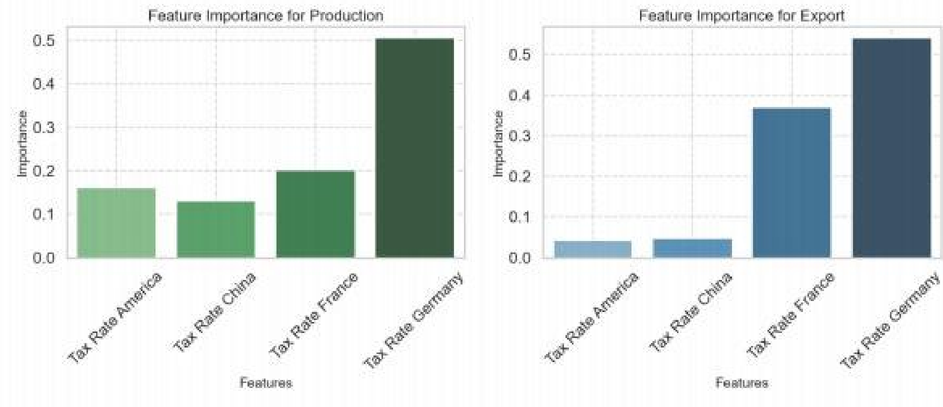

Figure 4 Analysis of the Impact of Tax Rates in Different Countries on China's Pet Food Production and Export

4. Conclusion

This study comprehensively analyzes the development of the pet industry, constructs a series of prediction models, and explores the impact of various factors on the pet - food industry. The results show that different factors play important roles in the development of the pet industry. The number of cats and dogs in China will change in different trends in the future, and global pet - food consumption has regional differences. The production and export of Chinese pet food are closely related to global demand, and international economic policies, especially tax rates in major European countries, have a significant impact on China's pet - food industry. These findings provide valuable references for the sustainable development of the pet industry, such as guiding pet - food producers to adjust production plans according to market demand, and helping policymakers formulate relevant policies to promote the healthy development of the pet industry. Future research can focus on improving data - collection methods, considering more complex factors such as cultural differences and emerging pet - industry trends, and further optimizing the prediction models to better understand

and predict the development of the pet industry.

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