Future Development Forecast of Pet Industry Based on Gray Prediction and Wavelet Neural Network Model

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Abstract. This study focuses on the development of China’s pet industry and its related sectors, providing an in-depth analysis and projections for its future growth. Using a gray prediction model, the paper forecasts that the market size of China’s pet industry will grow from RMB 3.29 trillion to RMB 4.10 trillion over the next three years. Furthermore, a wavelet neural network model is employed to analyze global demand for pet food. This model incorporates advanced techniques for determining hidden nodes, employs backpropagation for weight adjustment, and utilizes Adam’s algorithm to optimize the learning rate. The analysis predicts an increase in global pet food sales from $138 billion to approximately $149.7 billion within the same period. By integrating diverse factors and data sources, the comprehensive model offers valuable insights to industry professionals and researchers. This research aims to support strategic decision-making and promote the sustainable development of the pet industry in China and globally.

Keywords: Wavelet Neural Network, Gray Prediction Model, Adam Algorithm, Pet Market Growth.

1. Introduction

In the context of China’s rapidly aging society and the concurrent trend of decreasing birth rates coupled with an increase in single-person households, there is a profound shift in leisure activities and consumer behavior. The emergence of the "loneliness economy" has been particularly pronounced, with the emotional void experienced by "empty-nest youth" and "empty-nest elderly" groups leading to a surge in the demand for companionship and emotional support. In this scenario, pets have emerged as more than just animals; they are now considered emotional support objects that are integral to the development of the pet industry [1,2]. The emotional consumption aspect of the pet economy not only follows the logic of industrial upgrading but also holds significant market potential. This growth in emotional demand is a driving force behind the expansion of pet food, supplies, medical care, services, and other related industries [3,4].

The transformation in consumption patterns is not limited to China; overseas pet markets, such as those in Europe and the United States, are also experiencing rapid growth. This global trend underscores the importance of understanding the dynamics of the pet industry on a worldwide scale. Therefore, this paper aims to provide a rational and scientific forecast of the development of the pet industry in China and globally, taking into account the complex interplay of social, economic, and technological factors that are shaping this market.

The innovation of this paper lies in the novel combination of gray system theory and wavelet neural network technology to construct a composite prediction model. This integrated approach allows for more accurate predictions of future trends in the pet market, especially when dealing with small samples and uncertain data, showcasing unique advantages over traditional models. The ability to handle uncertainty is crucial in an industry where market demands can fluctuate rapidly due to changing societal and economic conditions.

Accurate forecasting of the development trends in China’s pet industry is essential for capturing market trends, guiding corporate strategic planning, and optimizing resource allocation. By forecasting the economic situation of the pet industry, enterprises can adjust their business strategies in a timely manner to cope with market changes. Moreover, these forecasts provide policymakers with decision-making references that promote the healthy and stable development of the industry and ensure its sustainable growth [5,6].

This study considers multiple factors and data sources, offering valuable insights for pet industry professionals and researchers to make informed decisions and foster the healthy development of the pet industry in China. Additionally, the model provides decision support for global and Chinese pet industry professionals, encouraging healthy growth in the global and Chinese pet industry. The findings of this paper are expected to guide strategic decisions of industry stakeholders and policymakers, helping them to understand market trends, develop products, and manage risks effectively.

2. Future Development of China's Pet Industry: Gray Forecasting Model

2.1. Assumptions and Justifications

(1) Market stability assumption: It is assumed that the development of China's pet market will not be seriously affected by major external events (e.g., epidemics, economic crisis, etc.) in the next three years.

(2) Factor Independence Assumption: it is assumed that the factors considered in the model (e.g., GDP per capita, proportion of ageing, number of internet broadband interfaces, etc.) are independent of each other in terms of their impact on the pet market.

(3) Global Market Growth Assumptions: It is assumed that global pet food sales in general exhibit exponential growth characteristics and can be predicted after normalisation.

(4) Economic environment stability assumption: It is assumed that the global economic environment will be relatively stable over the next three years, and that no large-scale economic fluctuations will affect the market demand for pet food.

2.2. Description of data sources and variables

In order to deeply investigate the development trend and influencing factors of China's pet industry in recent years, and to forecast the future of China's pet industry, it is necessary to collect relevant industry data and construct corresponding mathematical models to realize scientific analysis and forecast.The relevant data sources are shown in Table 1.

Table 1: data source

Data Types	Source
Pet Market Size	China International Pet Show (CIPS).
Elderly dependency ratio	China Statistical Yearbook
Internet broadband access ports	China Statistical Yearbook
Per Capita GDP	China Statistical Yearbook
Global Pet Food Sales	Grand View Research

Table 2 below shows the main variables used in this study and their descriptions.These variables were selected according to the AIC and BIC guidelines to ensure optimal model performance.

Table 2: notations

Symbol	Description
n	n is the number of hidden nodes, in this paper n is taken as 6 or 10(Based on AIC and BIC guidelines)
Ir_1	Adam's algorithm is used to adaptively tune the learning rates Ir_1 and Ir_2 to optimize the weight updating process
Ir_2	
W_{jk}	For the weights (W_{jk}) from the output layer to the implicit layer, the error gradient is computed by the chain rule
W_{ij}	For the weights (W_{ij}) from the implicit layer to the input layer, the error gradient is similarly computed by the chain rule

2.3. Correlation Analysis

The successive introduction of national normative documents and pet-keeping related policies/regulations will promote the standardized development of the pet industry [7]. With the improvement of residents' income, the upgrading of residents' consumption concepts and the emphasis on quality of life and investment in emotional consumption will promote the diversification of consumption in the pet industry. Changes in demographic structure, the increase in the number of empty-nesting elderly and empty-nesting young people, more and more people will be accompanied by the desire to pin it on the pet. At the same time, the advancement of new media technology and the outbreak of short videos and other social media have driven the development of "cloud pet sucking", bringing more market scale and potential consumers to the pet industry [8].

GDP per capita, old age dependency ratio, number of broadband interfaces, and size of the pet market are utilized to describe the factors such as increase in income of the population, change in demographic structure, advancement in new media technology, and indicators of the development of the pet market [9]. The heat map as shown in Figure 1 is obtained by Person correlation analysis of Statistical Package for the Social Sciences.

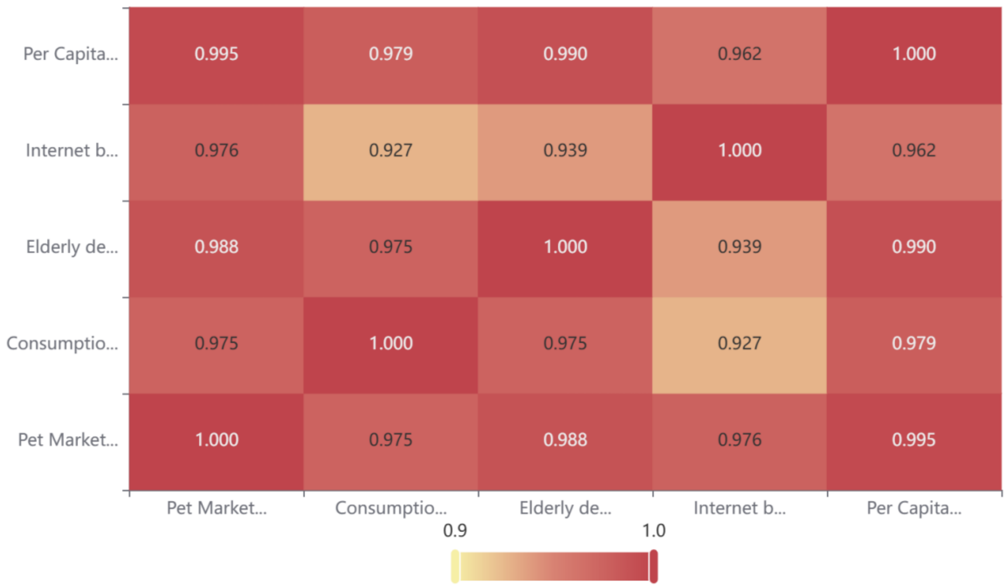

Figure 1. Neural network structure

It can be seen from Figure 1 that the increase in population income, the aging of the population, and the development of the Internet are important factors in the current development of the pet industry.

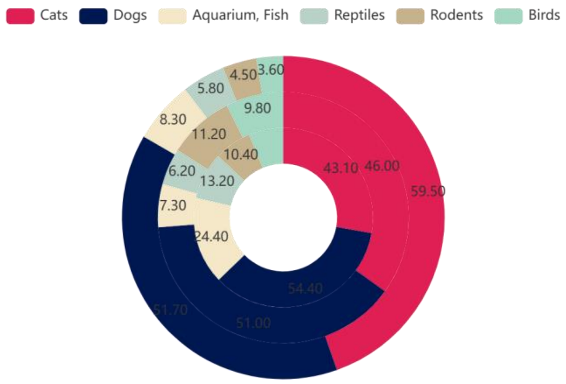

Figure 2. pet types

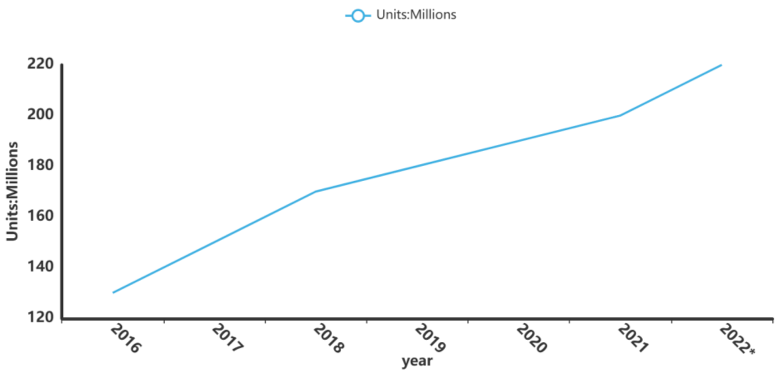

Figure 3. the total number of pets in China

As can be seen in Figures 2 and 3, the market size of China's pet industry has been expanding in recent years, with cats and dogs taking up the largest share, which can account for 70 to 80 per cent of the total.

2.4. The establishment of gray prediction model

Gray system theory is founded by Professor Deng Julong, GM (1, 1) model is the most basic prediction model in gray system, and it is also one of the most important methods in the gray system theory system. Compared with the traditional mathematical and statistical models, the biggest advantage of the gray GM (1,1) model is that there is no strict requirement on the sample capacity and probability distribution, only a small amount of data can be fitted, the operation is simple and the prediction effect is good, it is an effective way to study the problem of uncertainty such as small data and poor information [10].

The corresponding differential equation for the GN (1,1) model is:

$$x^{(0)}(k)+az^{(1)}(k)=b, \tag{1}$$

where $z^{(1)}$ is the background value of the GM (1,1) model and $x^{(0)}$ is a non-negative data series, here in order to predict the development of the pet market in the next three years, the size of the pet market in the last few years is used as the original non-negative data series $x^{(0)}$.

Then the least squares estimated parameters of the gray differential equation satisfy:

$$u=[a\ \ b]^{T}=(B^{T}B)^{-1}B^{T}Y, \tag{2}$$

where B and Y are the constructed data matrices and data vectors, the a is the development coefficient, and b is the gray role quantity.

Solving based on the formula:

$$\hat{x}^{(1)}(k)=\left[x^{(0)}(1)-\frac{b}{a}\right]e^{-a(k-1)}+\frac{b}{a} \qquad k=1,2,\cdots,n \tag{3}$$

2.5. The establishment of wavelet prediction model

Wavelet Neural Network (WNN) is a time series forecasting model that combines wavelet transform and neural network [11]. It utilizes the multi-scale analysis property of wavelet transform to effectively capture the local features and global trends of time series data, thus improving the accuracy and generalization ability of forecasting. WNN (n, Ir_1, Ir_2, W_{jk}, W_{ij}) model, where the calculation of hidden layers:

$$net(j)=\sum_{k=1}^{M}W_{jk}(j,k)\cdot x(k)+b(j), \tag{4}$$

where $net(j)$ is the output of the jth hidden node and $b(j)$ is the bias of the hidden node. $x(k)$ is the global food sales in the kth year.

Activation function:

$$AF(t) = e^{(-t^2/2)} \cdot \cos(1.75t), \tag{5}$$

where $AF(t)$ is the output of the activation function, t is the hidden layer output after translation and scaling.

Output layer calculation:

$$y(k) = \sum_{j=1}^{n} W_{ij} \cdot AF(t), \tag{6}$$

where $y(k)$ is the output of the kth hidden node.

3. Results

3.1. Solving the gray prediction model

(1) Step 1: Plot the image of the original data and perform an exponential law test, to use gray predictive data should first have a quasi-exponential law.

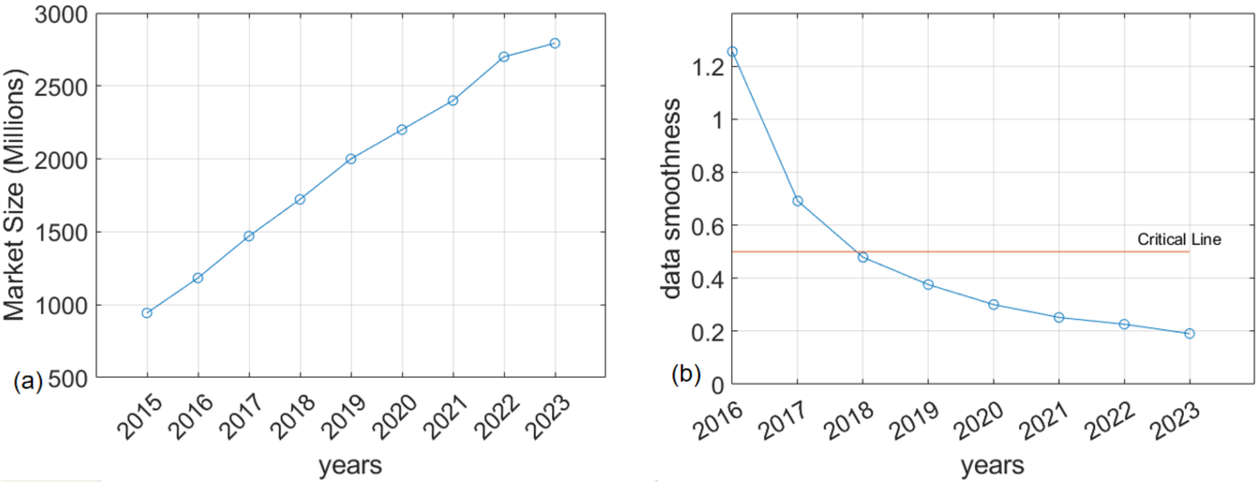

Figure 4. (a)raw data image, (b)exponential law test

As can be seen from Figure 4, Indicator 1: the percentage of data with a smoothness ratio of less than 0.5 is 75%; Indicator 2: excluding the first two periods, the percentage of data with a smoothness ratio of less than 0.5 is 100%, which are in line with the reference standard: Indicator 1 should generally be greater than 60%, and Indicator 2 should be greater than 90%.

(2) Step 2: Use the GM (1, 1) model to train the training data, and calculate the development coefficient and gray role quantity from the original data, from the development coefficient and gray role quantity can be constructed gray prediction model, their specific values are shown in Table 3.

Table 3: construction of the grey model

Development Coefficient	Grey action quantity	posterior error ratio C
-0.048	3804.148	0.011

The development factor indicates the pattern and trend of development of the series, and the gray quantities reflect the changing relationship of the series.

The a posteriori difference ratio can verify the accuracy of the gray prediction, the smaller the a posteriori difference ratio, the higher the accuracy of the gray prediction.

A general a posteriori difference ratio value of C less than 0.35 indicates a high model accuracy, C less than 0.5 indicates a qualified model accuracy, C less than 0.65 indicates a basic qualified model accuracy, and if C is greater than 0.65, the model accuracy is unqualified.

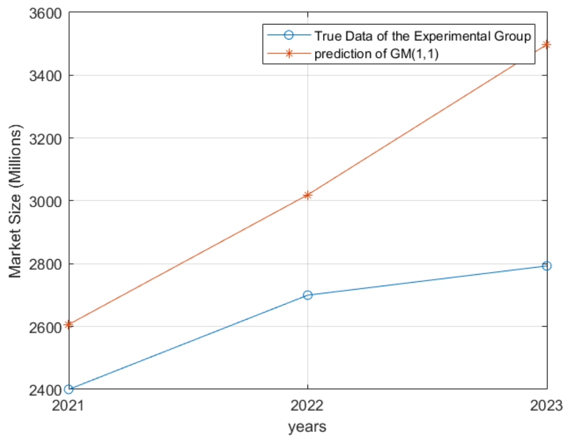

Figure 5. predicting the validation data

From Figure 5, it can be seen that the forecast results in the short term are roughly the same as the actual market direction.

(3) Step 3: Predictive results of the GM (1, 1) model (fitted plots with tabular data).

Table 4: model fitting results table

Year	Original Value	Predicted Value	Residual	Relative Error
2015	943	943	0	0
2016	1183	1286.419	-103.419	8.742
2017	1470	1486.128	-16.128	1.097
2018	1722	1695.613	26.387	1.532
2019	2000	1915.353	84.647	4.232
2020	2200	2145.851	54.149	2.461
2021	2400	2387.633	12.367	0.515
2022	2700	2641.252	58.748	2.176
2023	2793	2907.286	-114.286	4.092
2024	None	3286.874	None	None
2025	None	3670.784	None	None
2026	None	4099.536	None	None

It can be seen from the Table 4. In the next three years, China's pet industry shows an upward trend, and the size of China's pet market will grow from RMB 3,286,874 million to RMB 4,099,536 million.

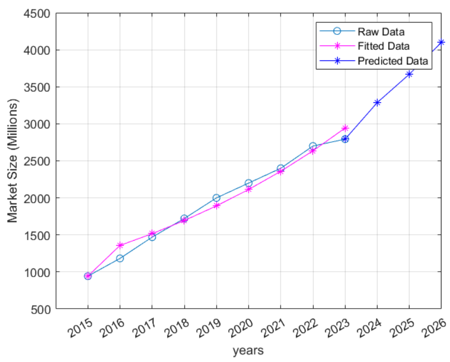

Figure 6. predicting the raw data

As can be seen in Figure 6, the pink fitted data line is very close to the blue raw data points, indicating that the selected model captures the trend of market size over time very well.

In addition, the predicted data is consistent in trend with the fitted data, further enhancing the credibility of the model in predicting future changes in market size.

(4) Step 4: Model evaluation of the GM (1, 1) model, the main methods are the test of rank deviation and the residual test of the predictive effect of the model.

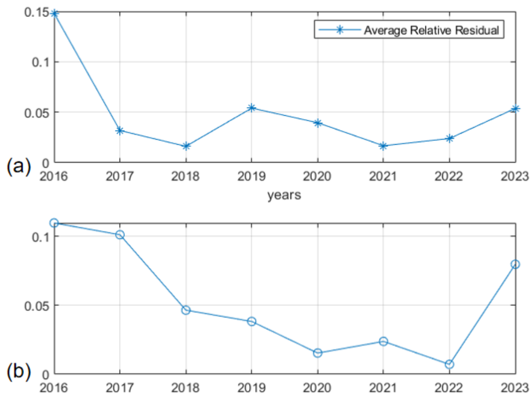

Figure 7. (a)residual and (b)relative error

As can be seen in Figure 7, the average relative residual is 0.048047, and the results of the residual test show that the model fits the original data very well. The average level deviation is 0.052726, and the result of level deviation test shows that the model fits the original data very well. Therefore, it seems that the GM (1, 1) model is more appropriate for the prediction of pet market size.

3.2. Solving the wavelet prediction model

The WNN model was used to fit and forecast the demand for food in the global pet market for the next three years.Table 5 illustrates the associated fitting and prediction results.

Table 5: model fitting results table

Year	Original sales (Billions of dollars)	Projected sales (billions of dollars)	
		n = 6	n = 10
2010	59.3	59.5665	59.5519
2011	62.4	61.5651	61.5607
2012	65.9	66.4071	66.4325
2013	69.6	70.5034	70.5441
2014	73.3	72.9221	72.9175
2015	77.7	74.5145	74.4358
2016	75.25	76.6416	76.5496
2017	75	80.3490	80.4014
2018	91.1	86.1125	86.6185
2019	93.9	93.8984	93.7056
2020	102.6	103.2947	102.4671
2021	123.6	113.6228	115.2314
2022	133.9	124.0327	124.9899
2023	59.3	133.6088	133.0990
2024	None	141.4914	138.5324
2025	None	146.9990	140.8229
2026	None	149.7282	140.0596
AIC	None	95.462	96.653
R2	None	95.90%	96.70%

According to forecast data, sales over the next three years are expected to grow the global pet food market from $138 billion to $141 billion to up to $149.7 billion.

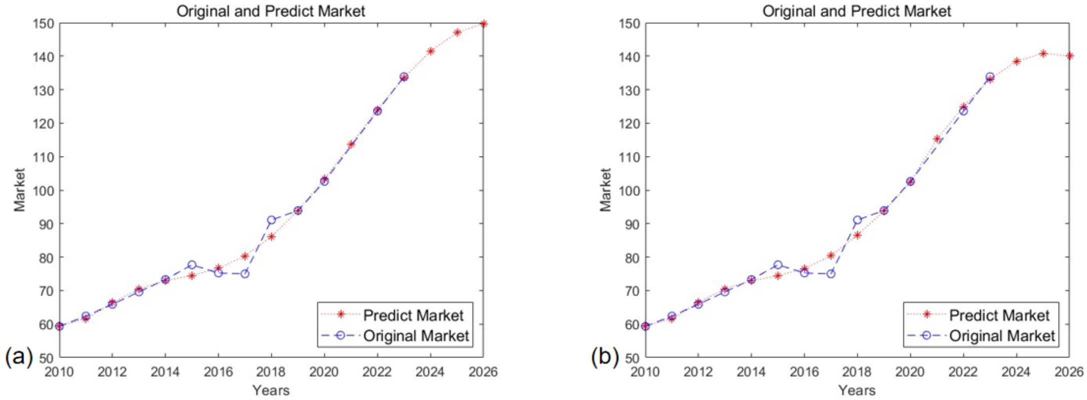

Figure 8. Original and predict market (a)n = 6, (b)n = 10

Figure 8 illustrates the prediction and fitting results for the pet food market for two scenarios where the number of hidden nodes n is 6 and 10, respectively.Plot (a) in Fig. 8 predicts that the pet food market will show rapid growth in the future, while plot (b) predicts that the pet food market will show a more moderate growth in the future.

3.3. Sensitivity Analysis

By perturbing the development coefficients in the GM (1, 1) model to different degrees, fluctuating changes in the predicted results can be observed, and the results are shown in Figure 9.

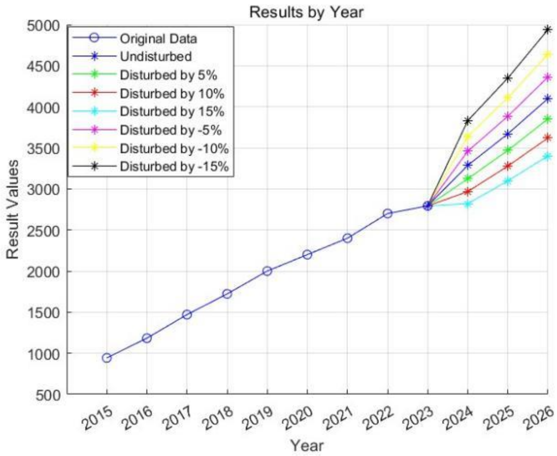

Figure 9. Sensitivity analysis

By comparing the original data and the data after perturbation, it is obvious that the model maintains a good growth trend under positive perturbation, which indicates that the model has a positive predictive ability under positive influences. Meanwhile, the performance of the model under negative perturbation also shows a certain degree of robustness, especially under smaller negative perturbations, the prediction results did not fluctuate significantly, which reflects the stability of the model in the face of unfavorable factors.

4. Conclusions

This paper has conducted an exhaustive analysis and forecasting of the Chinese pet industry and the global pet food market by integrating the gray prediction model and the wavelet neural network model. The study has been comprehensive, involving data collection from various sources, application of complex mathematical models, and evaluation of numerous influencing factors.

The gray prediction model has accurately forecasted a significant growth in China’s pet market, projecting an increase to RMB 4.0995360 trillion within three years. The wavelet neural network model has similarly predicted a rise in global pet food sales to approximately $149.7 billion. The models have demonstrated high precision and robustness, with the gray model exhibiting a posteriori difference ratio below 0.35 and the wavelet model showing strong fits with AIC and R2 metrics.

The study's strategic recommendations, including global market expansion, domestic market development, and collaboration with international partners, are designed to guide industry stakeholders and policymakers in making informed decisions. The innovative modeling approach has provided a novel and accurate method for predicting market trends, even with small samples and uncertain data.

Looking ahead, future research could focus on several areas to further advance the understanding and prediction of the pet industry's development:

(1) Innovation in Pet Products: Exploring consumer preferences and the potential for new product lines that cater to emerging trends in pet care and companionship.

(2) Digital Transformation: Assessing the role of digital technologies, such as e-commerce and social media, in shaping the pet industry's market dynamics.

(3) Cross-Cultural Studies: Conducting comparative studies across different regions to understand the diverse factors influencing the pet industry globally.

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