Research on Demand Analysis Model of Hot Product in Food Industry

Hao Zhang
Business School
Beijing Technology and
Business University
Beijing, China
zhhaozhhao@126.com

An Lin
School of E-commerce and
Logistics Beijing Technology and
Business University
Beijing, China
18092135042@163.com

Abstract—This article introduces the relevant situation of Hot Product and discusses the strategy of creating Hot Product from the perspective of enterprises. This article takes durian in the fruit industry as an example, and selects the annual imports of durian in China as the raw data. Based on the artificial neural network (ANN) algorithm, the article proposes a prediction model of annual imports of durian in China, and uses the trained model to predict the annual domestic durian imports in the next year. The model provides important guidance in forecasting the annual import volume of fruits and it could tell which type of fruit is going to become Hot Product in the near future. It can help enterprises and individual business to predict the import and export volume and sales of their products, and show them the prospects and market trends of these products.

Keywords—Hot Product, Matlab, artificial neural networks, annual import forecast

I. INTRODUCTION

There has been controversy over the definition of Hot Product. One side holds that when something becomes hot, it should have the best sales volume among its industry. Such advantages are perceptible to the customers, which contribute to its reputation. That "something" can be a product, a kind of service or a platform; the other side believes that a Hot Product should have its own target customers, and comply itself with the demand of consumers during its design, research, producing, packing and selling. The launcher of a Hot Product needs to be sensitive about business opportunities and what's lost in the market, so that his final product may bring millions even billions of money. From both definitions, the author concludes two key points for Hot Product. The first is sales volume, which means the product should have one or two sales rankings in its industry. The second is customers' satisfaction. That is to say after users use the product, they will form a reputation, bring praise, and be willing to share or even recommend it to others.

In the industrial era, Hot Product used to be featured with shortage of supply and high prices. However, due to the lack of rapid development of productivity at that time, the output of many popular products could not meet the demand in the market, and due to the lack of Internet technology, the number of Internet users was even smaller. And the final sales are far less than now. In 21st century, the emergence of the Internet led to the rapid development of many emerging industries and brought a large number of internet users.

These changes have boosted the development of e-commerce, which then allows products to sell in a shorter period of time. This gives rises to an increasing popularity of Hot Product. The emergence of Hot Product and its enormous economic benefits have attracted the attention of many enterprises. Companies need to plan carefully and conceive various strategies to promote their products and make them hot ones.

First of all, for a company, if it wants to make an extreme product, "similar and different quality" is very important. Hot Product must have a high quality different from ordinary products and possesses innovative qualities that could impress the market. Secondly, the customers of Hot Product are often young people who are generally more passionate about chasing fashion. Therefore, when designing and producing new products, companies should adjust themselves in accordance with the feedback of user experience, and provide tailored services to their customers. There is no need to excessively pursue functional innovation of products or excessively interpret the rational needs of consumers. In this way, the product is not just a cold tool used in people's daily life, but represents the personal characteristics of the users.

This article will take the fruit durian as an example to predict the Hot Product in the fruit industry and make corresponding analysis and suggestions.

Since the reform and opening up, Chinese people's demand for fruits keeps rising. In 2017, the fruit possession of China's residents per capita was 131kg, while the world's fruit possession per capita was 97kg. In the past 15 years, China's annual output of fruits has been ranking first in the world and maintains a stable and continuous growth. According to data released by the National Bureau of Statistics, China's orchard planting area increased from 864.8 hectares in 1997 to 1298.2 hectares in 2016, a growth of 50.1%. The domestic fruit output in 2010 was about 241 million tons, and the number increased to about 286 million tons by 2017. In terms of price, the domestic fruit wholesale price index in China in 2017 was 125.08, a year-on-year increase of 3.4%. Chinese residents' increasing demand for fruits is not only reflected in quantity, but also in the requirement for variety and higher quality. As a result, more and more imported fruits flow into Chinese market. Generally, imported fruits have stricter standards in their growing, picking, packaging, transportation, and greenness testing processes, which gives them several advantages over domestic fruits First, when fruits are exported, the trade unions in their original countries would take measures to control the selling of these products in their domestic market, and set a clear marginal price for these products. There are also professional institutions for the quarantine. In Chinese market, imported fruits excels largely because its quality. Secondly, in recent years, with the rapid development of transportation network, China has become more and more interconnected to the world. Over the years, long-distance transportation of imported fruits is difficult and tariffs are high, which has set up a barrier for its popularity. In

recent years, with the rapid development of communications and transportation in China and neighboring countries, it has been very easy to import fruits. Therefore, the circulation of fruits was accelerated. The efficiency of operation and sales have also been improved. All these changes above a solved an important problem of imported fruits: they reduced the added cost of transportation, storage, processing, and packaging. Plenty of time and spending on custom declaration are also saved thanks to these changes. Finally, the targeted consumers of imported fruits are mainly middle and high income groups. Usually, these people are particular about the health and safety of fruits, and are willing to spend more money on qualities. All the advantages illustrated above make imported fruits more competitive in the Chinese market. In 2017, durian, raisins, longan, oranges, and dragon fruit ranked the top five among the sales list of imported fruits, becoming well-deserved Hot Product in the imported fruit industry.

The Hot Product in fruit industry are usually seasonal, tasty, and are also difficult to buy from offline channels. Therefore, compared with domestic ordinary fruits, the high-end imported fruits are more likely to become Hot Product. Data show that in terms of imports, China's fruit imports have begun to exceed exports since 2014. In 2017, fruit imports reached 4.5627 million tons, and exports reached 3.6119 million tons. From January to July 2018, the import and export volume of fruits were 3.5563 million tons and 2.657 million tons respectively. In terms of fruit categories, the top eight of China's imported fruits in 2017 are: Fresh cherry, fresh grape, banana, fresh durian, fresh longan, fresh dragon fruit, orange, fresh kiwi. Among them, fresh cherry, fresh grape, banana, fresh durian and fresh longan have already accounted for more than 50% of the total imports.

In this article, the author seeks to answer the following questions: is there an omen for the appearance of Hot Product? What kind of indicators can determine the formation of Hot Product? Can we predict future Hot Product for highly relevant indicators and develop a forward-looking plan? This article builds a model to predict the future demand of the product and analyze whether it will become a Hot Product in a certain field, and then formulate a future marketing plan based on the conclusion. This article takes durian, as an example. Based on the analysis of the import volume in recent years, the consumption of the entire fruit industry, the market size, and the output of fruit, a durian Hot Product demand analysis model is established. This model predicts the number of durian imports in the next few years, analyzes the its probability to remain Hot Product based on the results, and makes analysis and suggestions for the development of durian and China's fruit industry. In addition, the establishment of this model is also beneficial for the major companies or individual businesses in the food industry to effectively predict the import or sales of products in the next year based on known data over the years. Enterprises or individual businesses can use this as a basis to formulate short-term or long-term strategic planning for such products, to maximize the benefits of this product.

According to the data, in terms of the sales volume of imported fruits in 2017, imported durians have topped the list, becoming a well-deserved Hot Product in the fruit industry in recent years. This article will take durian as an example, by analyzing data over the years, combined with artificial neural network algorithms, predict the future annual import volume of durian, and analyze whether it can continue to occupy the title of Hot Product in the fruit industry. Furthermore, this article will analyze the actual data: what kind of index fruit can be called Hot Product. The aim of this paper is (1) to establish a demand analysis model for Hot Product to quickly predict the possibility of a commodity becoming Hot Product in the future; and (2) to make recommendations for the indicators of Hot Product in the food industry, and to provide suggestions for applying this model to various links in the supply chain.

The remainder of this paper is organized in this way: In Section II, the author discussed relevant literature on product sales strategies, product sales or price predictions, and artificial neural networks. Section III introduces the algorithm and calculation steps of the model proposed in this paper. Section IV and V are analyzed based on the empirical results, and recommendations are made for the determination of Hot Product indicators of agricultural products. The future application and development of this model are expected.

II. LITERATURE REVIEW

A. Research on product sales strategy

Data was collected from 32 companies in two markets, revealing four stages of purchase evolution: Passive (price-centric), independent (cost-centric), support (solution / innovation-centric) and integration (strategy-centric). Researches show that each stage of the purchase evolution requires a sales company to develop a different selling strategy, and any mismatch in purchase development and sales strategy can affect sales (Paesbrugghe,B and Rangarajan,D 2017). Through the use of symbolic interactive views and ethnographic shadow research methods, the study illustrates the strategies that could affect consumers' value during the selling of a product, and offers some ideas in value creation through promoting activities. Then, by identifying three types of value strategies that strengthen or expand customer values through different social cognitive mechanisms, the framework of value creation in sales interactions is expanded (Hohenschwert,L and Geiger,S 2015). Lindsey-Mullikin,J and Bonin,N(2017)compare and contrast three different decision models:(1) Traditional media only (2) Traditional media and social media communication skills only (3) Traditional and social media with instant purchase add-on. Found that although the possibility of making purchases on social media will reduce the number of brands considered and evaluated, the number of purchases and brand advocacy will increase significantly due to the convenience of purchase.

Finally, some suggestions for future research are made. Terho,H and Eggert,A(2015), based on a large sample of 816 salespeople and directors from 30 sales organizations, and using a multi-layer structure equation model, they clarified a series of chain effects, and transformed chain sales strategies into organizational variables at the level of a single salesperson Earned sales performance. The survey results show that the company's selling strategy is related to market performance and directly or indirectly affects the sales performance of sales staff. In addition, each sales strategy dimension influences sales force performance in a unique way. The joint pricing and advertising issues of monopolistic enterprises considering the reference price effect are studied. By formulating joint pricing and advertising strategies, an optimization model is established to maximize the company's total profit (Lu,LH and Gou,QL 2016).

B. Research on product sales or price forecasts

A hybrid sales forecasting scheme was proposed by combining independent component analysis (ICA) with K-means clustering and support vector regression (SVR) (Lu,CJ and Chang,CC 2014). Chong,AYL and Ch'ng,EB (2017)investigate the contribution of online promotional marketing and online reviews as predictors of consumer product demand. They used online data from Amazon, and predicted whether online review variables will affect the demand of Amazon electronic products. These variables include price and number of reviews, (number of positive and negative reviews), as well as online promotional marketing variables such as discounts and free shipping. The results show that variables from online reviews and promotional marketing strategies are important predictors of product demand. Cerjan,M and Matijas,M(2014) combined statistical techniques for data preprocessing and multi-layer (MLP) neural networks for forecasting electricity prices and electricity price peak detection.The factors affecting electricity price prediction are discussed, including historical price, load, and wind production. A hybrid method for short-term hourly electricity price prediction is proposed. A prediction method based on iterative strategy is proposed to predict the normal price and price rise in the current energy market (Voronin,S and Partanen,J 2013). Ren,SY and Choi,TM(2015) proposed and explored a novel panel data-based particle filter (PDPF) model for fashion sales prediction, and evaluated the model's performance by using real data collected from the fashion industry. Chong,AYL and Li,BY (2016)investigate whether online reviews, online promotional strategies such as free shipping and discounts, and the sentiment of user reviews can help predict product sales. The study found that although online reviews, online promotion strategies, and online sentiment can predict product sales, the interactives effects of these variables are more important than the individual variables themselves. The author researched and designed a big data architecture that combines sentiment and neural network analysis to facilitate future business research to predict product sales in an online environment. By using publicly available data, an accurate regression model for online sales prediction is established. This model is a well-known regression model learner obtained through the novel feature selection method applied by the multi-objective evolutionary algorithm ENORA as a search strategy in packaging Random Forest-driven approach. Feature selection for regression, model evaluation, and decision making is integrated to select the most satisfactory model based on the posterior process in a multi-objective environment. (Jimenez,F and Sanchez,G 2017).

C. Application and research of artificial neural network

A precipitation prediction model based on artificial neural network (ANN) was proposed, in which the training parameters were adjusted using the automatic parameter calibration (PAC) method. The study found that the results produced by the ANN-PAC model are more reliable than those produced by ANN-TRI1, ANN-TRI2, and traditional regression models. In addition, due to the significant increase in calculation time, the calculation efficiency of the ANN-PAC model decreases with the increase of the number of increments within the parameter range, while the prediction error decreases due to the improvement of the model's ability to identify optimal solutions(Lo,DC and Wei,CC 2015). The purpose of the research is to improve the accuracy of wind speed prediction by proposing a more appropriate method.

Artificial neural network (ANN) and Kalman filter (KF) are used to deal with nonlinear and uncertainty problems, and the effectiveness of ARIMA will help determine the input structure of KF, ANN and their hybrid models. The study will use daily wind speed data from Iraq and Malaysia for a case study and find that the hybrid KF-ANN model is the most appropriate and provides the most accurate predictions (Shukur,OB and Lee,MH 2015). Combining artificial neural network and clustering technology, using a 7-year data set to simulate phytoplankton biomass in the Great Lakes, two ANN models have been developed for the downstream and upstream regions, and their performance is better than the ANN model for the entire lake, indicating that The success of the clustering technique in improving the ANN model to predict phytoplankton biomass in different subregions of the Great Lakes. This case study demonstrates the good performance of artificial neural network models in describing phytoplankton dynamics and the potential of combining artificial neural networks with clustering techniques to describe the spatial heterogeneity of natural ecosystems (Huang,JC and Gao,JF 2015). Artificial neural network (ANN) was used to estimate daily sediment load. Two different ANN algorithms were used, namely feed-forward neural network (FFNN) and radial basis function (RBF) and daily sediments from Johor and traffic data to train and test the neural network. The results show that combining flow data with sediment load data can provide an accurate model to predict the sediment load and the FFNN model has better performance than the RBF model in estimating daily sediment load (Afan,HA and El-Shafie,A 2015). A new hybrid model of artificial neural network (ANN) is proposed, which is optimized by particle swarm optimization (PSO) for predicting maximum surface settlement (MSS). The results show that the proposed PSO-ANN model can predict MSS with higher accuracy than the ANN results (Hasanipanah,M and Noorian-Bidgoli,M 2016). An artificial neural network (ANN) -based global solar radiation (GSR) prediction model was used to evaluate solar potential in Himalayas, Himachal Pradesh, western India. The most relevant input parameters were found to be temperature, altitude, and sunshine duration, while latitude, longitude, clarity index, and extraterrestrial radiation were the least affected parameters (Yadav,AK and Chandel,SS 2015). The accuracy of three different improved artificial neural network (ANN) methods are compared, among which the genetic algorithm's ANN (ANN-GA), particle swarm optimization ANN (ANN-PSO), and the imperialist competition algorithm (ANN-ICA). Accuracy based on precipitation, evaporation, and groundwater level (GWL). By trying various control parameters, the best ANN-GA, ANN-PSO and ANN-ICA models were obtained. The results show that the ANN-PSO model outperforms other models in simulating monthly groundwater levels (Kisi,O and Alizamir,M 2017). An optimized ANN based on the Imperialist Competition Algorithm (ICA) model was introduced and evaluated to estimate the bearing capacity of driving piles in non-cohesive soil. The prediction results are compared with a pre-developed ANN model to prove the function of the hybrid model (Moayedi,H and Armaghani,DJ 2018).

According to the literature review, scholars mostly optimize and improve a certain prediction method to predict the change of variables affected by complex factors or use artificial neural networks to predict the change of non-commercial substances. No artificial neural network has been used to predict the research of certain types of products in

China's food industry. On this basis, this article uses artificial neural networks to predict the number of durian imports in China's fruit industry in the next few years, analyzes its probability of, occupying a high share of China's fruit market, and becoming a Hot Product of the fruit industry. The author also endeavors to analyze the development trend of the imported fruit industry, and put forward analysis and suggestions for the development of China's fruit industry.

III. PREDICTION MODEL SETTINGS

Artificial Neural Network(ANN) has been a research hotspot in the field of artificial intelligence since the 1980s. It abstracts the human neuron network from the perspective of information processing, establishes some simple model, and forms different networks according to different connection methods. In engineering and academia, it is often known as neural network or neural network. A neural network is a computing model that consists a large number of nodes (or neurons) connected to each other. Each node represents a specific output function called activation function. The connection between each two nodes is called the weight, which represents a weighted value for the signal passing through the connection. It is equivalent to the memory of an artificial neural network. The output of the network varies according to the connection mode, weight value and incentive function of the network. The network itself is usually an approximation of an algorithm or function in nature, or it may be an expression of a logical strategy.

In the past ten years, the research of artificial neural network has been continuously deepened and great progress has been made. It has successfully solved many problems in the fields of pattern recognition, intelligent robots, automatic control, prediction and estimation, biology, medicine, economics.

The specific modeling steps are as follows:

A. Network initialization

Assume that the number of nodes in the input layer is n, the number of nodes in the hidden layer is one, the number of nodes in the output layer is m, the weight w_{ij} from the input layer to the hidden layer, and the bias value from the input layer to the hidden layer is a_j, the bias value from the hidden layer to the output layer is b_k. Learning rate is η, the activation function is the Sigmoid function for $g(x)$. In the form:

$$g(x) = \frac{1}{1 + e^{-x}}$$

B. Hidden layer output

As shown in the three-layer BP network above, the output H_j of the hidden layer is

$$H_j = g\left(\sum_{i=1}^{n} w_{ij}x_i + a_j\right)$$

C. Output of the output layer

$$O_k = \sum_{j=1}^{l} H_j w_{jk} + b_k$$

D. Calculation of error

We take the error formula as:

$$E = \frac{1}{2}\sum_{k=1}^{m}(Y_k - O_k)^2$$

Y_k is the desired output. We remember $Y_k - O_k = E_k$, E can be expressed as

$$E = \frac{1}{2}\sum_{k=1}^{m} e_k^2$$

In the above formula, $i = 1 \ldots n, j = 1 \ldots l, k = 1 \ldots m$.

E. Update of weights

The formula for updating weights is:

$$\begin{cases} w_{ij} = w_{ij} + \eta H_j(1 - H_j)x_1 \sum_{k=1}^{m} w_{jk}e_k \\ w_{jk} = w_{jk} + \eta H_j e_k \end{cases}$$

• Weight update from hidden layer to output layer

$$\frac{\partial E}{\partial w_{jk}} = \sum_{k=1}^{m}(Y_k - O_k)\left(-\frac{\partial O_k}{\partial w_{jk}}\right) = (Y_k - O_k)(-H_j)$$
$$= -e_k H_j$$

The weight update formula is:

$$w_{jk} = w_{jk} + \eta H_j e_k$$

• Weight update from input layer to hidden layer

$$\frac{\partial E}{\partial H_j} = \frac{\partial E}{\partial H_j} \cdot \frac{\partial H_j}{\partial w_{ij}}$$

among them

$$\frac{\partial E}{\partial H_j} = (Y_1 - O_1)\left(-\frac{\partial O_1}{\partial H_j}\right) + \cdots + (Y_m - O_m)\left(-\frac{\partial O_m}{\partial H_j}\right)$$
$$= -(Y_1 - O_1)w_{j1} - \cdots - (Y_m - O_m)w_{jm}$$
$$= -\sum_{k=1}^{m}(Y_k - O_k)w_{jk} = -\sum_{k=1}^{m} w_{jk}e_k$$
$$\frac{\partial H_j}{\partial w_{ij}} = \frac{\partial g(\sum_{i=1}^{n} w_{ij}x_i + a_j)}{\partial w_{ij}}$$
$$= g(\sum_{i=1}^{n} w_{ij}x_i + a_j) \cdot \left[1 - g(\sum_{i=1}^{n} w_{ij}x_i + a_j)\right]$$
$$\cdot \frac{\partial(\sum_{i=1}^{n} w_{ij}x_i + a_j)}{\partial w_{ij}}$$
$$= H_j(1 - H_j)x_i$$

The weight update formula is:

$$w_{ij} = w_{ij} + \eta H_j(1 - H_j)x_i \sum_{k=1}^{m} w_{jk}e_k$$

F. Offset update

The offset update formula is:

$$\begin{cases} a_j = a_j + \eta H_j(1 - H_j)\sum_{k=1}^{m} w_{jk}e_k \\ b_k = b_k + \eta e_k \end{cases}$$

• Bias update from hidden layer to output layer

$$\frac{\partial E}{\partial b_k} = (Y_k - O_K)\left(-\frac{\partial O_k}{\partial b_k}\right) = -e_k$$

The offset update formula is:

$$b_k = b_k + \eta e_k$$

• Input layer to hidden layer offset update

$$\frac{\partial E}{\partial a_j} = \frac{\partial E}{\partial H_j} \cdot \frac{\partial H_j}{\partial a_j}$$

among them

$$\frac{\partial H_j}{\partial a_j} = \frac{\partial g(\sum_{i=1}^{n} w_{ij} x_i + a_j)}{\partial a_j}$$

$$= g(\sum_{i=1}^{n} w_{ij} x_i + a_j)$$

$$\cdot \left[1 - g(\sum_{i=1}^{n} w_{ij} x_i + a_j)\right]$$

$$\cdot \frac{\partial (\sum_{i=1}^{n} w_{ij} x_i + a_j)}{\partial a_j}$$

$$= H_j(1 - H_j)$$

$$\frac{\partial E}{\partial H_j} = (Y_1 - O_1)\left(-\frac{\partial O_1}{\partial H_j}\right) + \cdots + (Y_m - O_m)\left(-\frac{\partial O_m}{\partial H_j}\right)$$

$$= -(Y_1 - O_1)w_{j1} - \cdots - (Y_m - O_m)w_{jm}$$

$$= -\sum_{k=1}^{m} (Y_k - O_k)w_{jk} = -\sum_{k=1}^{m} w_{jk} e_k$$

The offset update formula is:

$$a_k = a_k + \eta H_j(1 - H_j) \sum_{k=1}^{m} w_{jk} e_k$$

G. Determine if the algorithm iteration is over

There are many ways to determine whether the algorithm has converged. Common examples are the algebra of a specified iteration, whether the difference between two adjacent errors is less than a specified value, and so on.

At the same time, this paper also uses BP network to reduce the space and search for the optimal solution.

IV. ANALYSIS OF EMPIRICAL RESULTS

model can also scientifically predict the change trend of the sales volume of goods and obtain accurate and objective evaluation results.

This article will use durian as an example, based on artificial neural networks to analyze the amount of durian imports from 2009 to 2016, the overall consumption of the fruit industry, the market size and fruit output to predict the future durian imports. Secondly, this article will implement the above-mentioned specific modeling steps to establish a Hot Product demand analysis model and expand it to all aspects of the food field, effectively predict the sales of food. It also analyzes the possibility that the food becomes a Hot Product in its corresponding field, and provides a reliable basis for the company's subsequent strategic planning.

B. Setting of variables and data sources

1) Setting of variables

To study whether durian can remain Hot Product in the fruit industry, this article sets as input variables, and the imported amount of durian from 2010-2016 as output variable. This output variable is largely affected by the above three input variables, and it representatively reflects the durian sales situation and future market prospects.

2) Data Sources

The following data comes from the National Bureau of Statistics, China Customs, and Intelligent Research Consulting. The data are shown below.

TABLE I.   2009-2019 DURIAN AND FRUIT MARKET SCALE DATA

Input variable	2009	2010	2011	2012	2013	2014	2015	2019
Durian import value (10,000 USD)	12437	14956	23430	39957	54330	59262	56794	69330
Consumption in the fruit industry (10,000 tons)	20283	21343	22779	24059	25089	26240	27504	28387
Fruit industry market size (100 million yuan)	9756	11217	15622	16499	17951	22768	21433	19979
Total output of the fruit industry (10,000 tons)	20396	21401	22768	24057	25093	26142	27375	28351
Output variable	2010	2011	2012	2013	2014	2015	2016	2020
Annual durian imports (ton)	172205	210938	286396	321950	315509	298793	292310	Forecast data

A. Application of model in predicting Hot Product in the fruit industry

The model analyzed many factors that affect the sales volume of products. Traditional statistical economics methods are difficult to make scientific predictions of price changes due to their inherent limitations. Artificial neural networks are easy to process incomplete, fuzzy, uncertain or inconsistent data. Sales forecasting has advantages that cannot be compared with traditional methods. Then the import volume is also the same. Based on complex and changeable factors such as output, price, customer evaluation, and industry changes that affect the quantity of imported goods, a more accurate and reliable model is established. The
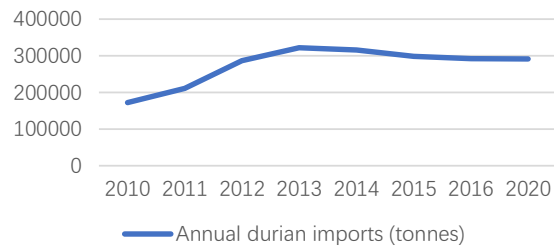

Annual durian imports (tonnes)

599

Fig. 1. Durian imports over the years and 2020 forecast

C. Model solving

1) Network structure design

- Design of input and output layers

The model takes the indicators of each group of data as input and the annual durian imports as the output, that is, the number of nodes in the input layer is 4, and the number of nodes in the output layer is 1.

- Hidden layer design

Related research shows that a neural network with a hidden layer can approximate a non-linear function with arbitrary accuracy as long as there are enough hidden nodes. This paper uses a three-layer multi-input single-output BP network with a hidden layer to build a prediction model. In the process of network design, it is very important to determine the number of hidden neurons. Too many neurons in the hidden layer will increase the amount of network calculations and easily cause over-fitting problems; too few neurons will affect the network performance and fail to achieve the expected results. The number of hidden neurons in the network is directly related to the complexity of the actual problem, the number of neurons in the input and output layers, and the setting of the expected error. At present, there is no clear formula for determining the number of neurons in the hidden layer, only some empirical formulas, and the final determination of the number of neurons still needs to be determined based on experience and multiple experiments. This article refers to the following empirical formulas on the problem of selecting the number of hidden neurons: $l = \sqrt{n + m} + a$. Among them, n is the number of neurons in the input layer, m is the number of neurons in the output layer, and a is a constant between [1,10]. According to the above formula, the number of neurons can be calculated between 4 and 12, and the number of hidden neurons is 4 in this experiment.

2) Selection of incentive function

BP neural network usually uses Sigmoid differentiable function and linear function as the network's excitation function. In this paper, the S-tangent function tansig is selected as the excitation function of hidden neurons. Since the output of the network is normalized to the range of [-1,1], the prediction model selects the S-type log function as the excitation function of the output layer neurons.

3) Model implementation

This prediction uses the neural network toolbox in MATLAB for network training. The specific implementation steps of the prediction model are as follows:

The training sample data is normalized and input to the network. The hidden and output layer excitation functions of the network are set to tansig and logsig functions, the network training function is traingdx, the network performance function is mse, and the number of hidden neurons is initially set to 4. Set the network parameters. The number of network iterations is 200, the expected error goal is 0.05, and the learning rate lr is 0.05. After setting the parameters, start training the network. The network completes learning after reaching the expected error through 24 repeated learnings. After the network training is completed, you only need to input the indicators into the network to get the prediction data. The forecast result is that the annual import volume of durian in 2020 is 291,469 tons.

D. Result analysis

In this paper, based on the machine learning algorithm mechanism of artificial neural network ANN, an ANN-based durian import quantity prediction model is proposed. This model can also be applied to the rest of the fruit industry forecast. This model normalizes historical data samples as input, trains the network through the ANN algorithm, and uses the trained network to predict the annual import volume of durian. The difference between the prediction results obtained in the test of the algorithm and the actual import volume is less than 5%, which meets the requirements of empirical error. It shows that the annual durian import forecast model based on ANN proposed in the paper is in line with actual work needs, and has certain significance for the subsequent fruit industry data forecast.

According to the prediction, the annual import volume of durian in 2020 is 291,469 tons. This conclusion is made due to the fact that from 2009 to 2016, the annual import volume of durian showed a steady upward trend, and the increase was large, about 88%. Since 2012, the growth trend of annual durian imports has stabilized, maintaining around 300,000 tons per year. According to the analysis of the data above, the import volume of durian has increased greatly in the past few years, and the upward trend is very obvious. After the increase of the import volume has flattened, it would maintain at a high level. Thus, one could make the prediction that durian would remain a Hot Product in the fruit industry. Fruit suppliers and major companies can use this conclusion or data to manipulate the production and sales of durian in the coming year. While the supply and demand of durian in domestic market reached a basic balance, higher profits are still attainable.

At the same time, for durian exporting countries like Thailand, Vietnam, and Malaysia, most of their durian products were exported to China. Farmers can also use this conclusion to plan their own planting in recent years, and to predict the sales volume of their products in China.

Given the results above, this article will make some suggestions on the Hot Product indicators and strategies.

- Suggestions for Hot Product indicators

Hot Product as a product means that a single product in a single year achieves the industry category first. Under such circumstances, product sales, word of mouth, and appeal are particularly important. The sales volume shows the degree of circulation of this product in the market during this period. Only more consumers contact it and use it, can this product really enter the society and people's lives. Followed by word of mouth, the public evaluation of a single product purchased and used by consumers is also very important. The public evaluation largely reflects the true quality, design and production value of this product, and even the comprehensive value of this product. The last is the appeal. When this single product has been purchased and used by many people, it has generated a good sales volume, and then everyone has a good word of mouth and established a good product image before the public. This single product has its own social appeal, so that it will integrate into the lives of the public, and will not be quickly eliminated as the society changes, and it has a certain position in the market. With its rapid sales growth and

600

steady high level, it can naturally be called Hot Product in a certain field.

Because there is no clear definition of what can be called Hot Product at home and abroad. According to the above analysis and conclusions, for the food industry, it is recommended that the following indicators be referenced when judging whether a product can become hot or not:

For seasonal fresh single products, the annual sales should exceed 100,000. For single products in other food fields, the annual order of the product have to be more than 1 million, or the annual public comment on this product more than 100,000.

On this basis, when establishing a Hot Product prediction model in the future, any of the three indicators above can be used as output variables to determine whether this product is hot or not. Such a model is more scientific and credible.

- Suggestions for strategic development of Hot Product

This article provides guidance on how to enact Hot Product strategies. First, while grasping the general trend of the market, it is also important for companies to pay attention to the popularity and word of mouth of their products in the past one or two years, so as to keep the enthusiasm of their customers as well as innovate and upgrade their products. At the same time, companies need to keep an eye on new products developed by their competitors, and adjust the design or promoting strategy of their own products to maintain competitive in the market.

Secondly, for consumers, when buying newly launched products, they can first observe the entire product market, or understand the company's positioning of this product and future development strategies, thus avoid spending money on unnecessary products. Likewise, consumers can also make a fair and timely evaluation of the products they use. The true evaluation of each customer would play a huge role in the development of this product and even its industry. Finally, for major e-commerce platforms, the current order volume and customer evaluation of each product are very critical to it. The development of the Internet has greatly changed people's lives. Online shopping has become popular and has no heat signs of decline. Therefore, for each consumer on the e-commerce platform, the recommendation of single products is very important. It is hoped that large-scale e-commerce platforms can truly enable each customer to purchase applicable and practical products.

V. CONCLUSION

The prediction model of annual durian imports based on ANN in this paper can be applied independently to the forecast of durian imports or the fruit industry. By changing the input variables, products in the food field can use this model to predict a certain variable. According to the input of relevant data in recent years, one can predict the output variables for the next year. It would also be possible for one to conclude whether this product can maintain its heat, based on its changing trend and the size of the data,

For businesses related to the fruit industry, they can adjust their selling strategy based on the final results. Therefore, they can decide whether to increase or cut the amount of purchases and storage, and predict market prospects so they can magnify their profits and save losses for the company in a timely manner. In dealing with fruit

products, the changes and development trends of people's love for this fruit should also be fully considered. Take the durian i in this article as an example, companies selling this fruit can maintain the size of the purchase last year or make small changes. It is not appropriate to increase the estimated sales volume to a large extent, which would cause the accumulation of inventory. Since that durian itself is not an easy-to-storage food, a large number of warehouses are not realistic. Therefore, relevant fruit companies can brainstorm ideas, make durians that are relatively fresh but have not been sold in time to prolong the shelf life of durian foods, and use the characteristics of durians to make products that attract the attention of durian lovers.

For individual merchants, they can better understand the fruit market based on the forecast results of various types of fruits. They can roughly summarize the market sales of various fruits in the recent period, people's popularity, and the purchase and storage of large enterprises, then clarify the general direction of the fruit industry. For example, in recent years, a very noticeable trend in China's fruit industry is that the sales volume of imported fruits has increased rapidly year after year. In addition to apples, pears, bananas, watermelons, grapes and other traditional best-selling fruits, imported fruits such as cherry, durian, mango, began to go viral with the popularization of Internet technology. Although their sales volume are still not as good as traditional best-selling fruits, its annual sales growth rate has repeatedly hit record highs. Given this situation, individual merchants can determine the proportion of the future purchase of this product to the purchase distribution ratio, try to avoid causing a backlog of the amount of goods in their own fruit store, to win more profits for themselves or reduce unnecessary losses.

For agricultural workers who grow all kinds of fruits, they can arrange their own planting plans based on the predicted imports of different fruits, and avoid conflicts with imported fruits. And you can also carefully observe the development prospects of various types of fruits, evenly distribute the planting area of each fruit. Try not to cause the market to be full of individual fruits.

REFERENCES

[1] Afan HA，El-Shafie A，Yaseen ZM，Hameed MM，Mohtar WHMW， Hussain A. ANN based sediment prediction model utilizing different input scenarios[J]. Water Resources Management，2015,29（4）：1231-1245.

[2] Cerjan M，Matijas M，Delimar M. Dynamic Hybrid Model for Short-Term Electricity Price Forecasting[J]. Energies，2014,7（5）：3304-3318.

[3] Chong AYL，Ch'ng EB, Liu MJ，Li BY. Predicting consumer product demands via Big Data: the roles of online promotional marketing and online reviews [J]. International Journal of Production Research，2017,55（17）：5142-5165.

[4] Chong AYL，Li BY，Ngai EWT，Ch'ng E，Lee F. Predicting online product sales via online reviews, sentiments, and promotion strategies A big data architecture and neural network approach[J]. International Journal of Operations & Production Management，2016,36（4）.

[5] Hasanipanah M，Noorian-Bidgoli M，Armaghani DJ，Khamesi H. Feasibility of PSO-ANN model for predicting surface settlement caused by tunneling[J]. Engineering with Computers，2016，32（4）：705-715.

[6] Hohenschwert L，Geiger S. Interpersonal influence strategies in complex B2B sales and the socio-cognitive construction of relationship value[J]. Industrial Marketing Management，2015（49）：139-150.

[7] Huang JC, Gao JF, Zhang YJ. Combination of artificial neural network and clustering techniques for predicting phytoplankton biomass of Lake Poyang, China[J]. Limnology, 2015, 16（3）: 179-191.

[8] Jimenez F, Sanchez G, Garcia JM, Sciavicco G, Miralles L. Multi-objective evolutionary feature selection for online sales forecasting[J]. Neurocomputing, 2017（234）: 75-92.

[9] Kisi O, Alizamir M, Zounemat-Kermani M. Modeling groundwater fluctuations by three different evolutionary neural network techniques using hydroclimatic data[J]. Natural Hazards, 2017,87（1）: 367-381.

[10] Lindsey-Mullikinv J, Bonin N. Why strategy is key for successful social media sales[J]. Business Horizons, 2017,60（4）: 473-482.

[11] Lo DC, Wei CC, Tsai EP. Parameter automatic calibration approach for neural-network-based cyclonic precipitation forecast models[J]. Water, 2015,7（7）: 3963-3977.

[12] Lu CJ, Chang CC. A Hybrid Sales Forecasting Scheme by Combining Independent Component Analysis with K-Means Clustering and Support Vector Regression[J]. Scientific World Journal, 2014.

[13] Lu LH, Gou QL, Tang WS, Zhang JX. Joint pricing and advertising strategy with reference price effect[J]. International Journal of Production Research 2016,54（17）: 5250-5270.

[14] Moayedi H, Armaghani DJ. Optimizing an ANN model with ICA for estimating bearing capacity of driven pile in cohesionless soil[J]. Engineering with Computers, 2018,34（2）: 347-356.

[15] Paesbrugghe B, Rangarajan D, Sharma A, Syam N, Jha S. Purchasing-driven sales: Matching sales strategies to the evolution of the purchasing function[J]. Industrial Marketing Management, 2017（62）: 171-184.

[16] Ren SY, Choi TM, Liu N. Fashion Sales Forecasting With a Panel Data-Based Particle-Filter Model[J]. IEEE Transactions on Systems Man Cybernetics-Systems, 2015,45（3）: 411-421.

[17] Shukur OB, Lee MH. Daily wind speed forecasting through hybrid KF-ANN model based on ARIMA[J]. Renewable Energy, 2015（76）: 637-647.

[18] Terho H, Eggert A, Haas A, Ulaga W. How sales strategy translates into performance: The role of salesperson customer orientation and value-based selling[J]. Industrial Marketing Management, 2015（45）: 12-21.

[19] Voronin S, Partanen J. Price Forecasting in the Day-Ahead Energy Market by an Iterative Method with Separate Normal Price and Price Spike Frameworks[J]. Energies, 2013, 6（11）: 5897-5920.

[20] Yadav AK, Chandel SS. Solar energy potential assessment of western Himalayan Indian state of Himachal Pradesh using J48 algorithm of WEKA in ANN based prediction model[J]. Renewable Energy, 2015（76）: 675-693.