ORIGINAL ARTICLES
SPECIAL ISSUE

PROPOSAL FOR PRODUCT DEVELOPMENT SUPPORT SYSTEM FOR PICKLES BASED ON *KANSEI* ENGINEERING

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Abstract: This report describes the construction and proposal of a support system for developing food products, particularly pickles that uses a database to provide quantitative and quick assessments of a new product. The system is intended to replace the conventional development approach, which relies on the developer's experience and intuition. Data about high-selling and popular pickle products are input into this system, which then provides predictions of the sales. It can contribute to the creation of products that will satisfy consumers' changing tastes.

Keywords: *Pickles, Product development, Neural network, Kansei engineering*

1. INTRODUCTION

Quite a number of new products have been developed in recent years. This has been particularly true for the candy industry, whose products generally have very short product lifetimes. New varieties of candy are constantly introduced to willing young and old buyers. During this same period, the pickle industry has generally continued its customary pattern of product development due to its nature as a traditional Japanese food. A result of this is that the indicators for assessing what kind of product will sell well are quite vague. In other words, it is difficult to predict sales for pickles.

The Japanese market for pickles has changed. The changes in Japanese culture and the long slump following the collapse of the economic bubble have affected the pickle market, curtailing sales in a continuing trend. There have been attempts to develop products for changing Japanese tastes by using a variety of existing data to turn sales in the other direction. Still, the available data from consumer polls and other sources cannot be considered to be sufficient, although some market strategies have brought producers some success in this sector [1]. Thus, we cannot expect any further development in this industry until the currently available fund of data has been put to more effective use to establish the direction of the business environment, predict the next successful products, and exploit the new product fields.

This study constructs a development support system that is easy to use and assesses products quantitatively with the eventual goal of expanding the product line in the market. The system proposed here estimates sales, and it

should be noted that it incorporates consumers' *kansei* (subjective evaluations) of pickle products as data for assessing popular tastes.

With the construction of this system, this paper proposes a new method for assessing products. An assessment system based on a neural network (NN) was designed to efficiently process the large volume of gathered and stored data on consumers' opinions about pickle products. A three-layered back propagation NN was employed to obtain simple and efficient processing [2, 3]. Data from market surveys of consumers' tastes in products and from previously gathered sales records were selected and digitized in order to minimize the number of input and output items. Surveys were taken to collect consumers' impressions of products and a unique system of assessment terminology was established to analyze *kansei* [4, 5]. Finally, the predictions of this system were validated by comparing its results for specific products with the results of a survey of consumers employing the assessment terminology used to gather their subjective evaluations of products. We also describe the ways in which this system can be used as a new method for future product development to replace the conventional standards of experience and intuition.

2. REVIEW OF THE PICKLE INDUSTRY AND BUSINESS ENVIRONMENT

Pickling has a long history in Japanese cuisine. It has been applied to *takuan* (radish) for a side dish in meal sets or bowl foods, *umeboshi* (plum) filling in rice balls, and *gari* (pickled ginger) on the side in sushi and other foods. Only rarely are pickles featured as the main dish in a meal,

but many Japanese feel a meal is incomplete if there are no pickle dishes. In recent years, however, Western foods have crept onto Japanese dining tables in ever-increasing amounts, and it has become less common to see pickles on the home menu. Commensurately, less shelf space is reserved for pickles in Japanese grocery stores, and it has become more difficult to distinguish consumers' tastes and preferences among pickles [1]. Since pickles are a traditional Japanese food, new forms have always been developed and introduced on the basis of the producers' experience and intuition. Because of this, producers have tended to stick to traditional patterns, and the market has made it difficult to introduce innovations. It has also been difficult to forecast sales of new products.

There have been some surveys on consumers' preferences in pickles, but they have not provided enough data to plan market strategies [1]. Pickles are not like candies, of which new types are constantly introduced in magazines as they appear in the market, usually with very short product lifetimes. Pickles are a traditional food for which the indicators for assessing market success remain vague. The mutual resemblance of different products, the shortened life cycles and the diversification of user needs are examples of how the pickle industry is saturated. Market risk has even further increased because the know-how that has served so well in previous times is becoming less and less valid. Now, it appears to be more important to respond to individual customers' needs and to build good relations with them, rather than simply aiming to "win" in a market whose nature has changed. The pickle industry will be forced to make better use of its old data. In other words, it will have to re-analyze its data on customers' tastes and actions, attract new customers, identify the direction for its products, and predict the next successful products. The above represents the authors' viewpoint in the design and development of products. We have analyzed the elements that stimulate consumers' *kansei*, incorporated those results in products, and conducted experiments to investigate the potential for expanding the sales of pickles [4, 5]. These results have convinced the industry to modify both the shapes of pickles and the design of the packaging, and have lead to other possibilities for further expanding sales [5]. This convinced the authors that it is necessary to include product elements that appeal to shoppers' *kansei*.

Therefore, this report describes an attempt to create a product development system that provides quantitative and simple assessments of products. The system employs a database of consumers' *kansei*.

3. OBJECTIVE OF RESEARCH

This report makes some observations of the pickle

industry and attempts to construct a quantitative and simple support system for evaluating developing products and evaluating their marketability. One of the features of this system is that it was specifically designed for the analysis of product development based on evaluations by human tastes and *kansei*. After this system was completed, the results were compared with those from surveys of consumers' impressions and subjective observations of products in order to verify whether the system is effective. The creation of this system has lead to an opportunity to review legacy data and to establish an index for understanding consumers' tastes. This system is expected to contribute to product development in the future.

4. PROPOSAL FOR SYSTEM TO SUPPORT PRODUCT QUALITY ASSESSMENTS

4.1 Design of the assessment system

A product development support system was constructed using a neural network as the basis for analysis. NNs are often able to extract meaningful information out of large volumes of data. The product data in the NN training signal that provided NN teaching was a collection of varied information about products developed in the past. The input items were spicing, price and product type, and the output item was the ranking (A, B or C) based on the market share of the product. A three-layer NN with learning by back propagation was employed in order to carry out the analysis as simply and efficiently as possible. Figure 1 shows the structure of the multi-layer NN.

4.2 Selection of input items

Let us begin with a brief recent history of trends in the pickle market in Japan. Several years ago, riding a popularity wave of Korean items, sales of *kimchi* products suddenly expanded. This was the sole bright spot in a market that generally saw languishing sales of other pickled products. At the same time, the number of people pickling fruit and vegetables domestically declined, with

Figure 1: Structure of the Multi-layer Neural Network Employed in this Study

this decrease being particularly noticeable among the young. Finding ways to expand sales among consumers will be one of the largest problems facing the pickle industry in times to come. There are several examples of consumer questionnaires conducted by the pickle industry, but they have not been very productive in terms of suggesting product strategies.

Therefore, it was decided to investigate the classifications of input data that would be needed to create a product evaluation system based on *kansei*. The data would chiefly be provided by surveys of young people, who will become the next generation of pickle consumers. The survey was designed to assist producers in developing products and addressed the 13 factors that young consumers are believed to consider when they select items in the market. The survey asked respondents to mark the factors with “Primary,” “Secondary” or “Tertiary”; the analyst scored each response as 3, 2 and 1 points, respectively. The survey population was mainly university students and there were 177 respondents of both sexes. Figure 2 summarizes the results. These results were used, along with elements added by the developers, to select appropriate categories for input into the NN. Other data items that were recorded during product development as keys to marketability were added to the final selection of inputs. Table 1 provides the list of selected classifications.

Figure 2: Results of Survey

4.3 Selection of output items

Sales data for already existing products were used to determine the output items from the NN in this system. The sales share of each product was extracted from the data and each product was classified into rank A, B or C according to the size of its share. This system was used to determine what elements of each of the low-ranking products needed to be improved and the extent of its role in the increase in profits was estimated.

4.4 Normalizing data

The input data used in this evaluation system were digitized for entry into the NN.

For the input items of the categories of Customer, Ingredients, Processing method, and Additives, input data were created by assigning specific numbers to each choice as a category value.

The continuous values employed to describe the Ingredient amount, Amount shipped, Additives, and Seasoning were converted to show the proportion of each amount to its range. Equation (1) is the conversion method that uses the minimum and maximum observed values for each item.

$$P = \frac{Q - R_{\min}}{R_{\max} - R_{\min}} \quad \dots (1)$$

Here, P is the converted input value and Q is the value of the input item. Generally, $R_{\max}$ and $R_{\min}$ are the maximum and minimum for calculations within the range of values observed, but it is possible that values would be found outside these bounds in the future when developing new products. In that case, input P would take a value greater than 1. The input data for a NN must have values in the range [0, 1], so the values actually used for minima and maxima were adjusted slightly beyond the values observed in the survey, in order to have some margin for

Table 1: Input Items

Category	Input items	Score type
Customer	Store	Categorical values
Ingredients	Ingredient	Categorical values
Ingredient amount	Solid weight	Continuous values
	Fluid weight	
Processing method	Slicing type	Categorical values
	Size	
Additives	Preservatives	Categorical values
	Dyes	
Spicing	Saltiness	Continuous values
	Acidity	
	Sweetness	
Price	Mean price	Continuous values
Amount shipped	Amount shipped	Continuous values

future calculations. No weighting was applied to the values in different categories during the conversion in the initial stage. Weighting is varied automatically during learning in the back-propagation learning algorithm.

5. PROTOTYPE ASSESSMENT SYSTEM

5.1 Definition and classification of data

As defined in Section 4 above, the 13 digitized groups of input item data for each product were defined as a single input data set. The data set input as the teaching signal in the NN was defined as the training data set. The training data set for each product incorporated a single input data set and the sales ranking of A, B or C for the product. The input data set for execution in the trained network was defined as the validation data set. No sales ranking data were included in the validation data set.

Data were prepared for a total of 300 products: 150 of these were training data sets and 150 were validation data sets. The sets were randomly assigned to one group or the other.

5.2 Learning by the neural network

The number of hidden layers in the NN was found by adding the total number of input features to the total number of output features and dividing by two. The output layer showed three responses (in the range [0, 1]) corresponding to the product ranking (A, B or C). The response with the highest value was the assessed ranking.

The convergence conditions for this NN were a maximum of 20,000 training iterations and a minimum-square error of 0.01. The learning rate η and momentum constant α were varied by the appropriate amounts as found empirically. The PC on which the operation was performed had a 2.6 GHz Pentium 4 CPU, 512 MB of memory, and ran on the Windows operating system.

The training data sets were entered with the product rankings into the NN for each of the 150 randomly chosen products and training was initiated. Figure 3 shows an example of the learning by the NN.

5.3 Verification of the effectiveness of the neural network

Once the training of the NN was complete, the validation data sets for the remaining 150 products were loaded and the product rankings were output. Table 2 shows the output results of the products for comparison with their actual rankings. The gray portions of the table indicate the probability of a correct assessment.

5.4 Observations

The mean rate for correct prediction of product ranking was 80%. This system can be described as providing

estimates with a high degree of accuracy. However, there was a somewhat high fraction of rank A products which had been underestimated as rank B. This can be explained as follows. The product rank, which was the output, was defined by the sales share. If the high-selling products account for a large fraction of the total sales, it then follows that the number of high-selling products is lower than the number of other products. It appears that the NN was not allowed to perform enough learning. Future analyses must have higher numbers of training data sets; also, the sales shares, which are the basis for the output items, must be re-analyzed in order to improve the precision of the assessment.

6. MARKET SURVEY FROM THE KANSEI VIEWPOINT

6.1 Survey of impressions of the product

It is essential in the survey of consumers to find the basis on which they decide to buy any given actual product in order to assess that product. Therefore, the authors polled consumers to obtain their *kansei*-based views of actual products. The subjects were shown samples of 24 products with the price tags attached and asked to choose which products (multiple products) they wanted to buy and which ones they did not want to buy. They were then asked to

Data at development + Product ranking

Figure 3: Learning by Neural Network

Table 2: Verification Results by Ranking

		Output results		
		A	B	C
Actual product ranking	A	76%	22%	2%
	B	15%	79%	6%
	C	6%	9%	85%

write down at least five reasons for their selections. The subjects were 24 men and women in their twenties and thirties. Figure 4 is a photograph of the survey.

6.2 Setting the assessment terminology

The written responses as to why the subjects wanted or did not want to buy the products allowed the authors to classify the reasons into personal likes/dislikes, taste, price, volume, appearance, packaging, and convenience. The fact that the reasons were classifiable meant that it was possible to limit the elements used for assessing the products during the selection. Therefore, the factors most frequently mentioned in the responses were picked out and a list of assessment terminology was selected. This list was used in all further analyses. These terms can be considered as critical factors when assessing products.

The selected terminology is shown in Table 3.

7. EXPERIMENT OF THE PRODUCTION DEVELOPMENT SYSTEM

This system employed past data for training, so it was appropriate to carry out further investigation of its applicability for product development. Some product samples developed with this system were assessed with the system; then, consumers were polled for their impressions of the products. The results of this system were compared with those of a conventional consumer poll, and the effectiveness of this system was verified.

7.1 Product assessment with the assessment system

In contrast to the data used to create this system (Section 5), six newly developed samples were prepared for assessment with this system. The samples were pickled ginger and plums. Figure 5 is a photograph of the newly developed products and Table 4 provides the assessment results. This system placed samples 1 and 4 in rank A, 2 and 5 in rank B, and 3 and 6 in rank C.

7.2 Product assessment from the *kansei* viewpoint

The new product samples described in Section 7.1 were assessed with the terminology given in Section 6 and the consumers' impressions of them were analyzed by the semantic differential (SD) test [6]. The effectiveness of the system was verified by comparing the results of the above survey with those gathered using this system.

Price tags were attached to the samples for the experiment, as shown in Fig. 5. Fifty males and females in their twenties and thirties were employed as subjects. A maximum of three people were polled at the same time. They were shown one sample of each product in a random pattern in order to avoid biases in the order of display.

Figure 4: Survey of Impressions of Products

Table 3 : Terminology for Assessment

Like	—	Dislike
Looks good	—	Looks unappetizing
Expensive	—	Inexpensive
Plenty of volume	—	Skimpy volume
Looks tough	—	Looks tender
Attractive	—	Unattractive
Good design	—	Bad design
Looks easy to eat	—	Looks difficult to eat

Figure 5: Photograph of Product Samples
Above, from left : Samples 4-6
Below, from left : Samples 1-3

Table 4: Results of Assessment with the System

	Ranking according to assessment system		
	A	B	C
Product samples	No.1	No.2	No.3
	No.4	No.5	No.6

Figure 6 shows an example of the survey. The survey form showed seven stages of reaction to the product, allowing the subjects to give responses such as “Extremely,” “Fairly,” “A little,” or “Neutral” for each response term. The subjects circled the level of response for each term to show their impressions. Figure 7 shows an example of the responses.

7.3 Results of written survey

Values of -3 to +3 were assigned to the seven levels to digitize the responses given on the survey forms and the mean values were found for each response classification describing the products. The products were of differing ranks. The Wilcoxon signed rank test was used to compare between ranks. Table 5 shows the differences in impressions between the ranks that were indicated by the test, but only the assessment terminology for which the subjects indicated strong differences in their choice of terminology are shown. For example, “A (1%)” for “Like” and “A / C” means that A has more significantly “Like” impression than C does and the figure in parentheses shows that the statistical significance level is 1%. In this survey, it was decided to exclude scores given for “Expensive,” “Plenty of volume” and “Looks tough,” as the assessment of these factors seemed to vary too greatly with the sample.

In the comparison between rank A and rank B items, the rank A items scored more highly on the factors of “Attractive” and “Good design.” Rank A items stood out more sharply in the A/B/C comparison; they scored higher on every one of the factors. Rank B items significantly outscored rank C items for the factors of “Looks good,” “Attractive” and “Good design.”

7.4 Observations

It was shown in this system that the higher the rank of the item, the better impression it made on the consumer. These results indicate that the predictions of this assessment system match with consumers’ *kansei* in terms of their desire to buy the products. Therefore, it seems that it is possible to use this system as an indicator for ranking products. Also, as shown in Fig. 8, when a product has been predicted to show low sales, the product parameters can be changed and the system can be re-used in another cycle of assessments. This system seems to have much potential to contribute to the development of products with high sales, and will help producers wean themselves from their dependence on experience and intuition in product development.

8. SUMMARY

This report describes an attempt to create a neural network-based product development support system for

Figure 6: Photo of Experimental Subjects

Extremely Fairly A little Neutral A little Fairly Extremely

1 Like
|
|
|
|
|
 Dislike

2 Looks
|
|
|
|
|
 Looks

good unappetizing

Figure 7: Example of the Survey form

Table 5 : Results of Wilcoxon Signed Rank Test (Significance)

		Comparison between ranks		
		A/B	A/C	B/C
Assessment terminology	Like		A (1%)	
	Looks good		A (1%)	B (1%)
	Attractive	A (5%)	A (1%)	B (1%)
	Good design	A (1%)	A (1%)	B (1%)
	Looks easy to eat	B (1%)	A (1%)

Figure 8: Product Development Support System

the pickle industry, whose producers have depended on experience and intuition for developing new products. A new development method employing a database was investigated for its effectiveness as an indicator of product marketability.

First, an assessment system based on an NN was designed and its reliability was verified in analyses of many data. An experiment examined the extent to which the rankings predicted by this system matched the actual historical rankings of products according to previous market research data, and the results verified that the system was effective. Next, a market survey of consumers was carried out and an original system of assessment terminology was selected to be used in creating a new product assessment and analysis system. The results provided by the product assessment by this system were compared with the results of a subjective evaluation by consumers using the same assessment system. This showed that the higher the ranking for a product by this system, the more the consumers were interested in buying it. This indicates a strong relation of *kansei* assessments by consumers with the product development support system proposed in this study. Thus, this system was shown to be very effective. This means that this system can be expected to provide quantitative and speedy estimates of sales.

Future issues are to carry out training with a larger fund of training data, to improve the precision of the NN, and to pursue the relationship between product rank and profit. Another essential issue is to survey the actual course of sales of products developed under the guidance of this system. The authors look forward to seeing this system contribute to the creation of successful products that satisfy customers.

This project was accomplished with the support of the Ministry of Education, Science, Sport and Culture Grant-in-aid C18500158.

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