Possible classification of pork products by ICP-MS

MOTOKI GODA^{*†} Member, YOHICHIRO KOJIMA[‡] Member

(Received February 18, 2019, revised April 15, 2019)

Abstract: Recently, repeated food adulteration cases have been observed; therefore, ensuring food safety has become essential. First, we examined the possibility of classifying pork products in this study. Second, we considered the practicality of measuring inorganic components of pork products via inductively coupled plasma mass spectrometry (ICP-MS). Additionally, we investigated whether classification collation using a neural network is possible by learning the inorganic components measured by ICP-MS. Classification collation of pork products was found to be possible for each category (product type, product part, and cooking method) using the inorganic component contents measured by ICP-MS.

Keywords: Pork product, Classification, Chemical components, Neural network, ICP-MS,

1. Introduction

To protect food safety, ingredient evaluation has been carried out by numerous chemical analysis methods. Recently, with various concerning factors such as increased food importation, production, fraud, and poisoning, it is more urgent than ever to ensure safety. From the background mentioned above, it is increasingly important to quickly match and accurately classify analysis results for many foods.

Conventionally, various chemical component contents have been quantified using chemical analyzers, such as atomic absorption spectrometry, fluorescent X-ray diffractometry, gas chromatography, mass spectrometry, and high-performance liquid chromatography. However, quantitative data collected by these methods is used from a nutritional aspect and are not for classification and identification of food types and forms, where consideration of its importance is increasing absent [1]~[3]. Therefore, the study group examined optimization and facilitation possibilities for food classification using the chemical substance content of food quantified and converted by quantitative chemical methodology procedures [4]~[13].

In this report, we examined whether classification of pork products into categories-product type, product part, and cooking method-is possible using 11 inorganic components-sodium, potassium, calcium, magnesium, phosphorus, iron, zinc, copper, iodine, selenium, and chromium-quantified by ICP-MS. For the examination, we used the neural network method and provided a preliminary results report and future development plans.

2. Materials and method

2.1 Pork products as subject data This study was conducted on 88 pork product types identified by the Ministry of Education, Culture, Sports, Science, and Technology. Using the 11 inorganic component content types obtained by ICP-MS[1], we classified the products according to seven product types, fourteen product parts, and nine cooking methods.

2.2 Data preparation considering ICP-MS analysis error Data was prepared considering analysis errors for the 11 inorganic components that can be quantified by ICP-MS. Therefore, expected measurement errors for the 88 pork products analyzed by ICP-MS were also considered.

The assumed measurement error for the 11 inorganic component types is $\pm 10\%$. Thereafter, classification and collation into each category (product type, product part, cooking method) was carried out using a neural network for

Figure 1: Image of neural network using inorganic components.

* Corresponding: gouda@njpc.co.jp

† Hokkaido University of Science
 7-Jo 15-4-1, Maeda, Teine, Sapporo, Hokkaido, Japan 006-858

‡ North Japan Port Consultants Co., Ltd
 S2E2, 8-1, Sapporo, Hokkaido, Japan 060-0052

Table 1: Each pork product category.

Product type	Product part	Cooking method
Red meat	Picnic shoulder	Roasted
Without subcutaneous fat	Picnic shoulder loin	Boiled
Lean and fat	Outside ham	Raw
Fatty meat	Ham	Smoked
Offal and byproducts	Loin	Paste
Ground meat	Fillet	Sausage
Meat substitute	Belly	Ham
-	Ground meat	Bacon
-	Pig's feet	Breaded and fried pork
-	Visceral meat	-
-	Cartilage	-
-	Gelatin	-
-	Meat substitute	-

(a) Determination rate and learning iteration plot

(b) Calculation time of neural network by learning iteration

Figure 2: Result of neural network analysis using inorganic component for pork products.

264 pork product types, considering errors. The contents of each category are listed in Table 1.

2.3 Calculation of discrimination rate by neural network From the 11 inorganic component types, it was determined whether the 264 pork product types could be classified into each of three categories: product type, product part, and cooking method by the neural network calculated discrimination rate.

A neural network is a mathematical model that expresses neurons and their connections in the human brain. It consists of input, output, and hidden layers [14] [15]. The information accepted at the input layer is judged at the output layer, and information conforming to each category is the output (Fig. 1). Among them, to prescribe the output value at output time, a hidden differentiable activating function layer is used.

For the calculation, we used the Weka statistical analysis

software (The University of Waikato) with Windows 10 OS, 8 GB memory, and Intel Core i5-8500 processor.

The discrimination ratio is determined by Eq. 1 below. This expression is obtained by dividing the number of samples correctly predicted for each category defined in the neural network by the total sample number, 264. In this report, the results set with five middle layers, and zero to 90,000 learning iterations, are shown.

$$\text{Determination rate(\%)} = \frac{\text{Positive discrim samples}}{\text{All samples}} \times 100 \quad (1)$$

3. Result and discussion

Figure 2 shows the neural network analysis results for each of the three categories using inorganic component contents contained in all pork products.

Table 2: Neural network analysis result by product type.

Product type	True	False	False rate	True rate
Red meat	36	3	7.7%	92.3%
Without subcutaneous fat	21	15	41.7%	58.3%
Lean and fat	36	9	20.0%	80.0%
Fatty meat	30	0	0.0%	100.0%
Offal and byproducts	33	0	0.0%	100.0%
Ground meat	5	1	16.7%	83.3%
Meat substitute	75	0	0.0%	100.0%
Total	236	28	10.6%	89.4%

Table 3: Neural network analysis result by product part.

Product part	True	False	False rate	True rate
Picnic shoulder	15	9	37.5%	62.5%
Picnic shoulder loin	21	3	12.5%	87.5%
Outside ham	12	12	50.0%	50.0%
Ham	22	8	26.7%	73.3%
Loin	32	1	3.0%	97.0%
Fillet	11	1	8.3%	91.7%
Belly	9	0	0.0%	100.0%
Ground meat	6	0	0.0%	100.0%
Pig's feet	3	0	0.0%	100.0%
Visceral meat	24	0	0.0%	100.0%
Cartilage	3	0	0.0%	100.0%
Gelatin	2	1	33.3%	66.7%
Meat substitute	69	0	0.0%	100.0%
Total	229	35	13.3%	86.7%

Table 4: Neural network analysis result by cooking method.

Cooking method	True	False	False rate	True rate
Roasted	11	7	38.9%	61.1%
Boiled	20	1	4.8%	95.2%
Raw	153	0	0.0%	100.0%
Smoked	2	1	33.3%	66.7%
Paste	2	1	33.3%	66.7%
Sausage	27	0	0.0%	100.0%
Ham	24	0	0.0%	100.0%
Bacon	2	7	77.8%	22.2%
Breaded and fried pork	6	0	0.0%	100.0%
Total	247	17	6.4%	93.6%

As shown in Fig. 2(a), the classification and collation of 264 pork products to product type caused the discrimina-

tion ratio to improve as the number of learning iterations increased. The highest discrimination ratio for product type, product parts, and cooking method was 89.4%, 86.7%, and 92.8% at 55,000, 75,000, and 55,000 learning iterations, respectively. After the maximum discrimination ratio was reached, no improvement in discrimination ratio was obtained with an increase in the learning iterations in any of the categories. For product part categories having more classification items, compared to product type and cooking method, the discrimination rate was lower and learning iterations needed were higher. It is conceivable that this correspondence to the classification item, which involved classification and collation by 11 inorganic components, was complicated by calculation.

As shown in Fig. 2(b), it was confirmed that the calculation time showed a positive correlation with learning iterations and that more calculation time was required as learning iterations increased. The trend of calculation time with respect to the number of learning iterations for each category showed similar calculation time for product type and cooking method; however, it confirmed that product part required more time compared to them.

Table 2 shows the correct discrimination ratio by product type. Consequently, fatty meat, offal and byproducts, and meat substitute had a 100% discrimination rate, while meat without subcutaneous fat showed a low value of 58.3%. Lean and fat meat and ground meat are also 80.0% or more, but about 20% misidentification was confirmed. This is because meat without subcutaneous fat, lean and fat meat, and ground meat contain fatty meat, and because the composition of inorganic components per 100 g of product is similar, higher misidentification rates are expected.

Table 3 shows the correct discrimination rate for product parts. Loin, fillet, belly, ground meat, pig's feet, visceral meat, cartilage, and meat substitute show high value of 91.7-100% for the normal discrimination rate, which indicates that the inorganic components can be classified and verified with high accuracy by neural network learning.

However, because picnic shoulder, picnic shoulder loin, outside ham, and ham are portions that are close to each other, the discrimination accuracy is lower than that of the others, between 50.0-87.5%.

Gelatin has a correct discrimination rate of 66.7%, which is an erroneously discriminated factor, as pig's feet also contains gelatin.

Table 4 shows the correct discrimination rate by cooking method. Boiled, raw, sausage, ham, & breaded and fried pork showed high accuracy of 95.2-100%.

However, the accuracy of roasted, smoked, and paste was low and between 61.1-66.7%, with bacon's at the lowest of 22.2%.

The results show that improving discrimination accuracy of alike parts is problematic; however, different parts can be classified and verified with high accuracy.

It was shown that pork products classification into categories can be performed and verified with inorganic components measured by ICP-MS. However, because an overall discrimination rate of 90% cannot be achieved outside of

the cooking method category, improving the further classification collation accuracy is a problem for further study.

4. Conclusions

In this report, we presented the possibility of classification collation of pork products using inorganic components that can be quantified by ICP-MS as a preliminary report. In the future, we will examine the hidden layer and learning iterations to improve the classification matching accuracy of each category, and we will actually determine to which category the product with unknown classification belongs.

Acknowledgment

This research was partially supported by the Ministry of Education, Science, Sports and Culture, Grant-in-Aid for Scientific Research(C), 2015-2019(15K00806, Yoichiro Kojima).

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Goda Motoki (Member) In March 2015, completed the master's program at Hokkaido University Graduate School of Environmental Science, and received a master's degree in environmental science. The same year, he joined North Japan Port Consultants Co., Ltd. and was assigned to the 1st Engineering Department Planning Team. In April 2017, appointed as a researcher at Hokkaido University of science. Engaged in research for port planning, behavior factor analysis, food quality control using AI / IoT and chemical component value information, and identification of deliciousness factors.

Kojima Yoichiro (Member) He received his BE, ME and Dr. Eng. degree, all in applied electronics engineering, from Hokkaido Institute of Technology in 1990, 1992 and 1995, respectively. He is now a Professor at Department of Electrical and Electronic Engineering, Faculty of Engineering of Hokkaido University of Science. His main research interests are focused on development of taste sensing. Dr. Kojima is a member of the Institute of Industrial Applications Engineers.