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Abstract

This study investigated the predictability of cooking loss of pork loin through relatively easy and quick measurable quality properties. The pH, color, moisture, protein content, and cooking loss of 100 pork loins were measured. The explanatory variables included in all linear regression models with an adjust-R^2 value of ≥ 0.5 were pH and the protein content. In the linear regression model predicting cooking loss, the highest adjust-R^2 value was 0.7, with pH, L* value, b* value, moisture, and protein content as the explanatory variables. In 30 pork loins, electrical conductivity was additionally measured, and as a result of linear regression analysis for predicting cooking loss, the highest adjust-R^2 value was 0.646 with electrical conductivity measured at 40 Hz, with pH and color as the explanatory variables. Ordinal logistic regression analysis was performed to predict the three grades (low, middle, and high) of loin cooking loss using pH, color, and 40 Hz electrical conductivity as the explanatory variables, and the percent concordance was 93.8%. In conclusion, the addition of electrical conductivity as an explanatory variable did not increase the prediction accuracy of the linear regression model for predicting cooking loss; however, it was demonstrated that it is possible to predict and classify the cooking loss grade of pork loin through quality properties that can be measured quickly and easily.

Keywords: cooking loss, electrical conductivity, pork loin, pork quality

Introduction

The production and consumption of meat are increasing worldwide yearly, and it is expected that the influence of income and price on the purchase of meat will gradually decrease and the influence of quality will become more important (Henchion et al., 2014; Shi et al., 2021). Consumers demand high-quality meat that is safe, enjoyable, and healthy when purchasing meat. They normally judge the quality of meat at the time of purchase through visible characteristics such as color and fat level, and they hope that this judgment will match the experience quality felt when eating the product (Park et al., 2022; Henchion et al., 2014). Therefore, there is an increasing demand in the meat industry for a method to rapidly and accurately detect the final meat quality experienced by consumers (Alkfeld et al., 2016; Lee et al., 2021a). Meat quality can be expressed by various parameters and it can be divided into physicochemical characteristics such as pH, color, water-holding capacity, moisture, and protein content measured in the laboratory, and sensory characteristics such as flavor, juiciness, and tenderness that consumers experience when eating the product (Antequera et al., 2021).

Cooking loss refers to the loss of liquid and soluble substances during the cooking of meat (Jeong et al., 2021; Kim et al., 2022). It is closely related to juiciness, which is a major quality property in pork and it determines the technical yield of meat (Aaslyng et al., 2003; Jin and Yim, 2022; Lee et al., 2021b). However, in order to measure the cooking loss of meat, it is necessary to collect the sample and heat it and the destruction of the sample and the time consumption are unavoidable. These processes are not suitable for measuring directly in the raw meat state before distribution to consumers. Therefore, Predicting the cooking loss in raw meat using quick and non-destructive or minimally destructive methods could help improve pork quality control in the meat industry.

Recently, several studies have reported methods for determining meat quality in non-destructive or minimally destructive ways (Damez et al., 2008; Leng et al., 2020; Shi et al., 2021). Electrical conductivity measurement is one of the minimally destructive methods for determining meat quality. Meat is composed of several cells surrounded by cell membranes with insulating properties, and intracellular and extracellular fluids are considered electrolytes (Damez et al., 2008; Pliquett et al., 2003). After slaughter, the muscle undergoes various levels of damage to the cell membranes due to post-mortem metabolism. Therefore, cell membrane permeability increases and the composition of intracellular and extracellular fluids changes, resulting in changes in the electrical properties of meat (Bai et al., 2018; Byrne et al., 2000; Castro-Giráldez et al., 2010). Previous studies have reported that the degree of ripening of beef during storage can be evaluated by measuring the electrical properties (Banach & Żywic, 2010), and the water holding capacity of pork muscle can be predicted by determining its pH and electrical conductivity (Lee et al., 2000). Therefore, because the change in electrical conductivity of meat reflects its quality properties, it is suggested that the factors affecting the final quality of meat may be predicted using electrical conductivity.

In this study, we established a linear regression model to predict cooking loss using various quality properties of pork loin, and the effect of electrical conductivity on the improvement of the accuracy of the regression model was determined.

Materials and methods

1. Experimental design

Pork loins (n = 130) were obtained from different carcasses 24 h after slaughter. The experiments were conducted in two steps: In experiment 1, 100 pork loins were used, and the pH, color, moisture, protein content, and cooking loss were measured. The correlation coefficient between the quality properties measured in loins and regression analysis for predicting the cooking loss of loins was analyzed.

Experiment 2 was performed to confirm the effect of adding electrical conductivity to the prediction accuracy of the regression model for predicting the cooking loss of pork loin. The pH, color, moisture, protein content, cooking loss, and electrical conductivity of 30 pork loins were measured, and regression analysis was conducted to predict the cooking loss of pork loins.

2. Meat quality analysis

A part of the pork loin was ground and the pH, moisture, and protein content were measured. The remaining part was cut to a thickness of 1.5 ± 0.5 cm and weight of 132.4 ± 14.7 and measured the color of the cross-section and cooking loss. In experiment 2, electrical conductivity was first measured in the whole loin and then the samples for the analysis were collected as described above.

To measure the pH of pork loin, pork loin samples (1 g) were homogenized in 9 mL of distilled water at 12,000 rpm for 1 min (T25 basic, IKA GmbH & Co. KG, Germany). The homogenates were centrifuged at 2,090 × g for 10 min (1580R, LaboGene, Lynge, Denmark). The supernatant was filtered using a Whatman No. 4 filter paper (Whatman, Maidstone, England), and the pH was measured using a pH meter (SevenEasy, Mettler-Toledo Intl Inc., Schwerzenbach, Switzerland).

The color of the raw pork loin slices was determined using a spectrophotometer (CM-3500d, Konica Minolta Inc., Tokyo, Japan). Measurements were performed at two different positions per loin sample with a 30 mm diameter of the illumination area. The results were analyzed using the SpectraMagic software (SpectramagicTM NX, Konica Minolta Inc., Tokyo, Japan) and expressed as CIE lightness (L*), redness (a*), and yellowness (b*).

The moisture and protein contents of pork loin were measured by slightly modifying the AOAC method. The moisture content was measured by drying the loin samples (2 g) at 102 °C for 15 h. The protein content was measured using the Kjeldahl method. The amount of nitrogen obtained was multiplied by 6.25 to determine the crude protein content.

To measure the cooking loss, vacuum-packed pork loins were cooked in a water bath at 80 ℃ for 30 min. After measuring the internal temperature of the loin using food thermometer and confirming that it reached 75 ℃, cooking was completed. The cooked loin samples were cooled to room temperature (20 °C) and weighed after removing the drip. The cooking loss (%) was determined by calculating the weight loss after cooking.

The electrical conductivity was measured using two types of instruments in the whole pork loin before collecting samples for other quality analyses. One was a portable LF-star device (Matthäus, Eckelsheim, Germany) and electrical conductivity was measured at one fixed point with a frequency of 1.2 kHz. The electrodes were two stainless steel electrodes with a distance of 15 mm. The other was an LCR meter (IM3533-01, Hioki Company, Japan). Electrical conductivity was measured using an LCR meter at a total of 200 points in the frequency range of 40 Hz-200 kHz. The electrodes used with the LCR meter were bar-type, with a size of 10 mm × 10 mm, and the distance between the electrodes was 10 mm. Electrical conductivity was measured three times per sample by inserting the electrodes of each device into a raw pork loin.

3. Statistical analysis

Statistical analyses were performed using the SAS software (version 9.3, SAS Institute Inc., Cary, NC, USA). The correlation coefficient between the meat quality properties was calculated using Pearson's correlation coefficient. Linear regression analysis was conducted to predict the cooking loss of pork loin using their quality properties as the explanatory variables. Multicollinearity among the explanatory variables was tested using variance inflation factors (VIF), and variables with a VIF greater than 10 were removed. Outliers were detected through studentized residuals, and outliers exceeding the ±2.0 range were removed in order from the greatest. Less than 10% of the data were removed. The accuracy of the linear regression model is expressed using the adjusted-R^2 value.

Based on the value of cooking loss measured in thirty pork loins in experiment 2, they were classified into three grades and ten samples were included in each grade; low (< 30% of cooking loss), middle (31-33% of cooking loss), and high (>33% of cooking loss). Ordinal logistic regression analysis was performed to predict the degree of cooking loss by selecting the explanatory variables identified in the previous linear regression analysis (experiment 1). The predictive accuracy of ordinal logistic regression was expressed as the percentage concordance. The descriptive statistics of pork loin quality obtained in this study are summarized in Table 1.

Results and discussion

1. Experiment 1

1.1. Correlation coefficient of pork loin quality properties

After slaughter, the pH of the carcass muscles gradually decreases because lactic acid is produced owing to postmortem glycolysis and thereafter it accumulates in the muscles. Changes of pH in muscles results in various changes in the physicochemical properties of muscles; therefore, it has been used as an indicator of meat quality (Huff-Lonergan and Lonergan, 2005). In this study, the pH had a moderately negative correlation with the *L** value in pork loins in which the correlation coefficient was the highest among the tested quality parameters such as pH, *L** value, *a** value, *b** value, protein content, moisture content, and cooking loss (Table 2). The *L** value of meat is affected by light reflection, absorption, and scattering, which are related to the distribution of water in the muscle and the structural properties of the muscle. When the pH declines near the isoelectric point of the major muscle protein, the net charges of myofibrillar proteins decrease. Consequently, the amount of water bound to proteins and the spaces within the myofibrils for holding water decrease, and thus, the intracellular water moves to the extracellular spaces and the surface of meat (Brewer et al., 2001; Huff-Lonergan and Lonergan, 2005; Hughes et al., 2014).

Therefore, with a decrease in the water-holding capacity of meat at low pH, the water on the surface of meat and extracellular spaces increases light scattering and reflection, resulting in an increase in the *L** value of meat.

However, the pH of pork loin exhibited a weak correlation with the cooking loss of pork loin (-0.35). As described above, the decrease in muscle pH after slaughter is related to the water-holding capacity of meat, which can lead to an increase in the cooking loss of meat (Bertram et al., 2003; Jo et al., 2022). However, it may be difficult to fully explain the change in water distribution in meat due to protein denaturation and cell structure decomposition during cooking using pH only (Betram et al., 2003). In particular, it is known that protein degradation in muscles after slaughter affects the water-holding capacity of meat (Kristensen and Purslow, 2001). After slaughter, proteolysis by endogenous protease and muscle cell apoptosis, and protein oxidation can affect the water binding capacity of protein (Huff-Lonergan and Lonergan, 2005; Pearce et al., 2011). Therefore, the water holding capacity of meat is complexly affected by physicochemical changes that occur after slaughter, as such, the correlation coefficient between the pH of pork loin and cooking loss might not be high.

The protein content had a weak correlation (-0.38) with cooking loss in pork loin. This result is similar to that reported by Jo et al. (2022) in which the correlation coefficient between the protein content and cooking loss in pork loin was -0.43. The water in the muscle can be categorized by bound chemically to protein, immobilized by capillary force in muscle cells, and free water (Huff-Lonergan and Lonergan, 2005). The bound water is highly resistant to stress, including heat treatment, and it increases with an increase in the protein content in meat (Huff-Lonergan and Lonergan, 2005). Therefore, the protein content of pork loin might be negatively correlated with the cooking loss of pork loin.

1.2. Linear regression analysis for predicting cooking loss

Multiple linear regression analyses were performed using pH, color, moisture, and protein content as the explanatory variables to predict cooking loss of pork loin; only regression models with adjusted-R^2 value ≥ 0.5 are summarized in Table 3. A total of 14 linear regression models were obtained, and pH was included as an explanatory variable for all regression models. The next most used parameter was protein content. This result was consistent with the significant correlations between cooking loss, pH, and protein content (Table 2). The highest R^2 value was 0.7, which was a regression model that included the pH, a* value, b* value, moisture, and protein content. Therefore, cooking loss could be predicted accurately using the quality parameters of fresh meat. However, among the parameters included in the regression model, moisture and protein content might be considered as inappropriate parameters for predicting cooking loss in the meat industry because they require the destruction of samples, use of reagents, and are time-consuming.

2. Experiment 2

2.1. Correlation between electrical conductivity and cooking loss

An additional analysis was performed on 30 pork loins to confirm the effect of electrical conductivity as a new explanatory variable for a regression model to quickly and accurately predict cooking loss.

The electrical conductivity of biological tissues is a frequency dependent factor. However, the optimal frequency for measuring meat quality has not been clearly determined (Banach and Żywica, 2010). Therefore, the electrical conductivity of the pork loin was measured using a portable device with a fixed frequency and an LCR meter with multiple points of frequency to confirm the frequency that was suitable for predicting cooking loss. Analysis of the correlation between the electrical conductivity value obtained by measuring using two types of devices (portable and LCR meter) and cooking loss demonstrated that the electrical conductivity value of the portable device was not significantly correlated with cooking loss (data not shown). In contrast, in the correlation analysis between electrical conductivity measured by the LCR meter and cooking loss, there were significant correlations in the range of 40 Hz-5 kHz. At a frequency of 40 Hz, it showed the highest significant correlation value of 0.48 and the correlation decreased with the frequency increased (data not shown).

In biological systems, three dispersions (α, β, and γ) of electrical conductivity (impedance) values appear according to the change in frequency. 40 Hz, the frequency with the highest correlation with cooking loss in this experiment, belongs to the α-dispersion region (Castro–Giráldez et al., 2010). The α-dispersion occurring in the low-frequency region below 1 kHz is associated with membrane ion channels and membrane permeability and may also be related to the extracellular water content (Bai et al., 2018; Castro–Giráldez et al., 2010).This is because it is difficult for the current to pass through the cell membrane at low frequencies and it mainly flows in the extracellular fluid; therefore, the electrical conductivity at low frequency mainly reflects the state of the extracellular fluid (Bai et al., 2018). In addition, the electrical conductivity at low frequencies can be affected by the accumulation of metabolites and released ions in the extracellular fluid during apoptosis and post-mortem metabolism after slaughter (Damez et al., 2008; Traffano-Schiffo et al., 2021). Therefore, it is suggested that the measurement of electrical conductivity at low frequency, which reflects the change of extracellular fluid by physicochemical changes during postmortem, will be helpful for predicting the quality of meat. There are several previous studies that measured the electrical properties at low frequencies to evaluate the quality of meat. In the study by Swatland (1997), it was reported that the quality of pork can be measured early through the electrical properties measured at 20 Hz and Banach and Żywica (2010) reported that the degree of ripening of beef during storage could be evaluated using electrical properties measured at 100 Hz. Therefore, it is suggested that the electrical conductivity at low frequency could reflect the change in the quality of meat. In this study, only the electrical conductivity value measured at 40 Hz was used for the regression analysis to predict the cooking loss.

2.2. Regression analysis of electrical conductivity for cooking loss of pork loin

Multiple linear regression analyses were performed on 30 loins using the same parameters as the regression model obtained from the analysis using 100 loins, and the change in the adjusted-R^2 value with electrical conductivity was identified (Table 4). Most of the R^2 values of the linear regression models were less than the R^2 values obtained in experiment 1. This result may be because the sample size (30 loins) in experiment 2 was less than the 100 loins in experiment 1. Nevertheless, the R^2 value increased in all linear regression models with the addition of the electrical conductivity values. The highest R^2 value was 0.646, and the explanatory variables included pH, color factors (L*, a*, and b* values), and electrical conductivity. From the results, we confirmed that adding electrical conductivity as an explanatory variable can predict cooking loss of pork loin with minimally destructive measured quality parameters, except for moisture and protein content, which are difficult to rapidly and accurately analyze in an industrial setup.

The cooking loss values in 30 pork loins were divided into three grades (low, middle, and high), and to predict these grades, ordinal logistic regression analysis was performed using pH, color factors, and electrical conductivity as the explanatory variables. The range of cooking loss of 30 loins was in the range of 26.86–36.17% and it was classified into three grades: low (<30%), middle (31–33%), and high (>33%). As a result of the ordinal logistic regression analysis for predicting cooking loss of pork loin, the percentage of cooking loss grades correctly predicted by this model was 93.8% (Table 5). In conclusion, it was demonstrated that the prediction accuracy can be improved by classifying the cooking loss value into grades and predicting them than predicting the cooking loss value itself. In addition, the possibility of predicting the cooking loss of pork loin accurately through factors such as electrical conductivity and color, which can be quickly measured in a production line with minimal destruction of the sample, is a significant advancement in the meat industry.

Conclusion

This study was conducted to investigate the predictability of the cooking loss of pork loin using a rapid and minimally destructive analysis method. Among the quality factors of the 100 loins, pH and protein content were significantly correlated with cooking loss. The highest adjusted-R^2 value in the multiple linear regression model for predicting the cooking loss of 100 loins was 0.7, and pH, L* value, b* value, moisture, and protein content were used as the explanatory variables. In 30 loins, the frequency of electrical conductivity with the highest significant correlation with cooking loss was 40 Hz. The highest adjusted-R^2 value of the linear regression model for predicting the cooking loss in 30 loins was 0.646, and 40 Hz electrical conductivity, pH, and color factors were included as explanatory variables. The ordinal logistic regression model predicting the cooking loss grade (low, middle, and high) exhibited a high percent concordance of 93.8%. Therefore, it is possible to use electrical conductivity to predict the cooking loss of pork loin in a minimally destructive way, and predicting the classification of cooking loss grade may improve the quality prediction accuracy of pork loin. However, the cooking loss grade set in this study was based only on the values obtained from our experiment. Thus, in order to apply it to the industry, it is necessary to confirm the degree of cooking loss of pork loin that can be accepted by consumers and industries and to determine the cooking loss grade based on this. In addition, further study is needed on classification accuracy when applied in industrial fields.

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Table1. Descriptive statistics of quality properties of pork loin.

	Mean	SD[1]	Min	Max
Experiment 1				
pH	5.87	0.26	5.48	6.83
*L** value	50.39	3.76	41.22	61.24
*a** value	6.74	1.35	3.58	10.26
*b** value	14.59	1.26	11.28	17.41
Moisture	73.13	1.30	69.39	75.53
Protein content	21.99	0.93	19.48	26.52
Cooking loss	28.62	4.69	14.77	39.63
Experiment 2				
pH	5.70	0.10	5.52	6.12
*L** value	52.59	1.57	49.22	55.16
*a** value	6.26	1.02	3.34	8.13
*b** value	15.58	0.67	14.00	16.97
Moisture	73.19	0.74	71.72	74.32
Protein content	23.80	0.72	22.51	25.46
EC-P[2]	11.75	0.37	10.55	12.00
EC-40[3]	2.50	0.43	1.47	3.02
Cooking loss	31.91	2.13	26.86	36.17

[1]SD: Standard deviation, Min: minimum, and Max: maximum.

[2]EC-P: Electrical conductivity measured using portable equipment.

[3]EC-40: Electrical conductivity measured using an LCR meter at 40 Hz.

Table 2. Correlation of pork loin quality properties (experiment 1).

	pH	L* value	a* value	b* value	Moisture	Protein
*L** value	-0.65***					
*a** value	-0.04	-0.28**				
*b** value	-0.48***	0.54***	0.50***			
Moisture	0.05	-0.15	-0.25*	-0.35**		
Protein	-0.10	-0.05	0.07	0.07	0.01	
Cooking loss	-0.35**	0.02	0.11	-0.15	0.15	-0.38***

*p<0.05; **p<0.01; and ***p<0.001

Table 3. Linear regression models for predicting the cooking loss of pork loin (experiment 1).

pH	*L** value	*a** value	*b** value	Moisture	Protein	Intercept	Adj-R^2
-14.01	-0.71				-2.65	205.16	0.685
-11.62		1.82	-1.96			113.63	0.569
-6.32				1.15	-3.01	48.25	0.544
-10.97	0.13	2.07	-2.26			105.76	0.567
-14.52	-0.73	-0.24			-2.72	212.12	0.684
-13.88	-0.66			0.19	-2.67	188.68	0.683
-11.75		1.81	-2.02	-0.17		127.80	0.566
-11.27		1.52	-1.96		-1.85	154.30	0.651
-9.54	0.41	2.22	-3.28	0.28		118.19	0.564
-13.05	-0.38	0.71	-1.10		-2.24	185.24	0.675
-14.33	-0.71	-0.21		0.14	-2.74	199.94	0.682
-14.26	**-0.59**		**-0.53**	**0.31**	**-2.74**	**187.62**	**0.700**
-11.16		1.44	-1.91	0.08	-1.88	148.68	0.653
-13.02	-0.38	0.71	-1.09	0.03	-2.25	182.81	0.672

Table 4. Linear regression models for predicting the cooking loss of pork loin (experiment 2) with addition of electrical conductivity.

pH	*L** value	*a** value	*b** value	Moisture	Protein	EC40	Intercept	[1]Adj-R^2	[2]Adj-R^2
-12.63	-0.79				0.32	3.09	130.51	0.513	0.115
-9.74		1.72	-3.06			1.76	120.45	0.468	0.260
-3.39				0.65	0.61	1.66	-14.79	0.276	0.184
-16.98	**-0.96**	**1.08**	**-2.09**			**3.52**	**196.94**	**0.646**	**0.420**
-12.94	-0.76	-0.36			0.72	3.29	122.85	0.487	0.097
-17.22	-0.93		-1.13		0.24	4.16	180.89	0.606	0.020
-9.84	-0.54			0.42	0.55	2.29	67.24	0.412	0.064
-7.45		1.82	-2.42	1.09		1.79	16.64	0.540	0.314
-9.85		1.49	-3.06		0.39	0.87	115.01	0.436	0.427
-15.33	-0.78	1.31	-2.30	0.35		3.21	155.39	0.639	0.378
-16.70	-0.94	1.08	-2.07		0.07	3.46	192.45	0.629	0.431
-9.14	-0.49	0.08		0.44	0.58	2.22	57.84	0.385	0.173
-12.22	-0.55		-0.61	0.49	0.59	3.00	83.07	0.511	0.118
-6.70		1.70	-2.09	0.97	0.56	1.53	4.51	0.553	0.414

[1]Adj-R^2: Adjust-R^2 value of the regression model including 40 Hz electrical conductivity.

[2]Adj-R^2: Adjust-R^2 value of the regression model excluding 40 Hz electrical conductivity.

Table 5. Logistic regression model for predicting cooking loss grades (low, middle, and high) of pork loin.

	Estimate	Standard error	P-value
Intercept 1	-347.4	127.5	0.006
Intercept 2	-343.1	126.3	0.007
pH	37.88	13.60	0.005
*L** value	1.13	0.82	0.170
*a** value	-3.84	1.79	0.032
*b** value	6.74	2.65	0.011
EC40	-4.97	1.96	0.011
Percent concordant	93.8		
Percent discordant	6.2		
Percent tied	0.0		