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CLASSIFICATION MODEL FOR EATING QUALITY OF PORK USING COMPUTER VISION

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I. INTRODUCTION

This study addresses that gap by focusing specifically on the prediction of pork's sensory eating qualities — sweetness, saltiness, umami, and fat-like flavor — which are key flavor attributes closely related to consumer satisfaction. These attributes were selected because they are among the most influential sensory factors in eating quality, as supported by prior research [1]. While traditional evaluation methods like sensory evaluations and chemical analyses offer precision, they are subjective, time-consuming, and destructive, making them impractical for large-scale industrial use [2, 3]. As a result, there is increasing interest in non-destructive and efficient alternatives. Computer vision (CV) has recently emerged as a useful tool for assessing meat quality by analyzing visual features such as color [4]. Previous studies have mainly focused on predicting freshness, oxidation, or texture using image-based features, while very few have addressed the prediction of flavor-related attributes. This study addresses that gap by focusing specifically on the prediction of pork's sensory eating qualities (sweetness, saltiness, umami, and fat-like) using color information extracted from digital images. Machine learning models were applied to both binary and three-class classification tasks. This study aims to develop a CV-based model for predicting pork eating quality using color values, offering an efficient, objective, and non-destructive method for eating quality assessment of pork.

II. MATERIALS AND METHODS

A total of 40 pork shoulder butt samples (500g each) were obtained from different local suppliers in Korea. The samples were bloomed for 30 minutes. Digital images of the pork samples were obtained using a SONY ILCE-6000 camera. A total of 80 images (including both sides of the meat) were collected. The pork samples (2 mm thickness) were pan-grilled at 170°C for 60 seconds on one side and 30 seconds on the other. Sensory evaluation was performed by 10 trained panelists using a 9-point scale, assessing fat-like, sweetness, saltiness, and umami. Image preprocessing was conducted using Python Open CV, including background removal, Region of Interest (ROI) selection, and CLAHE-based contrast enhancement, as illustrated in Figure 1. The dataset was divided into three ROI categories: entire sample, muscle region, and fat region. RGB, *L*a*b**, and HSV color features were extracted and analyzed for correlation with pork sensory attributes. Machine learning models, including Support Vector Machine (SVM), Gradient Boosting Machine (GBM), Logistic regression(LR), and Random Forest (RF) were applied to classify pork samples based on their sensory attributes. The best-performing model was selected based on F1-score from the test dataset. Performance metrics used in this study are defined as follows: Acc_{CV} (Cross-Validation Accuracy): Mean accuracy from k-fold cross-validation on the training dataset. $F1_{CV}$ (Cross-Validation F1-score): Mean F1-score from cross-validation. Acc_P (Prediction Accuracy): Accuracy on the independent test dataset. $F1_P$ (Prediction F1-score): F1-score on the test dataset, reflecting model performance under class imbalance.

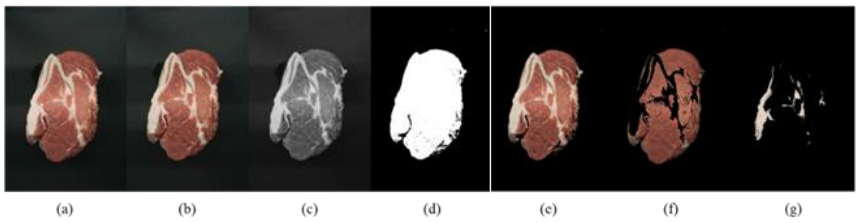


Figure 1. Pork image processing procedure.
(a) pork cut.
(b) illumination compensation.
(c) gray image.
(d) mask to remove background.
(e) entire region separated from the image.
(f) muscle region separated from the image.
(d) fat region separated from the image.

III. RESULTS AND DISCUSSION

The sensory evaluation was conducted by 10 trained panelists using a 9-point scale to assess the attributes of fat-like, sweetness, saltiness, and umami. The distribution of scores for these attributes is shown in Figure 2. The scores for fat-like ranged from 3.1 to 7.6, for sweetness from 2.7 to 5.7, for saltiness from 2.5 to 7.1, and for umami from 3.4 to 7.1. The distribution of scores for these attributes was generally uniform across the scale, suggesting a balanced range of evaluations.

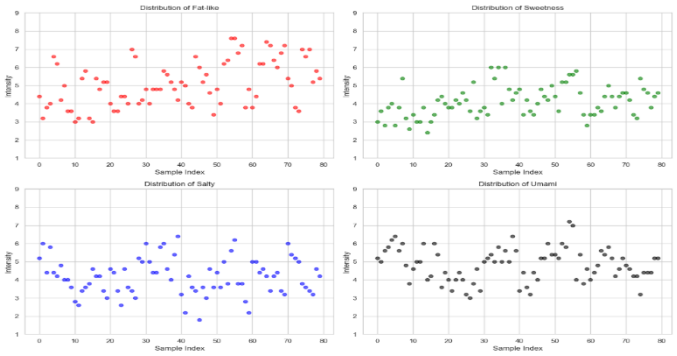


Figure 2. Scatter Plots of Sensory Attributes for Pork Samples

The binary classification of sensory attributes (on a 5.0 point scale) based on image segmentation was conducted using different machine learning models, including SVM, GBM, LR and RF. The best prediction models and their corresponding performance metrics are summarized in Table 1. For the fat-like attribute, the SVM model, using the 'V' feature from the entire image, achieved an F1 score for predictions ($F1_p$) of 0.676. For sweetness, the GBM model, using the features 'G', 'B', *'L', 'b'*, 'S' from the fat region, performed the best with an $F1_p$ of 0.771. In the case of saltiness, the RF model, utilizing the features 'G', 'B', *'L', 'a', 'b'*, 'S', 'V' from the fat region, achieved an $F1_p$ of 0.750. For umami, the RF model with the 'R', *'a'*, 'V' features from the entire image showed the lowest performance with an $F1_p$ of 0.686. The V (value) channel, which was commonly used across several models, may reflect differences in fat content through image brightness, suggesting that taste prediction could be partially influenced by fat-related visual cues [5]. In the 3-classification model (which divides the whole into thirds), sensory scores for each attribute were categorized into three levels: low, medium, and high based on their distribution. Machine learning models such as SVM, GBM, LR and RF were applied using color features extracted from different image regions (entire, muscle, and fat). Overall, the prediction performance was moderate, with $F1_p$ values of 0.508 for fat-like, 0.517 for sweetness, 0.508 for saltiness, and 0.523 for umami. Although the accuracy was not high, models utilizing the fat or entire image regions showed relatively better performance for certain attributes (data not shown).

for binary classification of sensory attributes (based on a 5-point scale) from image segmentation of entire and fat regions.

Attribute	Data set[a]	Model[b]	Parameters[c]				
			Selected Features	k Fold	Acc_{CV}	$F1_{CV}$	Acc_p	$F1_p$
Fat-like	Entire	SVM [c]	['V']	8	0.703	0.717	0.688	0.676
Sweetness	Entire	SVM	['R', 'G', 'B', 'L', 'a', 'b', 'H', 'S', 'V']	6	0.782	0.795	0.75	0.75
saltiness	Entire	SVM [c]	['R', 'G', 'B', 'L', 'a', 'b', 'H', 'S', 'V']	2	0.724	0.688	0.698	0.719
Umami	Entire	RF [d]	['R', 'a', 'V']	4	0.672	0.673	0.688	0.686

[a] Fat, fat region separated from the image; Entire, entire region separated from the image
[b] SVM, Support Vector Machine; GRM, Gradient Boost machine; RF, Random Forest
[c] Acc, Accuracy; F1, F1-Score; cv; cross-validation; p, predicted value

IV. CONCLUSION

In this study, machine learning models were developed to predict the sensory taste attributes of pork sweetness, saltiness, umami, and fat-like flavor using color features extracted from digital images. In the binary classification, most attributes achieved an F1-score above 0.67, demonstrating practical predictive performance. In particular, the GBM model using color features from the fat region showed the highest performance for predicting sweetness, with an F1p of 0.771, and the RF model achieved strong results for saltiness and umami, with F1p values of 0.750 and 0.686, respectively. The SVM model was effective in predicting fat-like flavor based on the 'V' channel from the entire image, with an F1p of 0.676. Although the overall performance of the three-class classification model was lower, certain attributes still showed meaningful prediction potential. These results suggest that with expanded data and further model optimization, multi-class quality classification could also be feasible. Overall, color information from the fat and entire regions was effective in predicting sensory attributes, and this study demonstrates the potential of a non-destructive, automated taste quality evaluation system for pork.

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