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Prediction of pork loin quality using online computer vision system and artificial intelligence model

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ABSTRACT

The objective of this project was to develop a computer vision system (CVS) for objective measurement of pork loin under industry speed requirement. Color images of pork loin samples were acquired using a CVS. Subjective color and marbling scores were determined according to the National Pork Board standards by a trained evaluator. Instrument color measurement and crude fat percentage were used as control measurements. Image features (18 color features; 1 marbling feature; 88 texture features) were extracted from whole pork loin color images. Artificial intelligence prediction model (support vector machine) was established for pork color and marbling quality grades. The results showed that CVS with support vector machine modeling reached the highest prediction accuracy of 92.5% for measured pork color score and 75.0% for measured pork marbling score. This research shows that the proposed artificial intelligence prediction model with CVS can provide an effective tool for predicting color and marbling in the pork industry at online speeds.

1. Introduction

Pork is currently the most consumed protein source globally (15.8 kg/capita/yr), followed by poultry (13.6 kg/capita/yr), beef (9.6 kg/capita/yr), and sheep and goat meat (1.9 kg/capita/yr) (FAOSTAT, 2014). Meat purchasing decisions are influenced more by product appearances, such as color and marbling, than any other quality factor (Font-i-Furnols, Tous, Esteve-Garcia, & Gispert, 2012). In 2016, Bachmeier et al. reported that the average for pork subjective color score is 2.85 ± 0.79 on a 6-point scale, with 3, 19, 45, 26, and 7% of samples being a color score 1, 2, 3, 4, and 5 respectively. The average for subjective marbling score (an estimate of intramuscular fat percentage) is 2.30 ± 1.07, with a distribution of 9, 47, 31, 10, and 3% for marbling scores 1, 2, 3, 4, and 5 or above, respectively. This shows that there is variation in pork quality in the retail market throughout the US.

Currently, pork color and marbling scores are determined by trained evaluators in the plant, which is subjective and lowly repeatable. It is also influenced by the condition of the evaluator, such as sickness or fatigue, or different environments, such as lighting or angle of viewing (Bohrer & Boler, 2017). In a laboratory environment, color and marbling can be assessed more objectively using a colorimeter, which can express color using L*, a*, and b*, and ether extract to determine the percentage of intramuscular fat (IMF). However, in 2013, Girolami, Napolitano, Faraone, and Brahier reported when regenerating a color by using the L*, a*, and b* values recorded by colorimeter, the color did not correspond to the true color of meat. Additionally, ether extract is a labor-intensive and time-consuming procedure, which requires an actual sample that could sabotage the integrity of and potentially de-value the product. This suggests that a new modern technology that is rapid, accurate, non-invasive, and highly repeatable could be beneficial for both research and industry.

The potential of using computer vision system (CVS) in the food industry has long been recognized (Timmermans, 1998). With recent advances in hardware and software, CVS has been allowed to become a technology even more cost-effective, more consistent, more rapid, and more accurate than ever before. A CVS is a system that is composed of three main elements: camera, lighting system, and image analysis software. A CVS allows for the capturing, processing, and analyzing of images, which enables the assessment of a desired target in an objective, non-destructive manner. This technology has been applied for numerous usages in the food industry such as classification of types of cereal grains (Paliwal, Visen, Jayas, & White, 2003), color grading for apples (Nakano, Kurata, Kaneko, Kazama, & Takizawa, 1992), and detection of bruises on strawberries (Nagata, Tallada, & Kobayashi, 2006). In the beef industry, CVS has been utilized to objectively measure features of beef quality such as marbling and yield percentage using the "beef cam" (Wyle et al., 1999). Research has shown the

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potential of CVS in predicting beef color (Larraín, Schaefer, & Reed, 2008), fat color (Chen, Sun, Qin, & Tang, 2010), tenderness (ElMasry, Sun, & Allen, 2012; Sun et al., 2012), and marbling (Chen et al., 2010). With CVS successfully applied in many different fields with different goals, it only seems reasonable to use this technology in the pork industry as well.

The objective of this study was to evaluate pork loin quality using online computer vision combined with artificial intelligence (AI) prediction model under industry requirement environment.

2. Materials and methods

2.1. Pork sample collection

Whole, boneless loins were obtained from seven different processing plants (n = 200 per plant). Each sample was selected by a trained evaluator from the deboning line. Samples were chosen to maximize the variation in pork quality for subjective color (SCS) and marbling (SMS) scores, which were assessed on-line according to National Pork Board standards (National Pork Board [NPB], 2011). After loins were selected, instrumental color (Hunter L*, a*, b*) assessed, and loins removed from the deboning line, an image of the lean surface of the loin was acquired using a CVS (Fig. 1), consisting of an industry camera (NI 1776C smart camera, National Instrument, Ltd., USA) with a 1/1.8" F1.6/4.4–11-mm lens (LMVZ4411, Kowa, Ltd., Japan), a 44-in. dome light (DL180, advance illumination, Ltd., USA), and a personal laptop (Lenovo, Ltd., China). The CVS was attached to a table to ease transportation of the dome light and to standardize the relationship of the camera to the dome light and the samples. A black, light-absorbent fabric was installed between the dome light and table to exclude light noise from the surrounding environment. Before each plant collection, a Minolta white tile was used for calibration. The white tile was placed in the center and corner of the CVS to ensure the evenness of light spread. When taking pictures of the white tile, red, green, and blue color space features were extracted and used as standards for calibration and setting of the CVS. Each sample was manually placed on a light-absorbing, black background surface for image acquisition. The color image was captured and stored using LabVIEW software (National Instrument, Ltd., TX).

After images were acquired, pork loins were vacuum packaged and transported in a refrigerated truck to the U.S. Meat Animal Research Center in Clay Center, NE. Loins were stored at 4 °C for 14 d. After 14 d, whole loins were cut into thirteen 2.54 cm thick chops. The 3rd and 10th rib chops were collected and images of each loin chop were taken using the same CVS as the whole loin. After imaging, chops were individually vacuumed packaged and transported to North Dakota State University for crude fat percentage (CF%) determination. After arrival at North Dakota State University, chops were trimmed of connective tissue and subcutaneous fat and freeze-dried for 48 h to remove moisture. After the freeze-drying period, CF% was determined gravimetrically using Soxhlet extraction with petroleum ether according to AOAC procedure (AOAC, 1990). This ether extracted value of CF% was used as the dependent value for establishing marbling prediction equations from loin images. The image IMF percentage (IMF%) was calculated by the CVS by distinguishing pixels associated with IMF from those associated with non-IMF image space. The average of the 3rd and 10th rib chops was used to represent the CF% of the entire loin.

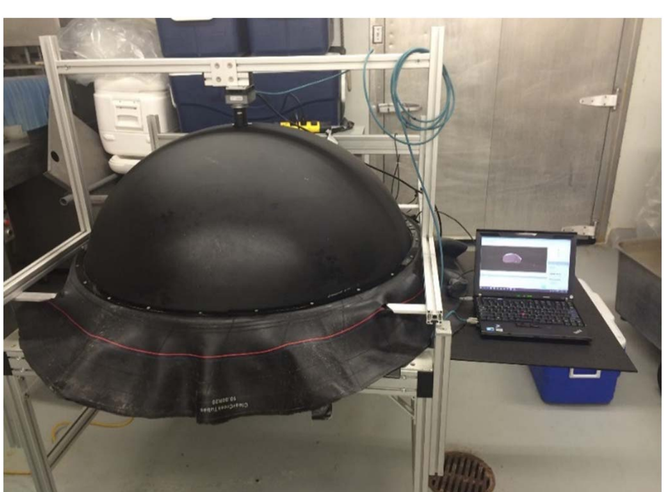

Fig. 1. Pork loin/chop computer vision acquisition system.

For pork loin quality assessment, tenderness was assessed at U.S. Meat Animal Research Center, utilizing chop numbers 5 and 6 that correspond approximately to the 11th rib region and following procedures previously established for slice shear force (SSF) on d 15 postmortem (Wheeler, Shackelford, & Koohmaraie, 2005). Chewiness, overall flavor, and juiciness were evaluated at Iowa State University on chop numbers 7 and 8 by trained panelists (Lonergan et al., 2007).

2.2. Image processing method

The boundaries of the original full loin (Fig. 2a) were first identified to allow for background segmentation (Fig. 2b). Next, a region of interest (ROI) was automatically selected for each loin to extract color and marbling features (green box in Fig. 2c).

Color image features were extracted from the ROI, including RGB (red, green, and blue), HSI (hue, saturation, and intensity), and L*a*b* (lightness, redness, and yellowness) color spaces. For each image, transformations from RGB color space to HSI and L*a*b* color spaces were performed. The mean (μ) and standard deviation (σ) of each color feature were calculated from the ROI for each pork loin sample.

For marbling feature extraction, the Sobel image processing method (Vincent & Folorunso, 2009) was used to recognize the marbling area within the pork loin ROI (Fig. 2d). The imaging system recognizes pixels within the ROI that are associated with IMF in the pork loin (Fig. 2e) and total IMF content is then expressed as a percentage of the total ROI area.

Images were next analyzed for texture features. Eighty-eight gray-level co-occurrence matrix (GLCM) image texture features were extracted according to Sun et al. (2012). These texture features were used by the image analysis software to predict quality parameters associated with loin texture (tenderness, juiciness, chewiness and overall flavor).

The ultimate product of the image analysis is an automatic calculation of quality (color and marbling scores) and palatability (tenderness, juiciness, and overall flavor) for each pork loin sample (Fig. 2f).

2.3. Data analysis

Pork loin eighteen color image features, image IMF feature, and eighty-eight texture image features were used as input indicators for pork quality prediction models.

Linear regression method was first performed for each pork plant and across all plants. For color prediction, objective hunter L* value was used as the dependent variable, the18 image color features and SCS were used as the independent variable (s) for comparison of AI and subjective evaluation methods. For marbling, CF% was used as the dependent variable, IMF% estimated using CVS and SMS were used as the independent variable for both AI and subjective models. For tenderness and sensory traits, the trait of interest was the dependent variable and image color, marbling, and texture features were used as the independent variables. Coefficients of determination (R^2) were calculated to compare the regression performance.

Artificial intelligence prediction model (support vector machine [SVM]) was used as a non-linear classification method to predict pork loin color and marbling scores which based on the Hunter L* value and CF% value (Cortes & Vapnik, 1995). For loin color, the measured color