Title: Prediction of pork quality using online computer vision system **#15-084**

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Industry Summary:
With the increasing demand of high quality of pork products from the global market the United States pork industry needs to seek new solutions for determining quality of pork products. In the current pork supply a great deal of variation exists when considering the eating quality of pork such as lean color, intramuscular fat, and tenderness. The technology validation we are proposing is a step forward in creating an accurate, rapid online tool that pork processors could use to sort, 'grade', or 'certify' product into categories or quality specifications for customers. This research invented an industry suitable online pork quality assessment system based on computer vision technology. The project results found by using our proposed computer system, pork loin color evaluation (coefficient of determination, R^2=0.90) was better than subjective evaluation (R^2=0.68), For pork marbling assessment, our computer vision system reached same evaluation level (R^2=0.62) as subjective assessment (R^2=0.63) method.

Keywords: Computer Vision, Image Processing, Online, Pork Loin, Quality

Scientific Abstract:
Currently pork color and marbling is assessed subjectively in the industry, because of the limited methods and tools that are suitable for the industry. In this project, we are devoted to developing a computer vision system for objective measurement of pork, which suits the industrial needs. Color images of pork loin samples were acquired using a Computer Vision System (CVS). Subjective color and marbling scores (SMS) were determined according to the National Pork Board standards (NPB, 2011) by a trained evaluator. Objective color measurement (Minolta Camera Co., Osaka, Japan) from colorimeter and crude fat percentage (CF%) according to ether extract method (AOAC, 1990) were used as control measurement. The results showed for pork loin color quality attribute, CVS reached the highest regression coefficient of determination (R^2) value to 0.90. For pork loin marbling attribute, the R^2 was reached highest value of 0.62 by using CVS. For tenderness, the CVS reached the regression R^2 to 0.89 highest. For pork juiciness, the CVS reached the regression R^2 to 0.92 highest.

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 appearance, such as color and marbling, than any other quality factor (Font-i-Furnols et al., 2012). In 2015, Newman 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. 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 et al. 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, which 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 et al., 2001), color grading for apples (Nakano et al., 1992), and detection of bruises on strawberries (Nagata et al., 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". Research has shown the potential of CVS in predicting beef color (Larraín et al., 2008), fat color, (Chen et al., 2010), tenderness (Sun et al., 2012; ElMasry 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.

Objectives:

1. Validate a novel tool to predict pork quality utilizing our vision method (Sun et al. 2012), which characterizes lean color and surface texture features, fat color and texture features, and marbling.
2. Establish a model to predict pork quality grading values using imaging software through correlation analysis between traditional objective and subjective pork quality measurements (pH, marbling, color, water holding capacity, tenderness (WBSF)) and image processing analysis.
3. Gather and correlate quality attributes from whole boneless pork loins of varying degree of quality to assess pork quality data. Quality data will be gathered by taking standard industry meat quality measurements and comparing them to imaging data from multiple locations on the whole loin. This includes longitudinal images of boneless loins and loin chops.
4. Use these data and tools created from this research to further quantify pork quality for research and industry use. These data will hopefully create a tool for future research on "whole carcass" quality with further implications for other pork primal cuts (hams, shoulder, and belly) and processed meats. Furthermore, we hope this will lead to future research where we can validate and establish time-points and locations for quality measurements during both slaughter and processing.

Materials & Methods:

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 (NPB) standards (NPB, 2011). After loins were selected and removed from the deboning line, an image of the lean surface of the loin was acquired using a Computer Vision System (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-inch 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, color space red green blue color features were extract 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 US 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 2.54 cm thick chops. The 3rd and 10th rib chops were collected, vacuumed packaged, and transported to North Dakota State University to determine crude fat percentage (CF%). After arrival at North Dakota State University, chops were trimmed of connective tissue and subcutaneous fat and then 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). The average of the 3rd and 10th rib chops were used to represent the CF% of the entire loin.

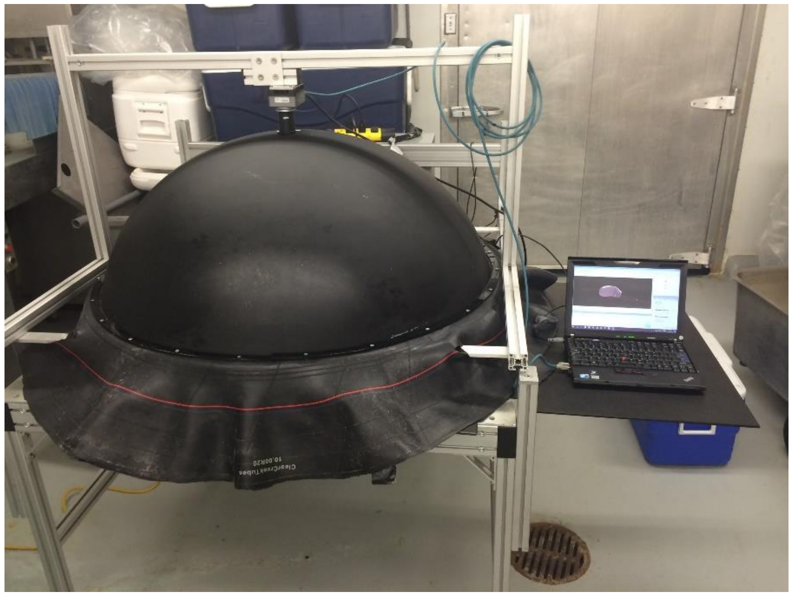


Figure 1. Pork Loin/Chop Computer Vision Acquisition System

IMAGE PROCESSING METHOD

***Pork loin picture processing method*.**

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

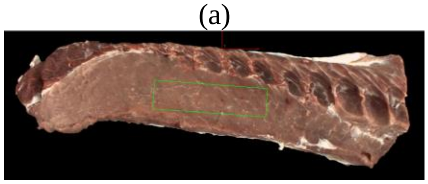
Color image features were extracted from the ROI, including, RGB (red, green and blue), HSI (hue, saturation, and intensity), and L*a*b* (lightness, redness, and yellowness) color spaces. For each image, transformations from RGB color space to HSI and L*a*b* color spaces were performed. The mean (μ) 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 and Folorunso 2009) was used to recognize the marbling area within the pork loin ROI (Figure 2d). The imaging system recognizes pixels within the ROI that are associated with intramuscular fat (IMF) in the pork loin (Figure 2e) and total IMF content is then expressed as a percentage of the total ROI area.

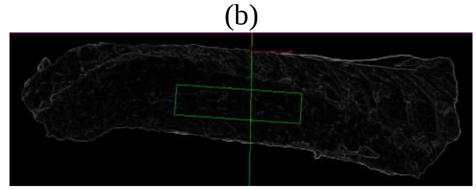
Images were next analyzed for textural features. Eighty-eight gray-level co-occurrence matrix (GLCM) image texture features were extracted according to Sun et al. (2012). These textural features were used by the image analysis software to predict quality parameters associated with loin texture (tenderness, juiciness, 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 (Figure 2f).

(a)

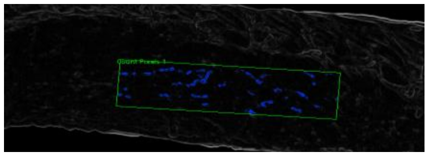
(b)



(c)



(d)



(e)

(f)

Figure 2. Pork Loin Color and Marbling Image Processing Procedure

(a) Original image; (b) Background segmentation; (c) Identification of the region of interest (ROI); (d) Image sobel transforming; (e) Identification of marbling pixel and percentage marbling; (f) Final output display.

Results:

ASSESSMENT OF FRESH PORK LOIN COLOR

Fresh pork loins were collected from the commercial processing table after approximately a 24 h chill and moved to a secure location for image acquisition. Hunter L* was obtained as a familiar pork quality measurement and was used as the dependent variable for the fresh pork loin color prediction model. Eighteen image color features were extracted from the loin images to be used as independent variables in linear regression. Likewise, subjective color scores were regressed on L* as a means of comparison with the electronically derived color score. Regression model results for electronically derived image color features are shown in Table 1 and subjective color score models in Table 2. These models are reported for each individual packing plant. From the result, we can see that the computer vision method achieved a most satisfactory regression coefficient of determination (R^2) for each plant pork loin samples with the highest R^2 reaching 0.90 and an overall R^2 of 0.64. On the other hand, fresh pork color prediction utilizing subjective color scores had a high R^2 of 0.61 and an overall value of 0.27.

These results indicate that the computer vision technology has the potential to replace the existing subjective color grading sorting method in the pork loin processing line.

Table 1 Linear Regression Model Result using Image Color Features for Color Attribute

Plant	r	R^2	Adjusted R^2	Standard Error
Plant 1	0.89[a]	0.80	0.78	1.40
Plant 2	0.95[a]	0.90	0.90	1.13
Plant 3	0.94[a]	0.88	0.87	1.24
Plant 4	0.91[a]	0.83	0.82	1.20
Plant 5	0.86[a]	0.73	0.71	1.78
Plant 6	0.93[a]	0.87	0.86	1.11
Plant 7	0.89[a]	0.78	0.77	1.32
Overall	0.80[a]	0.64	0.64	2.01

a. Predictors: (Constant), SDI, b*, a*, R, SDb*, SDH, SDa*, SDS, S, SDL*, H, SDR, L*

Table 2 Linear Regression Model Result using Subjective Scores for Color Attribute

Plant	r	R^2	Adjusted R^2	Standard Error
Plant 1	0.71[a]	0.51	0.51	2.12
Plant 2	0.78[a]	0.61	0.61	2.20
Plant 3	0.82[a]	0.68	0.00	3.37
Plant 4	0.73[a]	0.54	0.54	1.92
Plant 5	0.77[a]	0.59	0.59	2.11
Plant 6	0.69[a]	0.47	0.47	2.13
Plant 7	0.61[a]	0.37	0.37	2.16
Overall	0.52[a]	0.27	0.27	2.85

a. Predictors: (Constant), subjective color scores

ASSESSMENT OF FRESH PORK LOIN MARBLING

Each loin was processed into 2.54 cm thick pork chops; approximately 12 to 13 chops per loin. Numbering from the anterior (blade) end of the loin, chops 2 and 10 were removed, an approximate 5 x 5 cm square portion removed from the center of each chop, samples were labeled and packed together, frozen and stored for later ether extraction analysis to determine percentage of intramuscular fat (IMF%) for each loin. This ether extracted value of IMF% was used as the dependent value for establishing marbling prediction equations from loin images. As described above, IMF% was calculated by the CVS by distinguishing pixels associated with IMF from those associated with non-IMF image space. The CVS estimate was used as the independent variable in the equation as was subjective marbling scores as a means for comparison. Regression model results are shown in Table 3 for image marbling features and Table 4 for subjective scores. From these results we can see computer vision method achieved the highest R^2 which is 0.62 with the overall reaching 0.34. On the other hand, subjective score reached the same highest R^2 of 0.62 and overall value was 0.35. We recognize that both methods explain a low amount of the variation associated with marbling, however, some of this variability could be attributed to differences between IMF viewed on the cut lean surface of the loin regressed on IMF obtained by ether extraction of internal lean obtained from the anterior and posterior ends of the full loin. Also, much of the variation could be attributed to packing plant specific processing techniques. In other words, some plants removed loins from the back ribs with a greater amount of exposed lean on the loin while others had loins possessing more fat left on the loin piece. Fine-tuning this method of marbling analysis from the external images of whole loins is necessary as a means of assessing the IMF content of the pork chop. After all, the marbling in the pork chop is what the consumer sees when making a purchase decision at retail. These results indicate that the computer vision technology is at least as accurate as human subjective scoring. Perhaps more important is the image systems ability to predict actual palatability attributes as described in the next section of this report.

Table 3 Linear Regression Model Result using Image Marbling Features for Marbling Attribute

Plant	r	R^2	Adjusted R^2	Standard Error
Plant 1	0.69[a]	0.48	0.48	0.62
Plant 2	0.79[a]	0.62	0.62	0.60
Plant 3	0.60[a]	0.37	0.36	0.69
Plant 4	0.70[a]	0.52	0.51	0.65
Plant 5	0.34[a]	0.11	0.10	0.65
Plant 6	0.76[a]	0.58	0.58	0.49
Plant 7	0.79[a]	0.62	0.62	0.53
Overall	0.58[a]	0.34	0.34	0.71

a. Predictors: (Constant), Image Marbling

Table 4 Linear Regression Model Result using Subjective Marbling Scores for Marbling Attribute

Plant	r	R^2	Adjusted R^2	Standard Error
Plant 1	0.79[a]	0.62	0.62	0.65
Plant 2	0.72[a]	0.52	0.52	0.70
Plant 3	0.74[a]	0.55	0.54	0.59
Plant 4	0.77[a]	0.60	0.60	0.56
Plant 5	0.54[a]	0.29	0.29	0.56
Plant 6	0.79[a]	0.63	0.63	0.49
Plant 7	0.78[a]	0.61	0.60	0.53
Overall	0.59[a]	0.35	0.35	0.71

a. Predictors: (Constant), Subjective Marbling

ASSESSMENT OF FRESH PORK LOIN TENDERNESS

For pork tenderness, we used slice shear force (SSF) as the dependent variable for developing our prediction model. Image color, marbling and texture features were used as the independent variables. Regression model results were shown in Table 5. The image processing method performed very well across all packing plants with the highest R^2 reaching 0.89.

Table 5 Linear Regression Model Result using image color, marbling and texture features for Pork Tenderness Attribute

Plant	r	R^2	Adjusted R^2	Standard Error
Plant 1	0.91[a]	0.84	0.60	1.77
Plant 2	0.84[a]	0.71	0.34	2.44
Plant 3	0.90[a]	0.80	0.56	1.58
Plant 4	0.74[a]	0.54	-0.30	2.91
Plant 5	0.94[a]	0.89	0.22	2.07
Plant 6	0.79[a]	0.62	-0.09	2.44
Plant 7	0.88[a]	0.78	0.26	1.86

a. Predictors: (Constant), color, marbling, texture features

ASSESSMENT OF FRESH PORK LOIN FLAVOR, CHEWINESS, AND JUICINESS

For pork sensory attributes, flavor, chewiness, and juiciness were assessed by trained evaluators from Iowa State University. Image color, marbling feature and texture features were used as predictors (independent variables) and regressed on each sensory attributes. Flavor results are shown at Table 6 with the highest R^2 value reaching 0.96. For chewiness, the prediction model reached 0.87 R^2 value (Table 7) and for juiciness the R^2 reached to 0.92 (Table 8). These results suggest great potential for the prediction pork sensory attributes.

Table 6 Linear Regression Model Result using image color, marbling and texture features for Pork Flavor Attribute

Plant	r	R^2	Adjusted R^2	Standard Error
Plant 1	0.85[a]	0.72	0.31	0.82
Plant 2	0.73[a]	0.53	-0.06	1.04
Plant 3	0.87[a]	0.76	0.46	0.60
Plant 4	0.81[a]	0.66	0.02	0.89
Plant 5	0.98[a]	0.96	0.73	0.38
Plant 6	0.86[a]	0.73	0.23	0.49
Plant 7	0.86[a]	0.75	0.16	0.43

a. Predictors: (Constant), color, marbling, texture features

Table 7 Linear Regression Model Result using image color, marbling and texture features for Pork Chewiness Attribute

Plant	r	R^2	Adjusted R^2	Standard Error
Plant 1	0.91[a]	0.83	0.57	1.88
Plant 2	0.81[a]	0.65	0.22	2.68
Plant 3	0.86[a]	0.75	0.44	1.76
Plant 4	0.72[a]	0.52	-0.35	3.11
Plant 5	0.93[a]	0.87	0.05	2.46
Plant 6	0.75[a]	0.56	-0.27	2.88
Plant 7	0.88[a]	0.77	0.22	2.12

a. Predictors: (Constant), color, marbling, texture features

Table 8 Linear Regression Model Result using image color, marbling and texture features for Pork Juiciness Attribute

Plant	r	R^2	Adjusted R^2	Standard Error
Plant 1	0.89[a]	0.79	0.49	1.76
Plant 2	0.83[a]	0.69	0.30	2.12
Plant 3	0.88[a]	0.78	0.51	1.36
Plant 4	0.79[a]	0.63	-0.05	2.47
Plant 5	0.96[a]	0.92	0.43	1.67
Plant 6	0.88[a]	0.78	0.36	1.74
Plant 7	0.83[a]	0.68	-0.05	2.11

a. Predictors: (Constant), color, marbling, texture features

Discussion:

The studies conducted and presented in this dissertation have allowed for the opportunity to demonstrate the possibility of using computer vision system (CVS) as an objective measurement tool for predicting pork loin color and marbling quality attributes. Through our experiments, we have moved from a system that was laboratory based to a system that is industry friendly. When observing the surface of loin, it was noticed that there was a sizeable variation in color and marbling between the anterior and posterior ends of the loin. This, in conjunction with the online speed and the different standards of trimming between plants, could all potentially be factors that influenced CVS. Future research could focus on finding the most ideal anatomical sites that best correlate with the whole loin quality. Within the series of our study, the influence of pork marbling percentage and pork lean color has been established, this suggest that further research such as adding more loin surface features like textures features to increase model accuracy and robustness is needed. As a result, the possibility of using CVS as an objective measurement for color and marbling quality attributes in pork has been established. While in the past pork has always been more of a quantity over quality driven protein source, more and more research has proven the importance of pork quality which impacts consumers' willingness to purchase in meat and pork export quality demand. Therefore, further research is warranted and this will forever be an area to explore as the demand of pork quality continues to increase.

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