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Quality Assessment of Beef Using Computer Vision Technology

Abstract Imaging technique or computer vision technology has received huge attention as a rapid and non-destructive technique throughout the world for measuring quality attributes of agricultural products including meat and meat products. This study was conducted to test the ability of computer vision technology to predict the quality attributes of beef. Images were captured from *longissimus dorsi* muscle in beef at 24 hours post-mortem. Traits evaluated were color value (L*,a*,b*), pH, drip loss, cooking loss, dry matter, moisture, crude protein, fat, ash, Thiobarbituric acid reactive substance (TBARS), Peroxide value (POV), Free fatty acid (FFA), Total coliform count (TCC), Total viable count (TVC) and Total yeast-mould count (TYMC). Images were analyzed using the Matlab software (R2015a). Different reference values were determined by physicochemical, proximate, biochemical and microbiological test. All determination was done in triplicate and the mean value was reported. Data analysis was carried out using the programme Statgraphics Centurion XV.I. Calibration and validation model were fitted using the software Unscrambler X version 9.7. A higher correlation found in a* (r = 0.65) and moisture (r = 0.56) with 'a*' value obtained from image analysis and the highest calibration and prediction accuracy was found in Lightness (R^2_c = 0.73, R^2_p = 0.69) in beef. Results of this work show that computer vision technology may be a useful tool for predicting meat quality traits in the laboratory and meat processing industries.

Keywords beef quality, computer vision technology, correlation, calibration, validation

Introduction

Beef is a major source of essential amino acids needed in the human diet, and it attracts a premium price. Aside from being a source of protein, it is also a major source of other valuable

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nutrients such as vitamin, fat, and micronutrients, all of which are responsible for good human health. In recent years, meat quality has become a relevant topic for consumers concerning health and for meat industry stakeholders because it affects their profitability (Hocquette and Chatellier, 2011). Meat quality is usually defined by physical, chemical and biological attributes. With the current growing need for low production cost and high efficiency, the meat processing industry is facing several challenges, including maintenance of high-quality standards and assurance of food safety while avoiding liability issues. Meeting these challenges has become crucial in regards to grading beef for different markets. Traditionally, quality assessment of beef involves human visual inspection, in addition to chemical or biological determination experiments which are tedious, time-consuming, destructive and sometimes environmentally unfriendly. Meat processing companies and suppliers need accurate, fast, real-time, low-cost and non-chemical detection technologies to optimize quality assurance of meat to enable them to satisfy different market's needs, thereby raising their competitiveness and expanding their market share. Imaging methods have been recently applied successfully to visually assess the quality or to classify meat or food products on the processing line based on color, shape, size, surface texture features (Iqbal et al., 2010; Chmiel et al., 2011; Girolami et al., 2013; Jackman et al., 2011). Computer vision (CV) is one such method. It is a nondestructive, fast, cost-efficient, consistent and objective method for the inspection and assessment of food quality and safety in the processing line (Gümüş et al., 2011). It is an RGB color vision method that has achieved good results in the assessment of the external features of foodstuffs (Tan, 2004). CV has such advantages as being online, non-invasive and thus nonhazardous (Chmiel et al., 2016). As a rapid and non-destructive technique, imaging technique has received huge attention in recent times for measuring quality attributes of agricultural products including meat and meat products. Part of the reasons why

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computer vision has gained popularity in times includes the fact that it can obtain reliable and reproducible results (Yagiz et al., 2009). It is also able to replicable, hence, it can potentially replace human vision and perception of images in meat quality assessment and safety assurance. Furthermore, machine vision is capable of providing reliable descriptive data with human intervention, which speed up the overall evaluation or measurement processes. Finally, it is proved to be objective, effective, reliable, non-destructiverobust and capable of constant recording of food samples beingexamined and the effects of processing regimes which is suitable and important for further or subsequent analysis (Brosnan and Sun, 2004). The superiority of the imaging technique compared to traditional analysis methods is that they allow the display and overlay the distribution of the analyzed properties (Turgut et al., 2014). Computer vision system has been used for colour measurement in meat by Fatih et al., (2016). Researchers used computer vision technology for assessing water holding capacity in meat (Qiao et al., 2007; Monroy et al., 2010; ElMasry et al., 2011). Imaging analysis of images obtained from a digital camera is presently being used for assessing the external qualities of meat. However, these assumptions may be possible because one previous research reported that frozen breast meat with low water-holding capacity had more flat in shape during extended storage time (Lee et al., 2008). Direct measurements are inconvenient and time-consuming when used in the continuous processing of meat. Thus, image analysis with a digital camera may provide an alternative method for evaluating or predicting the quality attributes by determining the conformation parameters and surface appearance such as color, texture, bitonality etc. A number of high-performance techniques have been applied successfullyfor determining or predicting the quality characteristics of various meat and meat products, such as the hyperspectral imaging technique (Qiao et al., 2007; Iqbal et al., 2013), near-infrared (NIR) imaging (ElMasry et al., 2011), and

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nuclear magnetic resonance (NMR) (Bertram et al., 2001) have been used. However, these techniques require costly equipment, whereas image analysis using a digital camera is inexpensive. Although the machine vision has been originated during the dates back to the 1960s, it has not been introduced commercially in the food or processing industries until the 1990s. Machine vision has a distinct drawback such as its application during analysis of digital images, it is restricted to the identification and extraction of external image features or quality factors like color, size, and surface structure (Chmiel et al., 2011; Chmiel et al., 2012; Penman, 2001; Zhang et al., 2015). In consequence, it can not be used in chemometrics modeling in which chemical composition and internal quality characteristics of meat or samples under consideration (Peng and Dhakal, 2015).

Though the hypothesis of computer vision technology is related to conformation parameter of foodstuffs, an effort has been taken to find out the correlation between image value and chemical composition of beef through this experiment.

Materials and Methods

Sample preparation

Beef samples were collected from 45 carcasses between the 12^{th} and 13^{th} ribs (*longissimus dorsi* muscle) of young zebu bulls. All samples were collected from different abattoir at Mymensingh town, Bangladesh. The indigenous bulls were around two and a half years of age with a live weight ranges from 250 to 300 kg. Each steak was 2.5 cm thick and weight was around 130 gm. Samples were areal-packed and stored in the refrigerator for 24 hours at 4˚C as it takes at least 24 hours to convert muscle into meat. After 24 hours samples were removed from the refrigerator and then kept it in a tray for about 10-12 minutes to allow moisture to appear on

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beef surface. Then the surface of the samples were soaked gently with the help of blotting paper which subsequently used for better color value estimation.

Image acquisition

Image acquisition of the sample was performed with the help of imaging system (Computer Vision System, Figure 1) developed locally following the information reported by Iqbal et al, (2010) and Valous et al., (2009). The main components of the developed system are: an illumination source, a color digital camera (Canon IXUS, Model No. 190), and a computer-supported with an image acquisition software package (Matlab 2015a, The Mathworks, Inc, USA). Images of the samples were captured using the camera of imaging system and were stored in the computer for further processing. An image processing software (Matlab 2015a, The Mathworks, Inc, USA) was applied for image analysis.

Reference analysis

1. **Surface colour evaluation**

The surface colour of the samples were measured in terms of L* (lightness), a* (redness) and b* (blueness) values using a Chroma meter (CR-400, Konica Minolta, Japan) following the guidelines provided by CIE (Commission International de I'Eclairage) system (CIE,1976).

2. Physico-chemical analysis

(i) pH value recording: The pH value in beefwas measuredby meat pH meter (Model no. HI99163, Hanna Instruments, Inc, USA). The pH meter was adjusted with pH 7.01 buffer solution before the measurement. The electrodes were rinsed with cleaning solution after use.

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(ii) Drip Loss (DL) measurement: For DL measurement 30 g sample was hung with a wire and kept in an air tight plastic container for 24 hours. After 24 hours the sample was weighed and calculated the difference. It was expressed as percentage (%).

(iii) Cooking loss (CL) measurement: 30 g beef sample was taken in a poly bag and boiled it in water bath until the temperature rises to 71^0C in sample. Beef with 71^0C was taken out from the water bath and soaked it with tissue paper. Weight loss of the sample was measured during cooking beef. CL was calculated using following formula:

$$CL\% = \frac{\text{Wt. before cooking} - \text{Wt. after cooking}}{\text{Wt. before cooking}} \text{ x } 100$$

(iv) Proximate Analysis

Moisture, protein, fat, and ash was determined as per the Standard procedures of Associationof Official Analytical Chemists (AOAC, 2005).

3. Biochemical analysis

Three types of biochemical analysis were carried out in this study: (i) Thiobarbituric Acid Reactive Substance (TBARS), (ii) Free Fatty Acid (FFA) and (iii) Peroxide value (POV)measurement. Three types of analysis are discussed below:

(i) Thiobarbituric Acid Values (TBARS) measurement:

Lipid oxidation was assessed in triplicate using the 2-thiobarbituric acid (TBA) method described by Schmedes*et al* (1989). Samples (5 g) was blended with 25 mL of 20% trichloroacetic acid solution (200 g/L of tricholoroacetic acid in 135 mL/L phosphoric acid solution) in a homogenizer (IKA) for 30 seconds . The homogenized sample was filtered with Whatman filter paper number 1 and 2 mL of the filtrate was added to 2 mL of 0.02 M aqueous TBA solution (3 g/L) in a test tube. The test tube was incubated at 100^0 C for 30 minutes and cooled with tap water. The absorbance was measured at 532 nm using a UV-VIS

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spectrophotometer (UV-1200, Shimadzu, Japan). The TBA value was expressed as mg malonaldehyde per kilogram of sample.

(ii) Peroxide Value (POV) analysis (meq/kg):

Peroxide value (POV) was determined according to Sallam *et.al*. (2004). The sample (3 g) was weighed in a 250-mL glass stopper Erlenmeyer flask and heated in a water bath at 60^0 C for 3 min to melt the fat, then thoroughly agitate for 3 min with 30 mL acetic acid-chloroform solution (3:2 v/v) to dissolve the fat. The sample was filtered under vacuum through Whatman filter paper number 1 to remove meat particles. Saturated potassium iodide solution (0.5 mL) was added to filtrate and continue with addition of starch solution. The titration was allowed to run against standard solution of sodium thiosulfate (25/1).

The formula is expressed as:

$$\text{POV (meq/kg)} = \frac{S \times N}{W} \times 100$$

Where,

S is the volume of titration (mL),

N is the normality of sodium thiosulfate solution (n = 0.01) and

W is the sample weight (g).

Peroxide Value **(**POV) was expressed as milliequivalent peroxide per kilogram of sample.

(iii) Free Fatty Acid (%) analysis:

Free fatty acid value was determined according to Rukunudin *et al*. (1998). 5 g sample was dissolved with 30 mL chloroform using a homogenizer (IKA T25 digital Ultra-Turrax, Germany) at 10.000 rpm for 1 min. The sample was filtered under vacuum through Whatman filter paper number 1 to remove meat particles. After five drops of 1% ethanolic phenolphthalein was added

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as indicator to filtrate, the solution was titrated with 0.01N ethanolic potassium hydroxide. The formula is expressed as:

$$\text{FFA (\%)} = \frac{\text{Titrate required (ml)} \times \text{Normality of KOH} \times 28.2}{\text{Sample weight (g)}}$$

4. Microbiological analysis

Microbiological analysis was determined by Ikhlas *et al.* (2012). The procedures which were followed for microbial assessment of total viable count, total coliform count and total yeast-mould count, are described below:

(i) Enumeration of total viable count (TVC):

For the determination of total bacterial counts, 0.1 ml of each ten-fold dilution was transferred and spread on triplicate PCA agar using a sterile pipette for each dilution. The diluted samples were spread as quickly as possible on the surface of the plate with a sterile glass spreader. One sterile spreader was used for each plate. The plates were then kept in an incubator at 35℃ for 24-48 hours. After incubation, 30-300 colonies were counted with the aid of a colony counter. The average number of colonies in a particular dilution was multiplied by the dilution factor to obtain the total viable count. The results of the total bacterial count expressed as the number of organism of colony forming units per gram (CFU/g) of sample.

(ii) Enumeration of total coliform count (TCC):

For the determination of total coliform counts, 0.1 ml of each ten-fold dilution was transferred and spread on triplicate MA agar using a sterile pipette for each dilution. The diluted samples were spread as quickly as possible on the surface of the plate with a sterile glass spreader. One sterile spreader was used for each plate. The plates were then kept in an incubator at 35℃ for 24-48 hours. After incubation, 30-300 colonies were counted with the aid of a colony counter. The average number of colonies in a particular dilution was multiplied by the dilution factor to obtain

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188 the total coliform count. The results of the total bacterial count expressed as the number of
189 organism of colony forming units per gram (CFU/g) of sample.

190 **(iii) Enumeration of Yeast-Mould count (TYMC):**

191 For the determination of yeast and mould counts, 0.1 ml of each ten-fold dilution was transferred
192 and spread on triplicate PDA agar using a sterile pipette for each dilution. The diluted samples
193 were spread as quickly as possible on the surface of the plate with a sterile glass spreader. One
194 sterile spreader was used for each plate. The plates were then kept in an incubator at 25℃ for 48-
195 72 hours. After incubation, 30-300 colonies werecounted with the aid of a colony counter. The
196 average number of colonies in a particular dilution was multiplied by the dilution factor to obtain
197 the yeast and mould count. The results of the yeast and mould count were expressed as the
198 number of organism of colony forming units per gram (CFU/g) of sample.

199 **Statistical analysis**

200 Descriptive statistical analysis and Pearson correlations between the image data and reference
201 data were both determined using the statistical package, Statgraphics Centurion XV.I.
202 STATPOINT TECHNOLOGIES, INC. Warrenton, Virginia, USA with a significance level of
203 $P<.05$. The calibration and validation model were fitted using the software Unscrambler X
204 version 9.7.

205 **Results and Discussion**

206 **Color value estimation**

207 Color measurement is more important for the visual impression of the meat than an actual
208 quality parameter. Color is usually measured in the CIE lab L*a*b* scale where L* denotes the
209 brightness, a* the redness and b* the yellowness. The color values obtained from image analysis
210 in beef were 50.75±3.43, 13.08±6.96, 13.66±2.33 for L*, a*, b* respectively (Table 1). The L*,

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a*, b* values from direct measurement using colorimeter were 41.67±4.08, 14.35±2.1 and 10.44±1.89 respectively and shown in Table 1. Where Fatih et al. (2016) found 48.90, 24.21 and 12.31 for L*,a*,b* respectively from image analysis and 46.73±1.01, 21.94±1.24 and 13.11±1.00 for L*,a*,b* respectively from direct measurement and Kamruzzaman et al.(2016) stated L*, a*, b* values for beef were 47.25±5.19, 15.81±2.25 and 7.56±3.29 respectively. The L* and a* values obtained from colorimeter by Weglarz (2010) were 37.40 ±1.38 and 13.44±2.07 respectively that are almost similar to the findings of the present study.

Physicochemical properties

The descriptive statistic of pH, drip loss and cooking loss are shown in Table 1. Measurements of pH have proven to be an important analytical measurement. Muscle pH is the key to the conversion of muscle to meat. During the early post-mortem changes in muscles of slaughtered animals, the pH falls from around 7.0-7.2 in the muscle of a living animal to 5.5-5.8. The pH value found in the LD muscle was 5.9±0.12 which is close to the findings of Weglarz (2010) and Rahman et al., (2015). The loss of fluid from meat is important for the industry because of its economic implication. Drip loss and cooking loss obtained from the samples were 3.2±0.6 and 29.01±1.96, respectively. The results obtained by De Marchi et al., *(*2007) for drip loss and cooking loss as 3.87±1.72 and 23.8±3.55, respectively which are very close to the present study.

Proximate components

Dry matter, moisture, crude protein, fat and ash content of the sample has been shown in Table 1. The values were 24.79±2.26, 75.21±2.27, 20.88±2.69,1.57±0.63, 1.28±0.21 for dry matter, moisture, crude protein, fat, and ash, respectively. These findings are in close agreement with those reported by De Marchi et al., *(*2007).

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Biochemical properties

The oxidative stability of beef depends upon the balance of anti and pro-oxidants and the composition of these oxidation substrates (Bertelsen et al., 2000). Average TBARS, peroxide and free fatty acid value of beef *longissimus dorsi* were found 0.11±0.01, 1.85±0.35 and 0.04±0.01 respectively (Table 1) where researchers found almost same values in fresh beef from hind limb of bull (Rahman et al., 2000). The biochemical traits measured in this experiment were lower than the limit (TBARS:<0.6 mgMDA/kg, POV:<6 meq/kg and FFA<1.2) for rancidity.

Microbiological analysis

Microbiological traits measured by the laboratory method are presented in Table 1. The average values with standard deviations were 5.09±0.05, 5.91±0.07 and 7.7±0.08 for TCC, TYMC, and TVC respectively. The TVC level of this study was in close agreement with the findings of Saba et al., (2018) but the TCC and TYMC value were higher than results of Murshed et al., (2016), Afrin et al., (2017) and Alam et al., (2017). The possible cause of this variation in microbial load might be due to the differences in the aging period.

Correlation between computer vision technology and conventional analytical technology

Correlation between image data and reference data of beef *longissimus dorsi* is presented in Table 2. The L* value from image analysis had medium correlation with L*(0.46), pH (0.41), DL% (0.37), DM (0.31), CP (0.24) and Ash (0.25) obtained from laboratory method. A higher correlation found in a*(0.65) and moisture (0.56) with 'a*' value obtained from imaging technique. The 'b' value resulted from image analysis had a medium correlation with fat (0.33) and TVC (0.37) whereas Mello et al., (2015) measured intramuscular fat and Luo et al., (2018) determined marbling in beef using image processing. The imaging technique, computer vision system was very similar that were used for both the previous works and present study.

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Prediction of beef longissimus dorsi quality traits

It is known that the coefficient of determination (R^2) indicates the accuracy of model, varying from 0 to1. Table 3 presents the results of calibration and prediction of color, pH, drip loss, dry matter, crude protein, peroxide value and ash content of the meat samples using image data. The calibration coefficients, R^2 range from 0.21-0.73 and the range of prediction data R^2 is 0.01-0.69. The root mean square error for calibration and prediction are general low, less than 2.4. Lightness, L* has the most association with the image data in both calibration and prediction analyses. ElMasry et al.,(2012) predicted L* and pH values with coefficients of determination (R^2) of 0.88 and 0.73 and root mean square errors estimated by cross validation (RMSECV) of 1.21 and 0.06 respectively in beef. Chmiel et al., (2011) used computer image analysis to detect PSE defects in pork meat.They found higher values of L* (56.01±1.62) in PSE meat compared with normal meat (48.44±0.52). From image analysis they found significantly higher values of R, G, B components for PSE meat compared with normal meat. Sun et al. (2016) applied computer vision method for assessing the color score in pork meat. They found very significant correlation ($p<0.0001$) between L*,a*and b* features of images and Minolta colorimeter 0.91,0.80 and 0.66 respectively.They assessed the coefficient of determination (R^2) for predicted pork color features was 0.83. The coefficient of determination was found 0.85 for CD large in IMF feature of longissimus dorsi muscle in beef using an image processing algorithm by Du et al. (2008).

Conclusion

The study aimed at assessing the ability of the computer vision system to predicts beef quality traits. Samples were analyzed for color, physicochemical, proximate, biochemical and microbiological values by conventional analytical techniques. Computer vision technology has been standardized. After the standardization correlation coefficient was determined between

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image data and reference data. The calibration model and validation model was applied to find the level of accuracy of the computer vision technology. The highest calibration and prediction accuracy was found for colour Lightness (L*), medium accuracy was found in the redness (a*), pH, drip loss, crude protein and ash content of the sample. However, more samples and trials are to be conducted in future for the development of robust models and getting higher predicting values of the studied parameters.

Conflicts of Interest

The authors declare no potential conflict of interest.

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Author Contributions

Md. Faizur Rahman**:** Data curation, Investigation, Writing- Original draft preparation. Abdullah Iqbal: Conceptualization, Methodology, Software Data curation. Md. Abul Hashem: Supervision, Fund Acquisition, Visualization, Investigation, Writing- Review and Editing. Akinbode A. Adedeji: Writing- Reviewing and Editing.

Ethic Approval

This article does not contain any studies with human participants or animals performed by any of the authors. Meat samples were collected from the slaughterhouse.

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411 **Table 1**

412 Range, mean, standard deviation (SD) and coefficient of variation (CV) of beef *Longissimus*

413 *dorsi* muscle quality traits

Attribute	n	Range	Mean	SD	CV%
L^*_{image}	45	38.37-56.18	50.75	3.43	6.76
a^*_{image}	45	1.57-23.26	13.08	6.96	53.19
b^*_{image}	45	6.71-18.09	13.66	2.33	17.08
L*	45	37.18-49.72	41.67	4.08	9.79
a*	45	10.48-17.71	14.35	2.1	14.65
b*	45	8.14-15.24	10.44	1.89	18.08
pH	45	5.8-6.1	5.9	0.12	2.08
DL%	45	2.37-4.73	3.2	0.6	18.6
CL%	45	24.8-31.9	29.01	1.96	6.75
DM%	45	21.22-28.98	24.79	2.26	9.12
Moisture%	45	71.02-78.98	75.21	2.27	3.02
CP%	45	17.5-26.35	20.88	2.69	12.87
EE%	45	0.72-3.5	1.57	0.63	40.05
Ash%	45	0.88-1.67	1.28	0.21	16.1
TBARS	45	0.09-0.13	0.11	0.01	9.21
POV	45	0.99-2.65	1.85	0.35	18.8
FFA	45	0.02-0.06	0.04	0.01	26.37
TCC	45	4.93-5.16	5.09	0.05	0.98
TYMC	45	5.71-6.01	5.91	0.07	1.26
TVC	45	7.48-7.87	7.7	0.08	1.09

414 L*image, L*value from imaging analysis; a*image, a* value from image analysis; b*image, b*
415 value from imaging analysis; n, sample size; SD, standard deviation; CV, co-efficient of
416 variation; DL, drip loss; CL, cooking loss; DM, dry matter; CP, crude protein; EE, ether extract;

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417 TBARS, thiobarbituric acid reactive substance; POV, per-oxide value; FFA, free fatty acid; TCC,
418 total coliform count; TYMC, total east-mould count; TVC, total viable count.

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Table 2

Pearson correlation coefficients between image data and reference data for quality attributes ofbeef *longissimusdorsi* muscle

	L^*_{image}	a^*_{image}	b^*_{image}
L*	0.46***	-0.86***	0.05
a*	-0.24	0.65***	0.1
b*	0.05	0.29	-0.1
pH	0.41**	-0.75***	0.21
DL%	0.37**	-0.78***	0.29
CL%	-0.1	0.26	-0.04
DM	0.31*	-0.56***	0.28
Moisture	-0.31*	0.56***	-0.28
CP	0.24	-0.69***	0.16
EE	0.08	-0.17	0.33*
Ash	0.25	-0.72***	-0.03
TBARS	0.01	-0.21	-0.15
POV	0.1	-0.43**	0.03
FFA	-0.06	0.11	-0.21
TCC	-0.1	0.14	-0.05
TYMC	-0.16	0.23	0.16
TVC	-0.05	-0.1	0.37**

L*image, L*value from image analysis; a*image, a* value from image analysis; b*image, b* value from imaging analysis;DL, drip loss; CL, cooking loss; DM, dry matter; CP, crude protein; EE, ether extract; TBARS, thiobarbituric acid reactive substance; POV, per-oxide value; FFA, free fatty acid; TCC, total coliform count; TYMC, total east-mould count; TVC, total viable count *p<0.05, **p<0.01, ***p<0.001.

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Table 3

Best fitting predictions of ten quality traits on beef *longissimus dorsi* using image technology

Variable	n	R^2_C	$RMSE_C$	R^2_P	$RMSE_P$
L*	45	0.73	2.09	0.69	2.23
a*	45	0.47	1.52	0.34	1.69
b*	40	0.21	2.02	0.01	2.36
pH	45	0.59	0.07	0.52	0.08
DL	45	0.67	0.34	0.6	0.37
DM	45	0.37	1.77	0.26	1.93
Moisture	45	0.37	1.77	0.26	1.93
CP	45	0.53	1.83	0.43	2.00
Ash	45	0.56	0.14	0.45	0.15
POV	45	0.22	0.3	0.06	0.33

DL, drip loss; DM, dry matter; CP, crude protein; POV, per-oxide value; n, number of samples; R^2_C, coefficient of determination of calibration; $RMSE_C$, root mean square error of calibration; R^2_P, coefficient of determination of prediction; $RMSE_P$, root mean square error of prediction.

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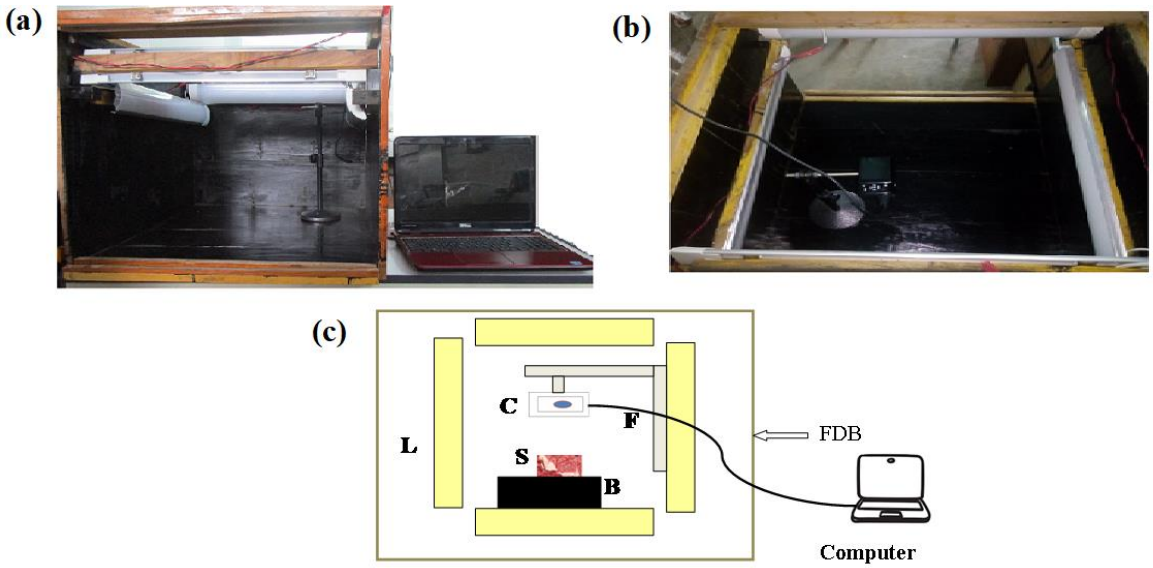

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437 **Figure 1. Computer vision system developed in the Laboratory: (a) Front view; (b) Top**
438 **view and (c) Schematic diagram with its components: L= Light sources, C=Camera,**
439 **S=Sample, B= Black background, F= Attachment for Camera, FBD= Frame with dark box.**

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