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Characterization of Tea (*Camellia sinensis*) Granules for Quality Grading Using Computer Vision System

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Characterization of tea (*Camellia sinensis*) granules for quality grading using computer vision system

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ABSTRACT

Tea (*Camellia sinensis*) has been found as an important medicinal beverage for human which is consumed all over the world. Primarily, the majority of tea is being cultivated in Asia and Africa, however it is commercially produced by more than 60 countries. Though substantial amount is produced, its processing system is still underdeveloped which leads to decrease in export opportunity as well as low monetary value. Moreover, the traditional method of tea grading and sorting is laborious, inefficient, and costly which ultimately produces the low-quality heterogeneous products. Processing and grading of tea granules after drying is very important task for maintaining quality. Computer vision (CV) applications in processing unit especially in grading and sorting of agro-products is very popular and reliable option to improve quality of produce. In this study, an attempt was taken to develop a machine vision system for quality grading of tea granules based on physical parameters of four standard tea grades namely BOP, GBOP, CD and PF. An image acquisition system with suitable illumination arrangement was developed to obtain high resolution image of tea granules. The images were analyzed to extract physical features like projected area, circularity, roundness, ferret diameter, aspect ratio and solidity. Tea granules (BOP, CD, PF and GBOP grade) were found significantly different for the textural features area, perimeter, circularity, roundness and ferret diameter. Projected area, perimeter, and feret diameter treated as a good indicator of the extracted features as the system has been able to significantly ($p < 0.01$) differentiate among the grade of tea. The developed characterization attributes based on physical features prior to an automatic sorting technology will improve the efficiency and enhance the cost-effectiveness which ultimately led to energize the international export market.

1. Introduction

Tea (*Camellia sinensis)*is the most popular beverage crop consumed all over the world which was first originated in East Asia and it is the second-largest crop that is being used to export after ensuring the local demand of Bangladesh [1]. After water, it is the most extensively consumed drink which is found beneficial to human health [2] and help to prevent cardiovascular diseases e.g. controls blood pressure, Alzheimer's diseases, breast cancer etc. [3]. On average 81,850 tons of tea is being produced in 53,856 ha of land under 166 tea estates across the country especially in the hill tracks region which is about 3% of global tea demand and ensures 12th place among largest tea producing countries all over the world. At least 4 million people are related to this sector for their livelihood and more than 75% of them are women. About 1% of the total GDP (Gross Domestic Product) in Bangladesh is earned from this sector.

However, tea production systems in least developed countries faces several problems for many years which causes failure to export projected amount of tea and acquire fair price. Absence of homogeneity in size and shape, presence of unwanted dust, and inaccurate color and texture of tea granules cause the fall of price in the global market. As the quality of tea defines its price, tea grading and sorting is the most important task among the post-harvest activity which have direct relation to the tea quality. To categorize tea granules, different wet chemical methods, computer vision, hyperspectral imaging are used widely in top tea producing countries but we are still in an antique sieve grading approach

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Table 1
Different tea grades.

Sl No.	Short name	Full name (Industry)	Identifiable characteristics
1.	BOP	Broken Orange Pekoe	• Main broken pieces of leaf
2.	GBOP	Golden Broken Orange Pekoe	• Second grade tea with uneven leaves and few tips.
3.	CD	Choramoni Dust	• Much finer than fannings, made of tea particles • Packed into teabags
4.	PF	Pekoe Fannings	• Fannings are finely broken pieces of tea leaf • Used in most tea bags

[4,5]. Moreover, mechanical grading method where the major physical quality attributes of tea (e.g. color, grain shape and size) are considered is inefficient, costly and inconsistent [6]. Therefore, to overcome such problems, computer vision (CV) techniques can be thought as an efficient alternative technique to support the conventional techniques. CV became a promising technique among other existing technologies in post-harvest processing, ensures efficient results, superior speed, and makes it consistent and cost-effective [7–9]. Besides, CV imparts an advantage in image analysis to classify or detect images based on the variance of spatial information of images like color or intensity [10]. However, Effective feature extraction is necessary to analyze and classify physical and textural features into different objects like tea granules [11]. Lopes et al. [12] proposed computer vision combined with Spatial Pyramid Partition ensemble (SPPe) technique to distinguish between naked and malting types of flours variety using image features and machine learning techniques.

For sorting and grading of tea, visual inspection technique is widely used by tea tasters for quality evaluation of black tea. Traditionally, the assessment of tea quality is carried out by highly trained people using an organoleptic method. However, this method requires good physical and psychological health conditions as it relies on the sensitivity of their taste and flavor sensory. That involves with physical verification based upon shape and size of the granules which in turn define the textural features which has significant relationship to the taste and organoleptic properties of tea. According to Ref. [13], by developing a quasi-steady-state model, initial dissolution rate was obtained and the result showed that at 80 °C the infusion rate of the 0.33 mm granules was found to be 98% of the dissolution rate as compared to 68% in case of 1.99 mm granules.

Various CV based techniques for characterization of tea has been developed by many researchers from past decade such as color and texture analysis, geometric and statistical approach but each method has its own advantages and shortcomings. For example, Laddi et al. [14], developed a non-destructive quick characterization technique based on textural features of tea granules based on image analysis where they analyzed five different features. Gill et al. [6], reported that, textural features based on gray tone spatial dependencies are used to discriminate four different tea grades where the multi-layer perception technique was incorporated for data classification and 82.33% accuracy was achieved. Oliveira et al. [15], classified cocoa beans into four grades of fermentation with 93% accuracy. Borah et al. [11], proposed a Wavelet Texture Analysis (WTA) based texture feature estimation technique to discriminate eight different grades of tea images considering range of different groups of images of the same granule size. Additionally, statistical texture features, namely variance, entropy and energy were analyzed. Textural analysis of tea granules requires machine vision setup consisting of digital color camera and suitable illumination which is universally acceptable technique used to measure physical properties of objects. Therefore, as an important aspect, suitable illumination often overlooked by researchers as it increases the accuracy of results.

Non-destructive post-harvest processing technology combined with CV and image processing capabilities is almost new concept in industrial crops processing in least developing countries and there is a tremendous opportunity for academic, collaborative, and interdisciplinary research in this area. Some tea industries are rising very rapidly but inadequate post-harvest processing is now major constrain for export business. To address this issue, developing a tea characterization technique based on physical features prior to an automatic sorting technology will improve the efficiency and enhance the cost-effectiveness. It is necessary to develop an analytical method for quality determination that can be done rapidly, non-destructively, and reliably. Moreover, tea industries will be benefited by accepting the technology to ensure the tea quality into export market. The aim of this study is to develop a computer vision system for estimating physical parameters of different tea grades as well as to classify tea granules into different grades based on their features prior to develop an automated sorting system.

2. Material and methods

2.1. Sample collection

The parameters used in determining the quality of tea include: (1) particle size, (2) density, (3) appearance, (4) liquor, and (5) infusion. The first and second aspects can be examined easily using standard and simple equipment. However, aspects 3–5 are usually measured by using human senses that may be strongly influenced by the physical, physiological, and environmental conditions of the taster panels. When any one of these conditions is not satisfied then the determination may be inaccurate. The highest grades for Western and South Asian teas are referred to as “orange pekoe”, and the lowest as “fannings” or “dust”. For this project the following Table-1 represents the tea samples, were selected which very popular and well-known grades in the export market.

Black cut-twisted-curled (CTC) tea samples having four different quality grades namely BOP, GBOP, CD, PF were collected twice from tea processing units from Siraj Nagar Tea Estate, Moulovibazar, and Duncan Brothers Bangladesh Limited, Sylhet which is situated in North-Eastern region of Bangladesh (24° 33′ 30″N, 91° 57′ 37″E) during November 2019. As the processing units sorts their product after drying with vibratory sieving method. Total 24 samples were collected randomly, and each sample has 100g of weight. To avoid any quality deterioration from moisture, these samples were filled in vacuum package and kept cool and dry place for 14 days.

2.2. Machine vision setup

As shown in Fig. 1., the machine vision setup consists of digital color camera: F mount digital single-lens reflex (DSLR) Nikon D5300 (Nikon Corporation, Japan) which has 24.1 MP DX format CMOS sensor without Optical Low Pass Filter (OLPF). A computer (Intel® Core™ i5-9400 CPU@2.90 GHz, 64–bit operating system, x64-based processor) was used to control and capture images from camera sensor by using USB 2.00 interface. A black coated cubic shaped aluminum frame ($Dimension: \ 24in \times 24in \times 24in$)was fabricated for image acquisition. Suitable illumination was supplied inside the structure and the camera was kept in a center point of another moveable steel body which was assembled with the middle point of the structure for capturing images. Additionally, black Poly aster cloth was used to cover the frame to eliminate the entrance of outside light thus it can reduce halation in captured images. A moveable stand was fixed to support the camera to impede the movement & swerving. It provides the stability and reduces camera shake as well as maintains a constant position to resist the lateral forces. Therefore, the structure also supports to achieve sharper images with a proper accuracy. Moreover, this controlled environment allows for acquiring images without minimum interference.

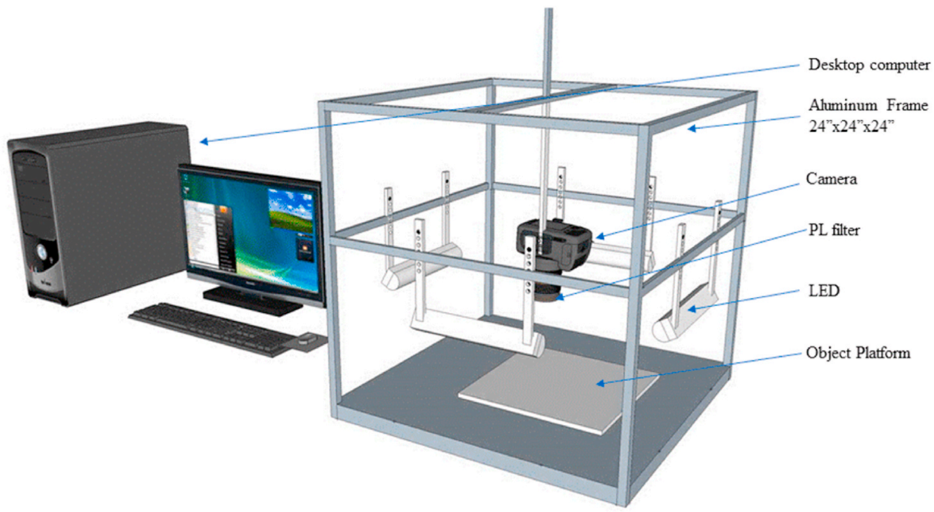

Fig. 1. Machine Vision unit for image acquisition of tea granule.

Table 2
Adjusted camera parameters for the image acquisition.

Camera parameter	Value
Shutter speed	1/800
Aperture	4.2
ISO	200
Iris position	Full position
Gain	900 dB
Gamma	100

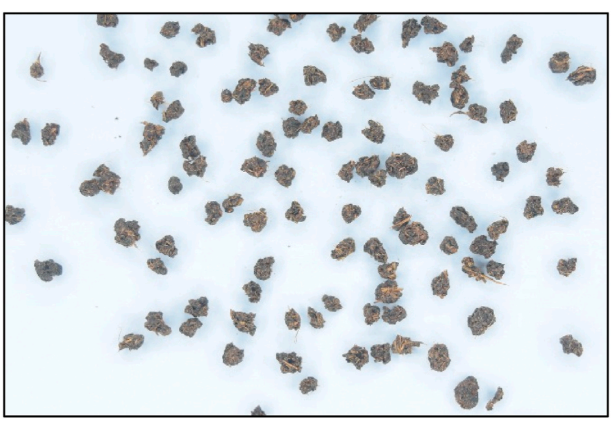

Fig. 2. 24-bit RGB color image captured by image acquisition system.

2.3. Lighting arrangement

Four eco-friendly white LEDs (50hz, Energypack, China) 20W each have been used for illuminating (50 lumens/watt) objects the inside of the structure. In this study, LEDs were used instead of fluorescent or incandescent lamps to avoid halation over the object surface [16]. Those LEDs were installed in four sides at a height of 12*in* inside the structure. To allow constant light intensity, 250V was supplied and connected with a parallel circuit (0.75 mm diameter with 6A capacity) during image acquisition. A regulator (Philips, China) was used to regulate the current flow through the LEDs allows us to adjust the illumination inside the control environment.

2.4. Image acquisition and processing

The first and fundamental step of computer vision system is the image acquisition. It defines the conversion of an object to digital encoded representation of visual and spectral characteristics of the object. In this study, the camera was connected to the desktop computer using USB 2.0 interface. Image acquisition and driver software (digicamControl, Ver. 2.1.2.0, Germany) was installed on the computer. Some trial images were captured prior to final image acquisition to check image quality thus helps to adjust the camera parameters. First, a white paper was kept under the camera and the captured images were analyzed until the RGB value of the image region is become in a range of 230–250. During image acquisition, optimum illumination was allowed, and it was done into an almost dark room. Furthermore, the black cloth was kept fully enclosed to avoid entrance of outside lights. After adjusting camera parameters on a trial and error, the best captured images were saved as in bitmap (BMP) format for processing.

After adjusting different camera parameters, the object (tea granules) was kept on a white paper for final image acquisition. Adjusted suitable camera parameter was shown in Table 2. During this time, the camera lens height was 220 mm over the object surface. Twelve images (24-bit RGB color image) were captured (4 grades of tea granules for three times randomly selected) where the granules were kept such a way that each granule can be identical thus helps to extract physical and textural features during processing of images. Additionally, an image of steel ruler was also captured to determine field size and resolution and the field of view was determined $143mm \times 95mm$. For the measurements, we divide the measured pixels by the pixels/mm. The pixels/mm is fixed throughout this study. Finally, those images were (Fig. 2.) saved as in BMP format into the computer memory.

For post-processing of resulting images of tea granules, the image processing software WinROOF 18 (Ver.4.4.0, Mitani Corporation, Japan) was used into Windows 10 operating system (© 2019 Microsoft corporation). Firstly, those images were loaded into WinROOF for morphological operations e.g., erosion, dialation, hole filling to overcome noise and errors. Then the images were converted into 8-bit gray level image. After then the image segmentation was done by thresholding which leads to search for adjacent pixels which have similar properties and within the ranges of defined threshold values. Region based 2 color threshold binarization was done to each image where the suitable threshold value (T) was found 42–162 as shown in Fig. 3. The binary images were then loaded into ImageJ Ver. 1.8.0 (Open-source Java based image processing program) software. From image features option under image measure was selected for obtaining the image pixel

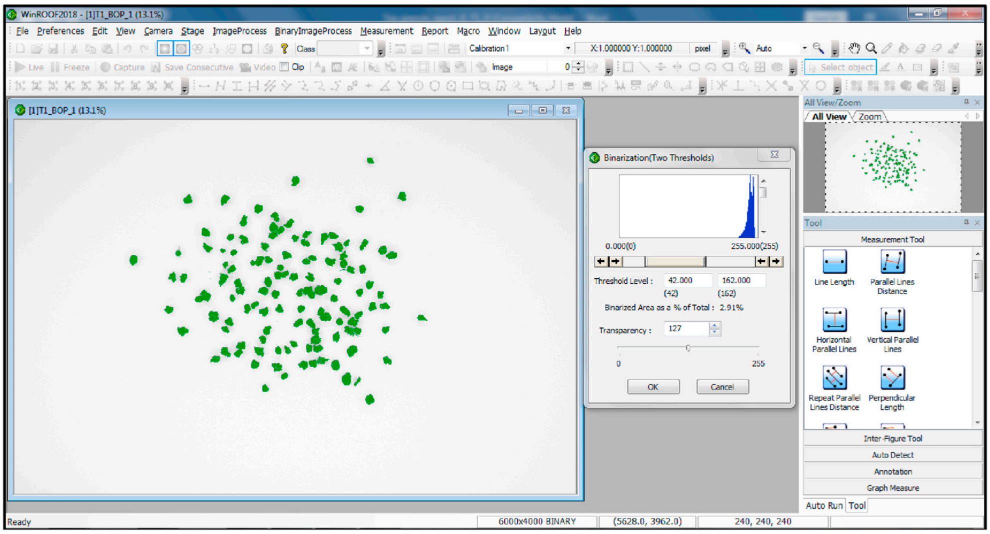

Fig. 3. Color binarization process in WinROOF software interface.

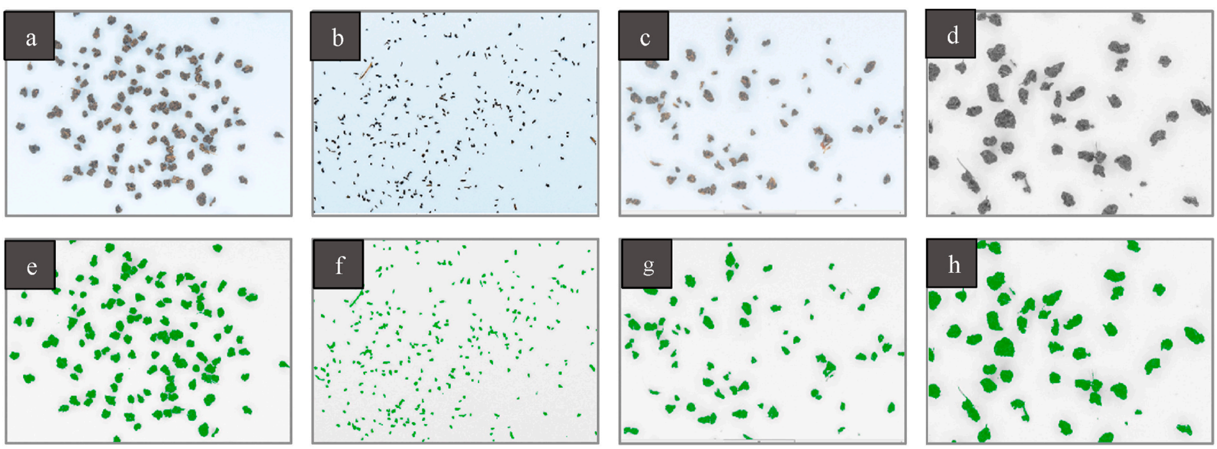

Fig. 4. Processed (8-bit gray level) binary images from WinROOF
4(a), 4(b), 4(c), and 4(d) represents BOP, CD, PF, and GBOP grades captured images respectively and 4(e), 4(f), 4(g), and 4(h) represents the processed binary images.

information from each granule. Image particle features like projected area, feret diameter, roundness and solidity [17] information were extracted and exported as comma separated value (CSV) into Microsoft Excel 2019 (Microsoft Corporation 2018) for further statistical analysis.

2.5. Features extraction

The textural features have a direct relationship to the drying, selecting the leaves, weathering, fermentation and all other processing tasks. These features like projected area, feret size, roundness, solidity was directly generated from ImageJ. The following equations were applied to obtain those parameters from image pixel information. Feret's diameter is the longest distance between any two points along the selected boundary, also known as a maximum caliper.

Area, ferret diameter and perimeter were detected directly from image pixel in mm^2, mm and mm respectively. The circularity was calculated from the Eqn. no. (1)

$$Circularity = 4\pi \times \frac{area}{perimeter^2} \tag{1}$$

A value of 1.0 indicates a perfect circle. As the value approaches 0.0, it indicates an increasingly elongated shape. Values may not be valid for very small particles. Additionally, the aspect ratio, roundness and solidity were obtained from Eqn. no. (2), (3), and (4)

$$AR\ (aspect\ ratio)\ =\ \frac{major\_axis}{minor\_axis} \tag{2}$$

$$Round\ (roundness) = 4 \times \frac{area}{\pi \times major\_axis^2} \tag{3}$$

$$Solidity = \frac{area}{convex\_area} \tag{4}$$

A Digital Microscope (1000x, China) was used to check the acquired information e.g. area and ferret size.

2.6. Statistical analysis

Boxplot (five numbers of summary statistics) and the error bar with 95% CI was obtained. The statistical significance of the mean differences of extracted features across different textural features of tea granules was evaluated using F test (ANOVA). All of the statistical analysis of image data was conducted by using IBM SPSS Statistics (Version 22) and R package (Rx64 4.0.2). Finally, the testing was performed by comparing the tea grades obtained through the threshold values with the measured individual pixel.

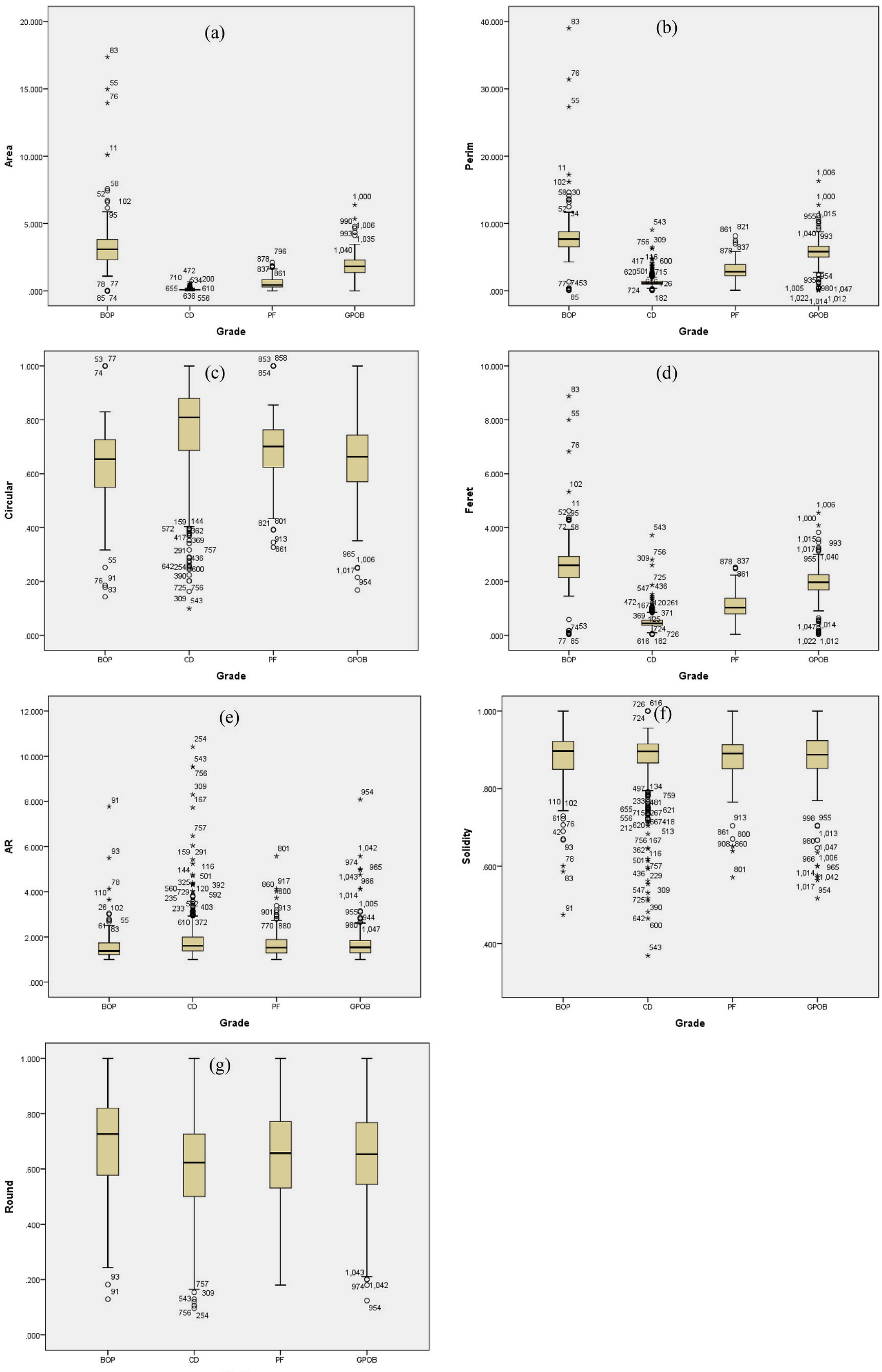

Fig. 5. Boxplot of tea grades for different physical features
(a): area, (b): perimeter, (c): circularity, (d): ferret diameter, (e): Aspect ratio, (f): solidity and (g): roundness.

Table 3
Mean difference of the extracted features across different class of the Tea.

Physical features	F-value	Sig.
Area	439.651	.000
Perimeter	430.651	.000
Circular	47.368	.000
Feret diameter	506.595	.000
Aspect Ratio	2.301	.076
Round	6.543	.000
Solidity	1.125	.338

NB: Between group differences among different tea granules.

3. Results and discussion

3.1. Validation of image acquisition system

From careful observation and the WinROOF data, it is clear that the acquired images have minimum interference e.g., noise and distortion. During binarization process, only 2.91% pixels' area compared to the area of full FOV was detected for BOP tea grade images. Similarly, 0.47% for CD, 0.75% for GBOP and 0.74% for PF grade was recorded. Fig. 4 shows captured and processed binary images of objects after processing. Fig. 4(a), (b), 4(c), and 4(d) represents BOP, CD, PF, and GBOP grades respectively and Fig. 4(e), (f), 4(g), and 4(h) represents the processed 8-bit gray level binary images extracted from WinROOF interface. As the image background is completely separated from the objects (tea granules), each granule is identical and ready to extract textural information in order to find threshold values. This indicates that the image acquisition system is working properly under suitable adjustment and can be followed for other products.

3.2. Classification of tea grades

The Boxplot (Fig. 5.) shows the five number summary statistics related to the tea images from four different grades. Some outliers were observed due to image noise and attaching the tea granules one with another. The summary statistics (especially median) was observed different for the tea granules (BOP, CD, PF and GBOP grade) of the physical features (area, perimeter, circularity, feret diameter, Aspect ratio, solidity, and roundness) whereas features of tea granules are almost similar for the roundness and solidity thus we cannot consider as a discriminative parameter for grading.

This is clear from Fig. 5(a) that the range of projected area of BOP grade varies from 2 to 3.5 mm^2. Similarly, for CD, PF, and GBOP categories can also be separated by the threshold values 0.03 to 0.15, 0.2 to 0.5, and 1.2–2.2 mm^2 respectively. The values from outside region of threshold range indicates that the particles also have some mixtures of other grades which was not precisely separated. Moreover, this also reveals that, some dust particles and foreign objects may present in the following tea grades. In addition to the area as a physical parameter, feret diameter was also obtained for four separate grades which have direct relationship with infusion process during tea preparation. In Fig. 5 (d), feret diameter ranges of BOP, CD, PF and GBOP grade shows as 2 to 2.75, 0.2 to 0.3, 0.75 to 1.5 and 1.6–2.3 mm. The threshold ranges can easily be used for constructing a grading algorithm which is prerequisite of developing automated grading machines. Additionally, the tea processing units from different tea estates can follow the methods and the threshold ranges for quick and accurate testing of their produce directly from production line.

3.3. Statistical analysis

The statistical significance of the mean differences of extracted features across different textural features of tea granules was evaluated using F test (ANOVA) in Table 3. Significant difference was observed among the different tea grades (BOP, CD, PF and GBOP) for the physical and textural features area, perimeter, circularity, roundness, feret diameter whereas the differences were found insignificant for aspect ratio and solidity. Furthermore, the Error Bar in Fig. 6 and the multiple comparison test (LSD) indicates that the tea granules grade (BOP, CD, PF and GBOP) were significantly different ($p < 0.01$) from each other for the Area, Perimeter and Feret diameter, as well as, all tea grades except GBOP and BOP were found significantly different for the circularity parameter. From the error bar, clear separation was observed for projected Area, Perimeter and Feret diameter, however, overlaps were found among the tea classes for other two features in Fig. 6.

Only two pairs BOP and CD & PF and CD were found significantly different for the textural feature roundness. This implies that the image processor has been able to accurately differentiate among the BOP, CD, PF and GBOP grade of tea granules in terms of area, perimeter, feret diameter and partially differentiate for the circularity and roundness. Therefore, projected area, perimeter, feret diameter can serve as a good indicator of the extracted features across different class of tea.

4. Conclusion

Tea quality depends upon several physical attributes such as color, granule shape, particle size and texture. In this study an attempt has been taken to define correlation and categorize among various grades of tea granules based on physical parameters and textural features. The extracted information related to the physical parameters are completely identical and can be easily categorize the tea grades and this information like threshold values may further be used to guide chemical analysis to develop a direct relationship between physical features and organoleptic property of tea. In this study, the developed image acquisition system is efficient and accurate to capture images under suitable light condition. Additionally, the images are easy to separate objects from its background. Tea granules (BOP, CD, PF and GBOP grade) were found significantly different for the features like area, perimeter, circularity, roundness, feret diameter. Since the system has been able to significantly differentiate among the BOP, CD, PF and GBOP grade of tea granules in terms of area, perimeter, feret diameter, so these features can serve as a good indicator of the extracted features across different class of tea. Moreover, the image pixel information helps to obtain threshold level of projected area for BOP, CD, PF and GBOP grade as 2.5 to 4.0; 0.03 to 0.15; 0.2 to 0.5; and 1.2–2.2 mm^2 respectively and feret size as 2 to 2.75, 0.2 to 0.3, 0.75 to 1.5 and 1.6–2.3 mm. Accuracy can be further improved by analyzing textural features to variations with the camera like CCD and illumination. This non-destructive method using MVS is almost new concept in post-processing in tea technology in developing countries like Bangladesh. The work in this area is being carried out to explore the possibilities of achieving better grading efficiency which may lead to an automated system. More efforts needed to establish the correlation of physiochemical results with textural and color attributes, the method could yield significant results. Moreover, tea industries will be benefited by accepting the technology to ensure the tea quality into export market.

CRediT authorship contribution statement

Md Towfiqur Rahman: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Resources, Investigation, Writing - review & editing, Visualization, Funding acquisition. **Sabiha Ferdous:** Methodology, Formal analysis, Writing - review & editing, Visualization. **Mariya Sultana Jenin:** Resources, Writing - review & editing. **Tanjina Rahman Mim:** Resources, Writing - review & editing. **Masud Alam:** Conceptualization, Formal analysis, Resources, Writing - review & editing. **Muhammad Rashed Al Mamun:** Conceptualization, Methodology, Investigation, Resources, Writing - review & editing, Funding acquisition.

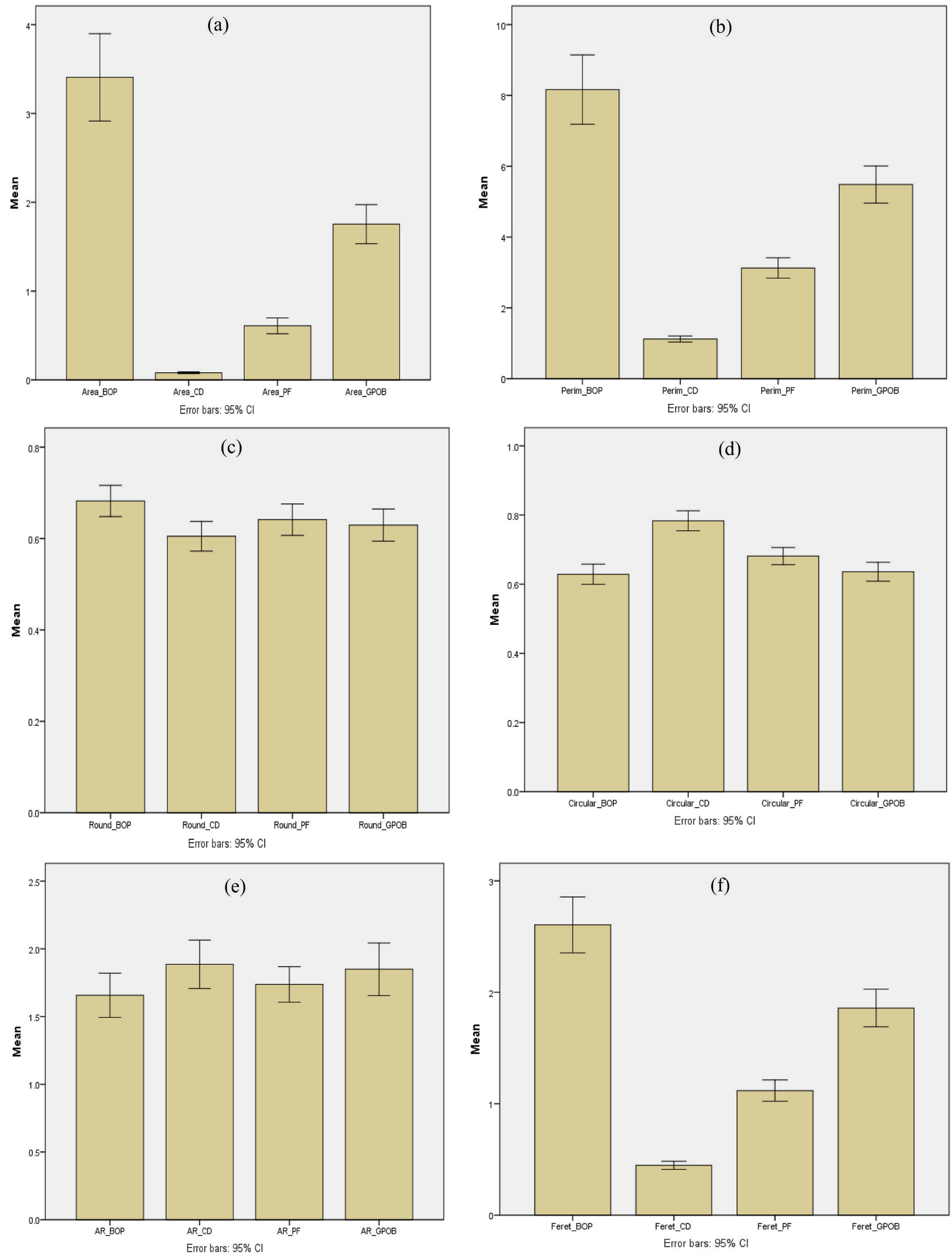

Fig. 6. Relationship between projected area, perimeter, roundness, circularity, aspect ratio, solidity and feret diameter of each tea granules grade class. Comparisons among different grade of tea granules due to projected area, perimeter, roundness, circularity, aspect ratio (AR), solidity and feret diameter

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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