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Research Article

Quality assessment of lettuce using image texture analysis

Phakhawat Hunchat[1], Wittaya Prompuge[2], Natthaphong Kaemthapthim[1], Nitikorn Leechai[1], Morakot Thongprom[3], Bunyarit Wangngon[1] and Suwan Aekram[2*]

[1] *Faculty of Engineering, Rajamangala University of Technology Lanna, Phitsanulok, 65000, Thailand*
[2] *Faculty of Science and Agricultural Technology, Rajamangala University of Technology Lanna, Phitsanulok, 65000, Thailand*
[3] *Faculty of Business Administration and Liberal Arts, Rajamangala University of Technology Lanna, Phitsanulok, 65000, Thailand*
* *Corresponding author: aekram@rmutl.ac.th*

Abstract - This research aims to develop an image processing method for monitoring and evaluating the quality changes in vegetables using image texture analysis, with lettuce as the sample. Thirty grams of lettuce were prepared by washing, trimming, and centrifuging in a salad spinner for 1 minute to remove excess water. The prepared lettuce samples were then packaged in LDPE bags and stored at different temperatures (4°C, 7°C, and 10°C, respectively). Images of the lettuce samples were captured every 24 hours for 8 days under D65 light at a resolution of 3024 × 4032 pixels. The images were saved in RGB format, converted to HSI color space, and the H (Hue angle) value was used to calculate image texture features using statistical calculation techniques, including Energy, Entropy, Correlation, and Homogeneity. The results of the study indicated that the Energy value could effectively monitor the rate of change in lettuce quality over time based on shelf life and storage temperature. The Energy value exhibited a significant decrease depending on the shelf life and storage temperature, with the decrease being statistically significant ($P < 0.05$) and proportional to the storage temperature. In contrast, Entropy, Correlation, and Homogeneity values were found to be ineffective for monitoring the rate of change in lettuce quality.

Keywords: Image texture, GLCM, lettuce quality change

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1. Introduction

Product quality is a crucial determinant for all types of produce. In the realm of agriculture, maintaining quality and extending shelf life are paramount. To achieve these goals, a variety of technologies are currently being employed. These technologies aim to preserve the quality of agricultural products for as long as possible, thereby ensuring their marketability and reducing waste. For vegetable products, visual quality stands out as one of the initial quality aspects discernible to consumers (Kays, 1999). The assessment of visual quality in vegetables often relies on color measuring devices, such as the Minolta chromameter and Hunter Lab colorimeters, etc. However, a constraint of traditional colorimetric instruments is their requirement for the sample surface to exhibit a relatively uniform color throughout. Measuring the color of a sample with diverse color variations poses challenges. Additionally, assessing the color of a large area sample using these instruments is both difficult and time-consuming (Oliveira & Balaban, 2006). For this reason, image processing technology has been applied to measure and analyze the color value of agricultural products (Aekram et al., 2023; 2024). However, the properties of images are not only color properties. Texture properties (surface images) are another outstanding feature of images.

Image texture analysis is a method that involves extracting quantitative measures from images to characterize the spatial arrangement of pixels and their variations in intensity or color. These measures provide valuable information about the surface properties, structure, and composition of agricultural products, which are often correlated with quality attributes such as ripeness, freshness, and defects. Several studies have demonstrated the effectiveness of image texture analysis in assessing the quality of agricultural and food products. For example, Han et al. (2016) used the dual-tree complex wavelet transform for optical grading of fruits, showing the utility of texture analysis in fruit quality assessment. Arakeri and Lakshmana (2010) developed an automatic grading system for tomatoes using computer vision techniques, which included extracting texture features like Energy, Homogeneity, Contrast, and Correlation, and employing neural networks for classification. This system achieved classification accuracies of 100% and 96.5% for tomato defects and ripeness, respectively. Moallem et al. (2017) extracted image texture features from apples and used a Support Vector Machine (SVM) to classify them into healthy and defect categories, achieving a recognition rate of 92.5%. Azarmdel et al. (2020) classified mulberry fruits into overripe, ripe, and unripe categories based on texture features combined with Artificial Neural Networks (ANN), achieving an accuracy rate of 99.1%. Khojastehnazhand and Ramezani (2020) used texture features with Support Vector Machine (SVM) to classify bulk raisins into 6 classes of good and bad raisins, achieving a classification accuracy of 85.55%.

According to the examples of research mentioned above, it is evident that image texture analysis can be effectively applied to assess the quality of agricultural products. Therefore, this research focuses on utilizing image processing techniques, specifically image texture analysis, to identify distinct characteristics that can be employed in assessing the quality of vegetable products, with lettuce serving as the primary example.

2. Materials and methods

2.1 Sample preparation

Lettuce samples were obtained from a local hydroponic farm in the morning. The lettuce was then cleaned, cut into pieces, and each piece weighed to a mass of 30 g. Subsequently, the lettuce was centrifuged in a salad spinner for 1 minute to remove excess water. The prepared lettuce samples were then packaged in LDPE bags and stored under normal atmospheric conditions at temperatures of 4°C, 7°C, and 10°C, respectively. The experiment was conducted with three replicates for each temperature condition.

2.2 Image acquisition system

The image acquisition system utilized in this study comprised a photographic box ((Studio Light Box, Shenzhen PULUZ Technology, China)) with dimensions of 25cm × 25cm, equipped with a D65 LED lamp serving as the light source. An iPhone 13 smartphone was employed to capture images of the lettuce samples, positioned 25 cm above the samples. Images of the lettuce were captured every 24 hours over an 8 day period, at a resolution of 3024 pixels × 4032 pixels, and saved in JPEG format with RGB color space.

2.3 Algorithm development

This research developed an algorithm for assessing the quality of vegetables using image texture. The algorithm is based on the statistical texture method, which employs statistical principles to calculate and identify features of the image that are indicative of the quality of salad vegetables. (Figure 1) illustrates the algorithm

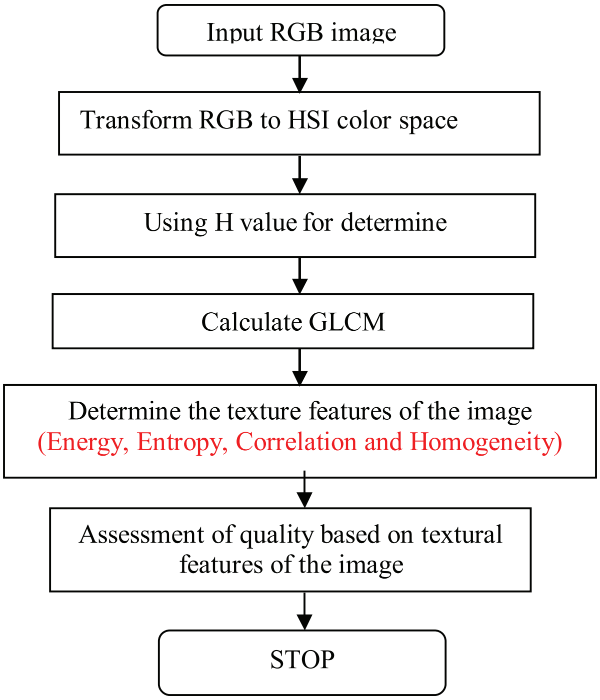

Figure 1. An algorithm to features of image texture that may be used to evaluate the quality of salad vegetables.

Images captured by cameras store the color of each pixel in the RGB color space. However, as this space does not align with human perception (Leon et al., 2006), converting the color values from RGB to another color space is necessary (Wu & Sun, 2013). The chosen color space for this research is HSI, where H (Hue) is used as the color value for analysis. HSI is preferred because it describes various shades that humans can easily perceive and understand (Ansari & Singh, 2022). The conversion from RGB to HSI can be calculated using Equations 1-4 (Kamiyama & Taguchi, 2021).

$$\theta = \cos^{-1}\left\{ \frac{\frac{1}{2}\left[(R-G)+(R-B)\right]}{\left[(R-B)^2+(R-B)+(G-B)\right]^{\frac{1}{2}}} \right\} \quad (1)$$

B ≤ G

B > G

$$H = \begin{cases} \theta \\ 360-\theta \end{cases} \quad (2)$$

$$S = 1 - \frac{1}{(R+G+B)}\left[\min(R,G,B)\right] \quad (3)$$

$$I = \frac{1}{3}(R+G+B) \quad (4)$$

Where H is Hue, S is Saturation and I is Intensity of each pixel. Then calculate the Gray-Level Co-Occurrence matrix (GLCM) using matrix size 8×8 at 1 pixel spacing and the angle for calculation is 0 degrees. The features of the image texture used in this research are Energy, Entropy, Correlation and Homogeneity which can be calculated from Equations 5 – 8 (Mutlag et al., 2020). The calculation of various values according to Equations 1 – 8 is done by the developed program created under a research project using MATLAB as a development tool.

$$Energy = \sum_{i=1}^{8}\sum_{j=1}^{8}\left(P(i,j)\right)^2 \quad (5)$$

$$Entropy = -\sum_{i=1}^{8}\sum_{j=1}^{8} P(i,j)\times\log(P(i,j)) \quad (6)$$

$$Correlation = \sum_{i=1}^{8}\sum_{j=1}^{8}\frac{(i-\mu_i)(j-\mu_j)P(i,j}{\sigma_i\sigma_j} \quad (7)$$

Where,

$$\mu_i = \sum_{i=1}^{8}\sum_{j=1}^{8} iP(i,j), \mu_j = \sum_{i=1}^{8}\sum_{j=1}^{8} jP(i,j)$$

$$\sigma_i = \sum_{i=1}^{8}\sum_{j=1}^{8}(i-\mu_i)^2 P(i,j), \sigma_j = \sum_{i=1}^{8}\sum_{j=1}^{8}(j-\mu_j)^2 P(i,j)$$

$$Homogeneity = \sum_{i=1}^{8}\sum_{j=1}^{8}\frac{1}{1+(i-j)^2}P(i,j) \quad (8)$$

where *P(i, j)* value refers to the member in the GLCM matrix.

3. Result and discussion

(Figure 2) illustrates the textural features of lettuce stored at 4ºC, including Energy, Entropy, Homogeneity, and Correlation. The analysis revealed that the Energy value decreased steadily over time, while the Entropy value exhibited an increasing trend. The Homogeneity value remained relatively stable throughout the storage period. Additionally, the Correlation value displayed variability without a discernible trend, fluctuating with the shelf life of the lettuce. Similarly, the results for lettuce stored at 7ºC and 10ºC, depicted in (Figure 3) and (Figure 4) respectively, demonstrated paternsconsistent with those observed for letucestored at 4ºC.

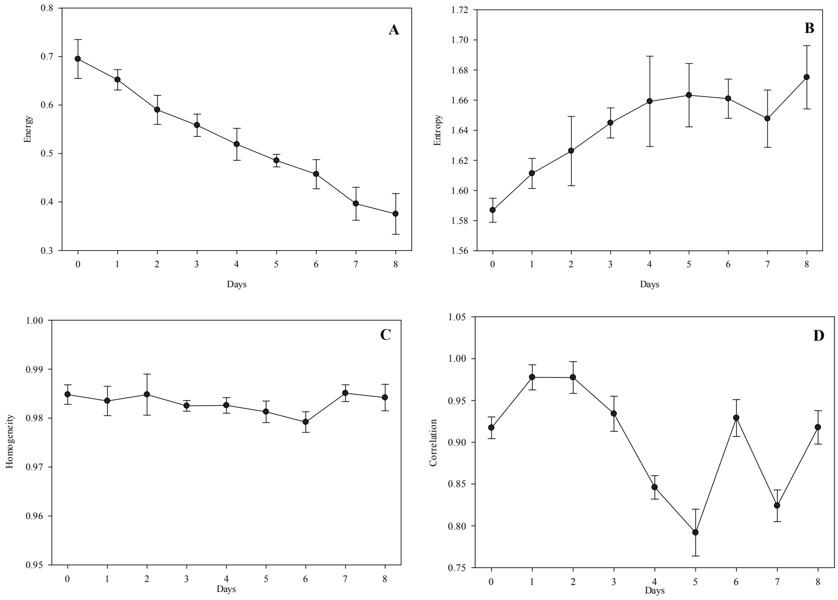

Figure 2. Value of Energy (A), Entropy (B), Homogeneity (C) and Correlation (D) of lettuce at storage temperature of 4ºC

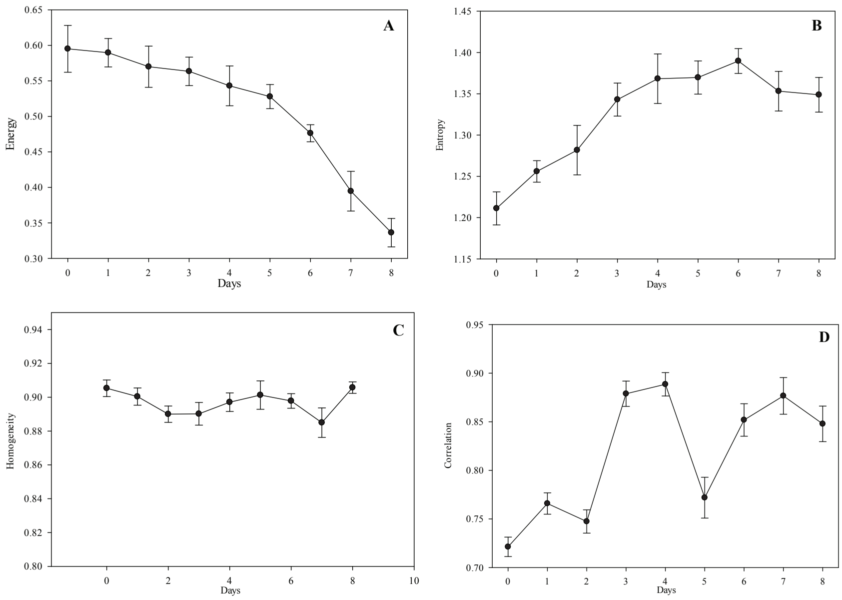

Figure 3. Value of Energy (A), Entropy (B), Homogeneity (C) and Correlation (D) of lettuce at storage temperature of 7ºC

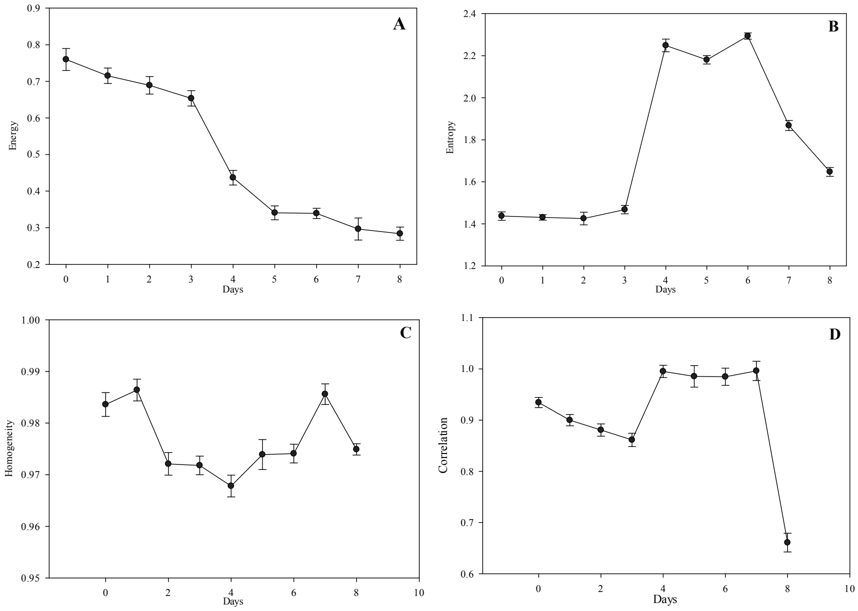

Figure 4. Value of Energy (A), Entropy (B), Homogeneity (C) and Correlation (D) of lettuce at storage temperature of 10ºC

Statistical research indicated that only Energy value showed a significant correlation with shelf life and storage temperature ($P < 0.05$), suggesting that Energy value can be used to assess lettuce quality. The entropy value, which indicates the uncertainty or complexity of an image—specifically in terms of the disorder of pixel values—reveals that a high entropy value signifies a high diversity of pixel values and increased complexity. However, since the images analyzed consist of single lettuce leaves and backgrounds, there is insufficient pixel value diversity to use entropy as an index for detecting quality changes in the lettuce. Similarly, the homogeneity value, which reflects the uniformity or similarity of pixel values, remains relatively constant because the lettuce images, consisting of single leaves and backgrounds, show consistent quality changes each day. Lastly, the correlation value, indicating the linear relationship between pixel values at different positions within the image, suggests that a high correlation indicates a relationship between adjacent pixel values. However, due to the non-patterned nature of the lettuce images, this value exhibits significant variability, making it unsuitable for tracking quality changes in the lettuce. Consider Figure 5, which compares the Energy value during the shelf life on days 1 – 8 to the Energy value on the first day (Day 0). The Energy value reflects the consistency of the image (Zhang et al., 2017; Han et al., 2019); as the Energy value decreases, so does the image's uniformity (Baraldi & Panniggiani, 1995). The study indicated that at a storage temperature of 4ºC, the Energy value declined little, indicating that the quality of salad vegetables from days 1 to 8 of shelf life remained comparable to the initial day. For lettuce stored at 7ºC, it was found that the Energy value during the first 5 days of storage was relatively similar to the initial day. However, a significant decrease in Energy value was observed during the 6 days of storage. This indicates a severe loss in quality of the lettuce starting from that storage period onwards. Similarly, the results for lettuce stored at 10ºC showed a significant decrease in Energy value when stored until the 4 days, which is consistent with the findings for lettuce stored at 7ºC. Based on the aforementioned results, it is evident that image texture analysis is a valuable tool for monitoring lettuce quality.

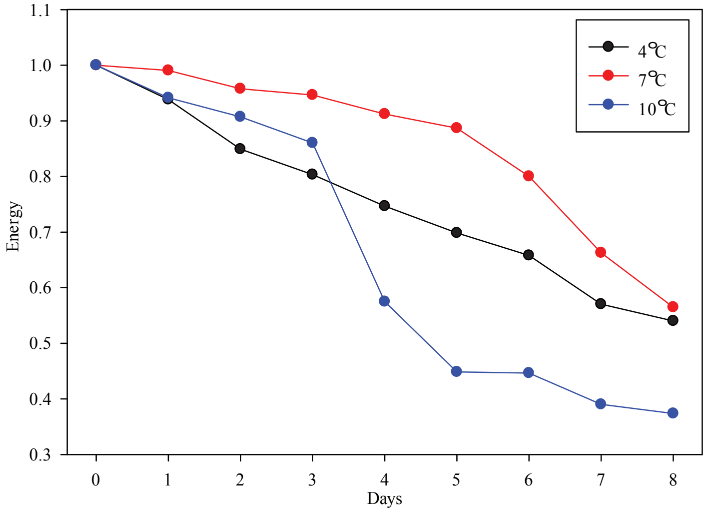

Figure 5. Energy value of lettuce at storage temperature of 4ºC, 7ºC and 10ºC

4. Conclusion

The study concluded that image texture analysis is a viable method for assessing lettuce quality, with the Energy value of the image texture being a key indicator. While the Entropy value is also sometimes used as an indicator, it is not as straightforward as the Energy value. Conversely, values such as Correlation and Homogeneity are not suitable indicators of lettuce quality. The experiment involved storing lettuce at temperatures of 4°C, 7°C, and 10°C for 8 days. Analysis of the Energy values over the storage period revealed that at 4°C, the Energy values decreased slightly compared to the initial day, suggesting that the lettuce maintained its quality. However, at 7°C and 10°C, there was a significant decrease in Energy values on days 6 and 4, respectively, indicating a severe loss in lettuce quality from those storage periods onwards.

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