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Enhancing the destructive egg quality assessment using the machine vision and feature extraction technique

Ehsan Sheidaee[1]*, *Pourya Bazyar*[2]

[1]*Biosystems Engineering Department, Tarbiat Modares University, Tehran, Iran*
[2]*Department of Mechanical Engineering and Production Management, Hamburg University of Applied Science, Hamburg, Germany*

**Corresponding author: sheidaee.ehsan@ut.ac.ir*

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Abstract: The rapid growth of the food industry necessitates rigorous quality control, particularly in egg production. This study explores advanced methodologies for egg quality assessment by integrating the Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and k-Nearest Neighbour (KNN) with machine vision techniques. While traditional destructive methods like measuring the Haugh unit (HU) offer direct insights, but render eggs unusable, non-destructive techniques, such as imaging and spectroscopy, allow continuous quality monitoring. Over a 20-day period, egg samples were evaluated using a digital camera to capture key parameters like the albumen and yolk heights. The study's image processing involved noise reduction, feature extraction, and calibration. The PCA captured 90.18% of the data variability, while LDA achieved 100% classification accuracy, and KNN demonstrated 80% accuracy. These findings underscore the effectiveness of combining machine vision with statistical methods to enhance the egg grading accuracy, contributing to consumer safety and industry standards.

Keywords: haugh unit; image processing; classification; quality control; albumin height

The food industry has experienced significant growth and development worldwide in recent decades (Wik et al. 2008). This expansion is driven by the increasing consumer demand, advancements in technologies, and globalisation (Lambin & Meyfroidt 2011). As the industry continues to evolve, the importance of maintaining high standards of product quality has become paramount (Teece 2000). The implementation of efficient methods for calculating product quality factors is essential (Earle & Earle 1997). These methods ensure that food products meet the required standards for safety, nutrition, and consumer satisfaction. The accurate and reliable quality assessment not only helps in maintaining consumer trust, but also in complying with regulatory requirements and enhancing the overall competitiveness of food products in the global market (Kotsanopoulos & Arvanitoyannis 2017). By adopting advanced methods and technologies, manufacturers can better monitor and control various factors that influence the quality of their products (Ammar et al. 2021; Sheidaee et al. 2022). This proactive approach enables the industry to deliver consistently high-quality food products, ultimately contributing to the health and well-being of consumers worldwide (Augustin et al. 2016; Farhangi & Sheidaee 2024). Eggs are a vital component of the human diet, renowned for their rich nutritional profile that includes protein, minerals, vitamins, and fatty acids (Karsten et al. 2010; Anderson 2011). As a significant segment of the food industry, egg production and processing require effective management and cost-efficient measures to ensure the quality of the

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input products (Mooee & Sandgeound 1956). Destructive methods involve breaking the egg to directly measure various quality indices (Hamilton 1982). One significant advantage of these methods is the direct access to the Haugh unit (HU), a widely recognised measure of egg quality that correlates the egg weight with the height of the albumen (egg white) (Ahammed et al. 2014). The precise measurement of the Haugh unit provides valuable insights into the freshness and internal quality of the egg (Karoui et al. 2006). Despite the loss of the egg in the process, the accuracy of the data obtained through destructive testing is highly beneficial for research and industry standards (Karoui et al. 2009). Non-destructive methods, on the other hand, allow for the assessment of egg quality without compromising the integrity of the egg (De Ketelaere et al. 2004). Techniques, such as imaging and spectroscopy, enable the evaluation of external shape and internal egg characteristics, including the shell quality, albumen, and yolk measurements (Loffredi et al. 2021). These methods are particularly advantageous for large-scale operations where preserving the egg for sale or further processing is crucial (Asche et al. 2018). Non-destructive testing is also beneficial for the continuous monitoring of egg quality, enhancing the ability to maintain consistent standards and detect issues promptly (Chen et al. 2021). In a notable study by Omid et al. (2013), a sophisticated system based on machine vision and artificial intelligence techniques was developed to grade egg samples. This innovative approach employed the Hue-Saturation-Value (HSV) colour space to accurately detect the size, cracks, and breakage of eggshells. By integrating the Mamdani fuzzy logic method with the centre average method for defuzzification, the researchers achieved remarkable classification rates: 95% for size detection, 94.5% for crack detection, and 98% for breakage detection (Omid et al. 2013). Ramírez-Gutiérrez et al. (2019) conducted a study to explore the use of computer vision for detecting any deformations on the curved surfaces of eggshells. The research involved analysing 75 eggs without deformations and 75 eggs with deformations. The vision system employed consisted of a camera with a charge-coupled device (CCD) sensor and a laser-structured light pattern, operating under lighting conditions with concentrations lower than 1 lux to capture the images accurately (Ramírez-Gutiérrez et al. 2019). Zhang et al. (2015) utilised a combination of hyperspectral imaging and multivariate analysis to evaluate the internal quality of eggs. The hyperspectral imaging system comprised a CCD camera, an imaging spectrometer, a light unit, a motorised horizontal stage, and the Spectral Image System (v10E software). A spectral analysis was employed to estimate the Haugh unit (HU), while a morphological analysis of the images detected bubble formation and scattered yolk. The support vector classification (SVC) model achieved precision rates of 90.0% for detecting internal bubbles and 96.3% for identifying scattered yolk, with an HU estimation accuracy of 84%. This approach demonstrates the potential of advanced imaging and analytical techniques in enhancing the destructive assessment of egg quality (Hamilton 1982; Mertens et al. 2011). Non-destructive methods for egg quality assessment allow one to evaluate internal characteristics without damaging the egg to assess the chicken egg fertility (Zhihui et al. 2015; Adegbenjo et al. 2020; Saifullah & Dreżewski 2022), egg grading system (De Ketelaere et al. 2004), shell egg quality and freshness evaluation (Liu et al. 2020; Loffredi et al. 2021), raw egg freshness (Dutta et al. 2003; Akbarzadeh et al. 2019; Qi et al. 2020), internal quality (Mehdizadeh et al. 2014; Zhang et al. 2015), egg content determination in dry pasta (Fodor et al. 2011), detect abnormal chicken eggs (Kim et al. 2022), visualisation of the gel springiness of preserved eggs (Li et al. 2021; Chen et al. 2023), yolk index (Sun et al. 2016), egg cracking (Li et al. 2012; Shi et al. 2022), storage the egg (Narushin et al. 2023), to calculate the egg volume and surface area (Narushin et al. 2020; Narushin et al. 2021), determine the S-ovalbumin content in egg storage (Fu et al. 2019; Yao et al. 2022; Yao et al. 2023), and to identify the gender of chicken eggs (Zhu et al. 2021; Schreuder et al. 2024). The analysis of the egg quality is a pivotal aspect of the food industry, ensuring the delivery of high-standard products to consumers (Eddin et al. 2019). Traditional assessment methods are often subjective and labour-intensive, highlighting the need for more efficient and precise techniques (Okinda et al. 2020; Castro et al. 2023). This study introduces an advanced approach by utilising image processing in conjunction with principal component analysis (PCA) (Uysal & Boyaci 2020), linear discriminant analysis (LDA) (Zhao et al. 2010), and k-nearest neighbour (KNN) (Rachmawanto et al. 2020). These techniques facilitate the detailed measurement of critical parameters, such as the albumen height, yolk height, and yolk diameter. By integrating PCA, LDA, and KNN, this research aims to establish a robust and objective framework for the egg quality analysis, significantly enhancing the accuracy and reliability of the grading process.

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This work aims to develop a novel method for the egg quality assessment based on advanced machine vision techniques. PCA, LDA, and KNN were employed to extract and analyse key egg quality features, including the albumen height, yolk height, and yolk diameter. The relationship between these parameters and the egg quality, measured by the Haugh unit (HU), was assessed. This integrated approach offers a precise model for egg grading, with potential applications in enhancing the food quality control analysis.

MATERIAL AND METHODS

Preparation of the samples

In this study, two hundred fresh, intact egg samples were purchased from a store in Karaj, Iran, and kept in a laboratory at 26 ± 2 °C, out of the refrigerator. The egg samples were divided into five groups of forty eggs. The testing period spanned 20 days, with evaluations performed at four-day intervals (Sheydaee & Bazyar 2021). A box was simulated in 3D using SolidWorks software (version 2018) and constructed from wood to minimise any environmental noise effects (Figure 1). The box dimensions were 60 × 60 × 50 cm, and it included a light box measuring 15 × 15 × 20 cm, containing a 7-W surface-mount device (SMD) bulb. To ensure uniform light orientation for the morphological analysis, a dark environment was designed in the box (Stinco et al. 2013; Yu et al. 2013).

An HTC One X9 smartphone was used to acquire the sRGB images within an imaging system that included a digital camera, an illumination box, and a computer. The phone camera, with a resolution of 4 160 × 2 368 pixels and a focal length of 27 mm, was fixed approximately 200 mm horizontally from the egg centre. Data were transferred to a Lenovo laptop (Windows 10 Enterprise, Intel Core i5, NVIDIA GeForce GT740M, 4GB RAM) via a USB for image processing (Figure 1) (Sheydaee & Bazyar 2021).

Egg Weight

The nutrient content of eggs is influenced by multiple factors, with the weight of the egg being a primary determinant. These factors include the heredity, breed, strain, age of the hen, body size, feed and water consumption, ambient temperature, and the presence of diseases (Şekeroglu & Altuntaş 2009). The egg weight stands out as a crucial indicator of an egg's quality. To evaluate this, samples are weighed using an electronic balance scale, specifically a Jadever scale model, which offers a precision of 0.01 g. This level of accuracy ensures that even slight variations in egg weight are detected, providing reliable data for assessing the egg quality.

Images pre-processing and data preparation

Images captured by a smartphone camera were stored in.jpg format and processed using MATLAB® (version 2022b). The processing involved an algorithm designed to identify the height of the albumin in the egg, consisting of two main steps:

(i) Image Pre-processing: This step involved evaluating the best methods for filtering and segmentation to reduce the noise and enhance the image quality during the test period. The goal was to modify any noise present in the image and to extract the necessary information about the eggs.

(ii) Image Analysis: This step focused on analysing the light pattern within the image to extract features from the selected pixels.

The initial step of pre-processing involved extracting useful information from the RGB image to separate the important regions from the basic image. This important region is known as the region of interest (ROI). One of the important steps in pre-processing images for the albumin height

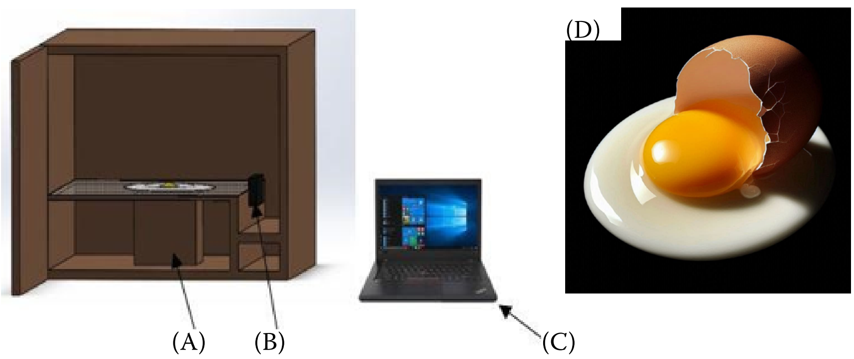

Figure 1. Illustrates the egg quality assessment system, which includes the following components: (A) a light box, (B) a smartphone, (C) a laptop and (D) broken egg on a surface

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detection is the application of low-pass filter operations (Figure 2A). This technique is instrumental in exploring significant relationships between the spatial and frequency domains of the images (Davies 2012). In this study, Gaussian and median smooth filtering were employed to eliminate signal components with high spatial frequencies. These filters effectively reduce the noise and enhance the image quality, facilitating a more accurate analysis of the albumin height in the eggs. In our method, a binary process is employed to identify objects within a white sample set against a black background. This is achieved using the Otsu thresholding method (Ye et al. 2001), which automatically calculates a threshold for a grayscale image. By employing the I_{binary} function (Equation 1), this method minimises the interclass variance of black and white pixels to obtain a binary image. This binary image is crucial for accurately distinguishing and analysing the objects within the sample.

$$I_{binary} = \begin{cases} 0 & if\ I_{image} \leq T_{otsu} \\ 255 & (otherwise) \end{cases} \quad (1)$$

where: I_{binary} – the binary image; I_{image} – the intensity of pixel of grayscale image; T_{otsu} – the limit of Otsu threshold; T_{yolk} – limit for red channel; I_{yolk} –the pixels including yellow colour; $I_{albumin}$ – the pixels including white colour

In this research, the height of the albumin was determined using morphological operations based on image processing functions to segment the yolk and albumin areas in the image. To distinguish the egg yolk, the processing method focused on the red channel (:,:,1) of the RGB colour image. This approach followed the T_{yolk} method for yolk identification (Equation 2), ensuring the accurate segmentation and measurement of the yolk and albumin regions (Figure 2B).

(A)

(B)

(C)

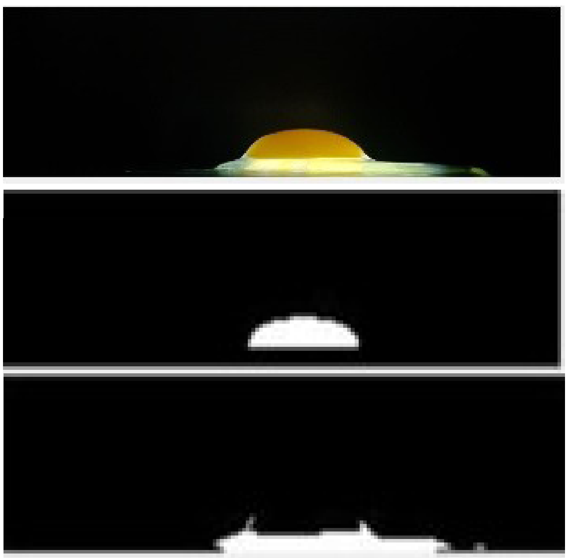

Figure 2. The process of egg images

(A) original image; (B) yolk separation; (C) albumin separation

$$I_{yolk} = \begin{cases} 0 & if\ I_{image} \leq T_{yolk} \\ 255 & (otherwise) \end{cases} \quad (2)$$

where: I_{yolk} –the pixels including yellow colour; I_{image} – the intensity of pixel of grayscale image; T_{yolk} – limit for red channel

At this stage, the albumin image ($I_{albumin}$) is calculated by subtracting the yolk image (I_{yolk}) from the binary image (I_{binary}), as described in Equation 3. This subtraction operation, applied to the images of the same size, is used to extract the area of interest, specifically isolating the albumin region from the rest of the image (Figure 2C).

$$I_{albumin} = I_{binary} - I_{yolk} : [w \mid w \in I_{binary}, w \notin I_{yolk}] \quad (3)$$

where: $I_{albumin}$ – the pixels including white colour; I_{binary} – the binary image; I_{yolk} –the pixels including yellow colour; w – proposed pixels extracted from images

Calibration is essential to validate the extracted features in our image processing method. The region of interest (ROI) in the image measured 60 mm (943.31 pixels) in width and 220 mm (3 493.41 pixels) in length. This method allows the pixel count of the image to be accurately scaled to millimetre units. The discrepancy between the actual millimetre size and the image processing results is less than 0.32 mm, ensuring high accuracy in the measurement and validation process. The network algorithm presented in this research was implemented in Python software (version 3.6) using Keras library on TensorFlow platform to perform all the processing and classification processes of the egg images.

Haugh Unit

According to the Haugh unit (Brant 1951), eggs are categorised into three quality grades based on their firmness: grade AA: firm, top quality (Haugh unit ≥ 72); grade A: reasonably firm, lower quality (Haugh unit 60–71); grade B: weak, deteriorated quality (Haugh unit < 60).

The Haugh unit score is calculated using the weight of the egg and the height of the albu-

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min for each individual egg, based on the formula (Equation 4) established by Haugh (1937):

$$\text{HU} = 100 \log_{10} (H - 1.7\ W^{0.37} + 7.6) \qquad (4)$$

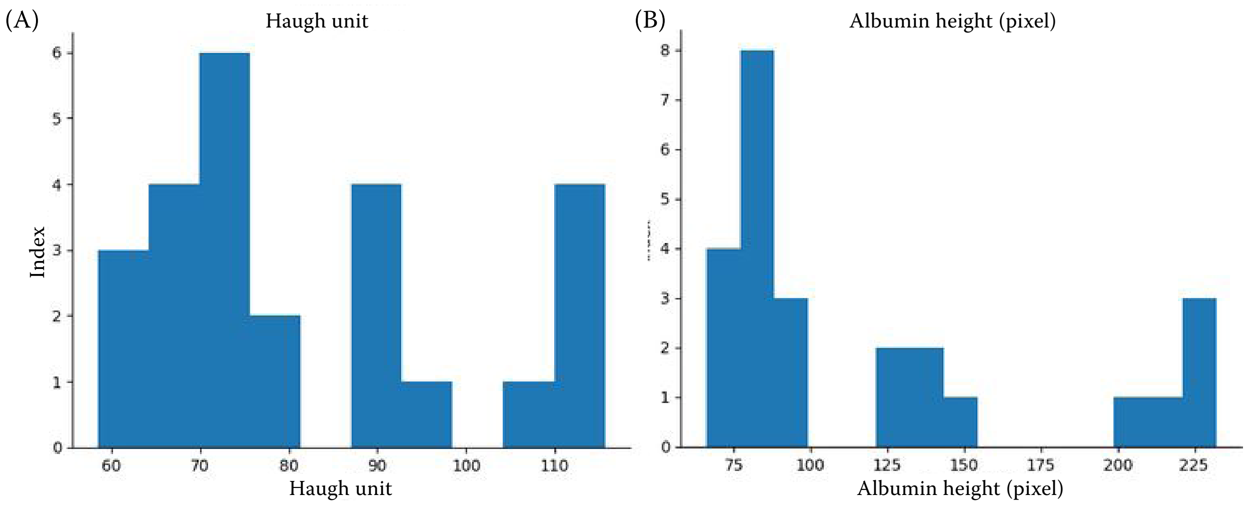
where: HU – the observed Haugh unit; H – the height of the albumin; W – the weight of the egg (Haugh 1937)

This formula provides a quantitative measure to assess the quality of eggs.

RESULTS AND DISCUSSION

The results from the image processing analysis of I_{yolk} and $I_{albumin}$ images, reveal a decline in egg quality over time-based on the albumin height and Haugh unit measurements. Initially, on the first and fourth days, the eggs maintained a high Haugh unit, indicating they were intact and of AA-grade quality. By the eighth and twelfth days, some eggs had dropped to grade A. By the sixteenth day, with the mean Haugh unit falling below 72, the eggs were downgraded to either grade A or B, necessitating further quality assessment to ensure their suitability for consumption (Figure 3A).

Based on the analysed images, six distinct features were extracted from the dataset, offering comprehensive insights into the characteristics and quality of the eggs. These features include egg weight, which measures the overall mass of the egg; albumin height, indicating the height of the egg white (albumin); and yolk height, which denotes the height of the egg yolk. Additionally, the yolk diameter is measured to understand the size of the yolk, while the yolk index, a ratio of the yolk height to yolk diameter, provides insight into the yolk's quality and firmness. Collectively, these features enable a detailed analysis of the egg quality, essential for meeting consumer standards and optimising industrial processes. The analysis of the obtained data reveals three distinct classes observed over consecutive days, distinguished by variations in the height of the albumin and the ratio of the yolk height to the yolk diameter. These classes indicate consistent patterns and trends in the egg quality metrics over time.



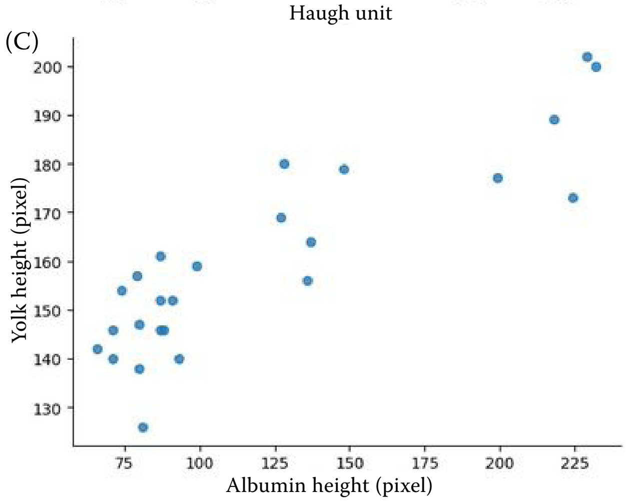


Figure 3. Performance of various classifiers in grading egg quality
(A) haugh unit; (B) albumin height; (C) albumin height vs yolk height

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The height of the albumin is an important indicator of egg freshness, with higher values generally signifying fresher eggs (Figure 3B). Meanwhile, the ratio of the yolk height to the albumin height, provides insights into the egg quality (Figure 3C). By categorising the six features into these three classes, it becomes possible to track and predict changes in the egg quality, aiding producers in maintaining high standards and optimising storage and handling processes to ensure the delivery of fresh, high-quality egg production.

Principal component analysis. Principal Component Analysis (PCA) is a powerful dimensionality reduction technique widely used in data analysis and machine learning (Hasan & Abdulazeez 2021). By transforming high-dimensional data into a lower-dimensional space, PCA can reveal patterns and simplify the analysis of complex datasets (Ray et al. 2021). PCA transforms the original features into a new set of orthogonal features known as principal components (Wold et al. 1987). These components are linear combinations of the original features, ordered by the amount of variance they explain in the data (Demšar et al. 2013). By focusing on the top principal components, we can capture the most significant patterns in the data while reducing the complexity (Aschard et al. 2014). Our dataset consists of six features and one target variable. The features are numerical variables that describe various aspects of the data, while the target variable represents different classes or categories. For our dataset, we performed a PCA and extracted five principal components. This number of components was chosen to capture most of the variability in the data while keeping the model interpretable and manageable. Principal Component Analysis (PCA) has proven to be a robust method for retaining critical information in datasets, as evidenced by its ability to explain 90.18% of the total variation with just five components. Breaking this down further, the first principal component (PC1) accounts for 27.0% of the variation, the second principal component (PC2) captures 30.0%, and the third principal component (PC3) explains an impressive 43.0% of the variation (Figure 4).

Additionally, there was clear separation between the three egg qualities which can be marketed as AA, A and B, with one sample containing its quality situated in among the three groups.

Linear discriminant analysis. Linear discriminant analysis (LDA) is a powerful classification technique used to differentiate between categories based on multiple features (Xanthopoulos et al. 2013). In this study, LDA was employed to classify eggs into three quality categories: AA, A, and B. The classification was based on six essential features: the egg weight, albumin height, yolk height, yolk diameter, yolk index, and Haugh unit (HU). The LDA model demonstrated remarkable performance, achieving 100% accuracy in classifying the eggs into their respective categories. This per-

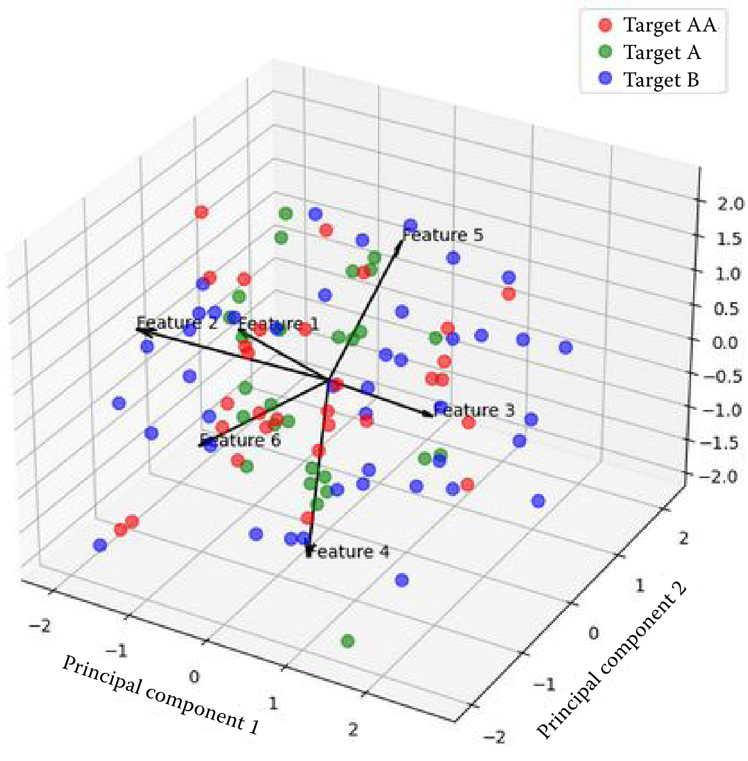

Figure 4. 3D scatter plot of the three principal components (PC1: 27%, PC2: 30%, and PC3: 43%) with features and targets: AA (firm), A (reasonably firm), and B (weak)

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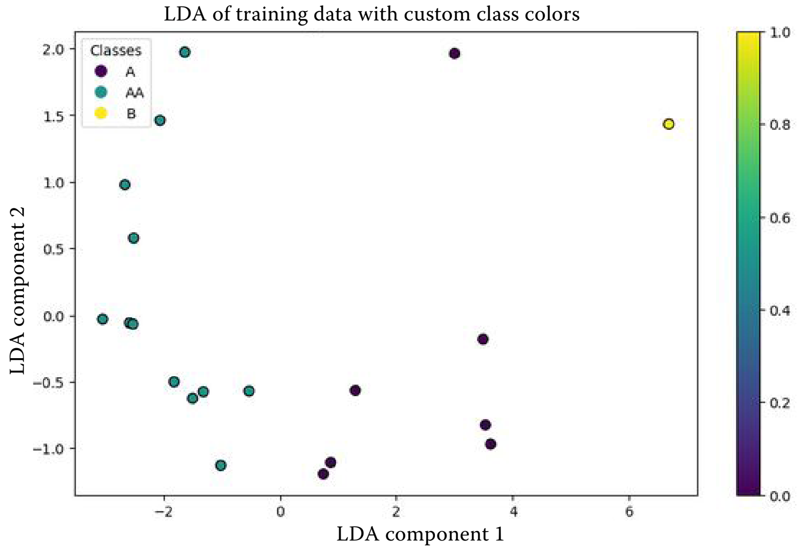

Figure 5. Linear discriminant analysis (LDA) classifier for the egg quality – scatter plot

fect classification indicates that the selected features are highly effective in distinguishing between different quality grades of eggs, ensuring no misclassifications occurred. The effectiveness of the LDA model was further validated through a scatter plot (Figure 5).

Additionally, the analysis revealed a clear separation between the three egg quality categories AA, A, and B though one sample was positioned among these groups. This observation further reinforces the capability of linear discriminant analysis to effectively distinguish between different egg grades, ensuring the precise classification across the varying quality levels.

K-nearest neighbour algorithm. The K-nearest neighbour (KNN) algorithm, a cornerstone in machine learning for classification and regression tasks, operates on the principle that data points with similar features are likely to have similar outcomes (Xie et al. 2024). Recently, this technique was employed to classify eggs based on six specific features: the egg weight, albumin height, yolk height, yolk diameter, yolk index, and Haugh unit.

The KNN model achieved an accuracy rate of 80%, demonstrating its effectiveness in distinguishing between the different egg categories. The model's performance is further evaluated through a confusion matrix for test data (Figure 6), which provides a detailed breakdown of correct and incorrect classifications, offering insights into the model's accuracy and highlighting areas for potential refinement.

Future work

In future research, the integration of deep learning techniques could significantly enhance the accuracy

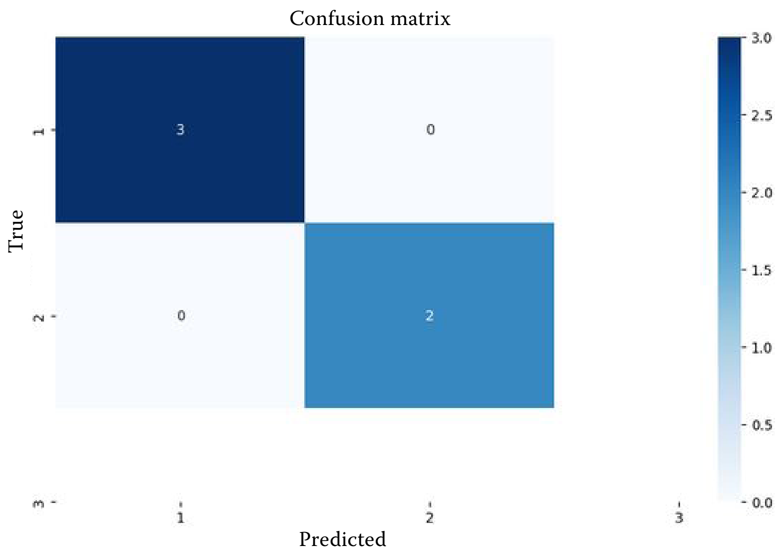

Figure 6. Confusion matrix depicting the K-nearest neighbour (KNN) algorithm performance in the egg quality classification

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and efficiency of egg quality classification. Deep learning models, such as convolutional neural networks (CNNs), offer the ability to automatically extract complex features from high-dimensional image data, potentially improving the detection of subtle quality variations that traditional methods might miss. Implementing a deep learning-based classifier could streamline the process, allowing for a more nuanced analysis of egg characteristics beyond the capabilities of conventional image processing methods. Additionally, exploring the use of transfer learning, where pre-trained models are adapted for specific egg quality tasks, could accelerate the development process and yield high-performing models with minimal training data. By combining deep learning with existing methodologies like SVM, LDA, and KNN, future work could deliver a more robust and comprehensive system for egg quality assessment, further advancing the food industry's ability to ensure product excellence.

CONCLUSION

In conclusion, this study advances the field of egg quality assessment by integrating sophisticated machine vision techniques with statistical analyses, such as PCA, LDA, and KNN. By employing these methods, the research effectively enhances the accuracy and reliability of egg grading systems, which are crucial for maintaining high standards in the food industry. The innovative approach allows for the precise measurement of key egg quality parameters, such as the albumen height and yolk characteristics, and provides a robust framework for the continuous monitoring and classification. Notably, the LDA model demonstrated exceptional performance, achieving a perfect accuracy rate of 100%, thereby ensuring flawless classification of egg quality grades. This high level of accuracy underscores the effectiveness of the selected features and the robustness of the LDA model. The integration of these advanced techniques not only improves the efficiency of quality control processes, but also ensures that consumers receive eggs that consistently meet safety and nutritional standards, thus contributing to overall public health and industry competitiveness.

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