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Translucency of chicken eggs: proposal of an automated system for analysis and classification

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A R T I C L E I N F O

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A B S T R A C T

Eggshell quality is a determining factor in food safety, production efficiency, and the commercial acceptance of eggs. This study proposed the development and validation of an automated system for measuring eggshell translucency using computer vision and machine learning. A total of 326 commercial eggs from different production systems, with white and brown shells, were analyzed. Images were captured in a controlled environment and digitally processed to extract quantitative translucency measurements. The obtained values were compared with traditional visual classification and used in supervised classification models (KNN, SVM, and Random Forest). The SVM model showed the best performance, with accuracy exceeding 90 % in distinguishing translucency levels. Additionally, predictive models (Multiple Linear Regression and SVM) were tested to estimate intrusive variables based on translucency, revealing moderate correlations, particularly with shell thickness and shell weight. It is concluded that translucency can be accurately quantified through automated techniques, with potential application in the screening and quality control of commercial eggs, although it should be used as a complementary indicator alongside other technical parameters.

Introduction

Evaluation of egg quality is a crucial process in the poultry production chain, directly impacting commercialization, consumer acceptance, and food safety. Qualitative aspects such as shell thickness and strength, as well as size, weight, integrity, and internal composition, are key to ensuring the quality of the final product (Okinda, 2020; Roberts, 2004; Wengerska et al., 2023), whether it be a table egg (infertile) or a day-old chick (fertile egg). Moreover, egg quality influences production efficiency, as structural defects can lead to significant economic losses and indicate the need for adjustments in the management of laying hen farms (Ledvinka et al., 2012). Therefore, the adoption of precise and efficient methods to assess these characteristics is essential to meet market quality standards and health regulations (Atwa et al., 2024).

Traditionally, egg quality assessment involves intrusive measurements that may compromise the integrity of the product and lead to waste, rendering the analyzed eggs unsuitable for consumption or incubation. In this context, eggshell translucency has emerged as a potential variable gaining prominence in research on the quality of commercial eggs (Xuan & Zheng, 2024). This characteristic provides relevant information about shell composition and integrity, as its ability to transmit light may be associated with shell thickness and potential microstructural deformations, directly influencing egg strength and durability (Shi et al., 2023). Wang et al. (2017), for example, suggest that the formation of translucent eggs is related to variations in shell and membrane structure, with translucent eggs presenting thicker shells, thinner membranes, and lower final membrane resistance compared to opaque eggs.

Including translucency as a new parameter in egg quality evaluation opens new research possibilities for optimizing the production chain. Chousalkar et al. (2010) demonstrated that eggshell translucency is associated with a higher risk of bacterial penetration, including Salmonella Infantis and E. coli, especially at room temperature, highlighting the importance of refrigerated storage to minimize contamination. In the field of genetics, Zhang et al. (2021) analyzed shell translucency in different chicken breeds, identifying variations in

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the intensity of this phenomenon among purebred, commercial, and local lines. In the context of commercial incubation, Neto et al. (2024) found that highly translucent eggs exhibited greater weight loss, lower hatchability, and higher embryonic mortality between days 11 and 18 of incubation.

Traditional methods for assessing shell translucency include visual inspection using dark environments and controlled lighting (Neto et al., 2024; Orellana et al., 2023). Modern and validated methodologies allow for classification of eggs into three translucency levels: 1) mild (few and small translucent spots on the shell); 2) moderate (translucent spots more evenly distributed across the shell); and 3) severe (presence of multiple spots and even large translucent areas across the entire shell). Although functional, such methodology still requires time and human expertise for accurate classification.

In addition to the adoption of new variables, such as translucency, the ongoing pursuit of greater efficiency and quality in poultry farming has led to the incorporation of innovative technologies in the sector. Technologies such as system automation, artificial intelligence, and precision livestock farming have been widely studied to enhance egg production and make processes more efficient (Narushin et al., 2025; Ren et al., 2020; Yang et al., 2024). Among these innovations, the use of computer vision and digital image processing stands out as a promising alternative for non-invasive egg quality assessment, enabling the automated measurement of important variables such as width and length (Aragua & Mabayo, 2018; Abd Aziz et al., 2020), estimation of volume and weight (Nyalala et al., 2021; Okinda, 2020), defect identification (Yang et al., 2023), and fertility (Ahmed et al., 2025; Çevik et al., 2022).

Furthermore, machine learning techniques have already been established as powerful tools for assessing egg quality. Machine learning algorithms enable the analysis of large datasets throughout the entire production chain, from bird nutrition to egg processing, allowing the identification of complex patterns that might go unnoticed with conventional methods (Bischof et al., 2024; Subramani et al., 2025). In quality control, for example, Sehirli and Arslan (2022) applied machine learning techniques to classify commercial eggs based on the Haugh unit. Similarly, Oliveira-Boreli et al. (2023) investigated the combination of image analysis and machine learning to validate the use of the Shape Index as a non-destructive method for classifying chicken egg quality.

Given this context, different approaches have been proposed to quantify eggshell translucency more objectively. Wang et al. (2019) developed a system based on grayscale recognition and colorimetry, allowing the extraction of variables such as the number, diameter, and average area of translucent spots. More recently, Wang et al. (2020) presented an automated computer vision system capable of detecting dark spots on the shell using techniques such as K-means clustering and unsharp masking enhancement, achieving high processing speed (0.5 s per image) and segmentation accuracy. Despite this technical advancement, the study focuses exclusively on the superficial quantification of spots, without considering correlations with other morphological traits or internal egg quality parameters.

By combining two emerging themes in the evaluation of commercial and fertile egg quality - translucency as a qualitative indicator and process automation through computer vision - this study proposes the development of an automated system for measuring egg translucency using image processing and machine learning. Additionally, the study aimed to correlate translucency with other quality parameters, enabling more accurate and reproducible analyses.

Material and methods

Experimental samples

For this study, a total of 326 commercial eggs were analyzed, comprising 162 brown-shelled and 164 white-shelled eggs. To ensure greater morphological diversity in the sample set, the eggs were sourced from nine different brands, representing three production systems: conventional (caged), free-range, and cage-free. Additionally, the eggs were commercially classified into three weight categories: large, extra, and jumbo. The storage time of the samples ranged from 5 to 19 days, taking the day of evaluation as the reference point. At the beginning of the experimental phase, each egg was properly labeled and subjected to all automated (section 2.2) and manual (section 2.3) tests described in this article.

Automated metrics

Image Database. The experiment was conducted in a climate-controlled chamber at the Department of Biosystems Engineering, "Luiz de Queiroz" College of Agriculture, University of São Paulo, Brazil. This environment was chosen and conFig.d to prevent any light input, whether external (absence of windows) or internal (0 lux illumination). Image acquisition took place from early to mid-October 2024. Since the chamber offers controlled lighting and temperature, images were collected throughout the day without time restrictions or influence from external conditions.

The system developed for image capture aimed to record the full structure of each egg, providing a perspective similar to that used in conventional translucency assessment (Orellana et al., 2023). Image capture was performed using two main components: a digital camera and a standardized light source. For this purpose, a smartphone (iPhone 13, Apple Inc., United States) equipped with a 12-megapixel camera, conFig.d with wide-angle and ultra-wide-angle lenses, was used. To ensure stability, the device was mounted on a platform with vertical angle adjustment.

A commercial candling device (Chocmaster, Brazil) equipped with a white-toned LED light was used as the light source. The standard ring size recommended for chicken eggs, as indicated by the manufacturer, was used. Although precise light intensity values were not recorded, preliminary tests indicated that this setting provided sufficient contrast between the egg and the background, consistent with approaches validated in previous studies (Alikhanov et al., 2018; Dal'Alba et al., 2020; Sokovnin, 2021; Wang et al., 2019).

In total, 326 images were recorded, corresponding to each egg in the experimental sample. This sample size aligns with previous studies on image processing applied to eggs (Alikhanov et al., 2018; Ab Nasir et al., 2018; Soltani et al., 2015). All images were stored and cataloged in a cloud-based database for further analysis. The images had dimensions of 3024 × 4032 pixels, portrait orientation, and were saved in JPG format to optimize computational processing.

Model Development. The translucency of the eggshell was calculated through a digital image processing procedure aimed at non-destructively quantifying the proportion of more translucent regions visible under controlled lighting. The algorithm was developed using MATLAB® (version R2022b, United States), employing image segmentation and morphological analysis functions. The system was designed based on the fundamental principles of computer vision systems (Alikhanov et al., 2018; Aziz et al., 2020; Nyalala et al., 2021), encompassing stages such as digital image preprocessing, identification and isolation of regions of interest, and subsequent extraction of relevant features (Fig. 1).

Initially, the color image of the egg was converted into a monochromatic image by extracting the red channel from the RGB composition. This choice was based on a qualitative analysis of the acquired images, which revealed greater contrast between the shell and pores in the red channel under backlighting. Converting the image to grayscale simplified the segmentation process, as the light intensity could then be directly manipulated to distinguish regions with different optical properties (Gonzalez & Woods, 2010).

From this grayscale image, the total area of the egg was segmented using a light intensity threshold. Although adaptive thresholding methods were initially tested, the imaging setup provided a controlled

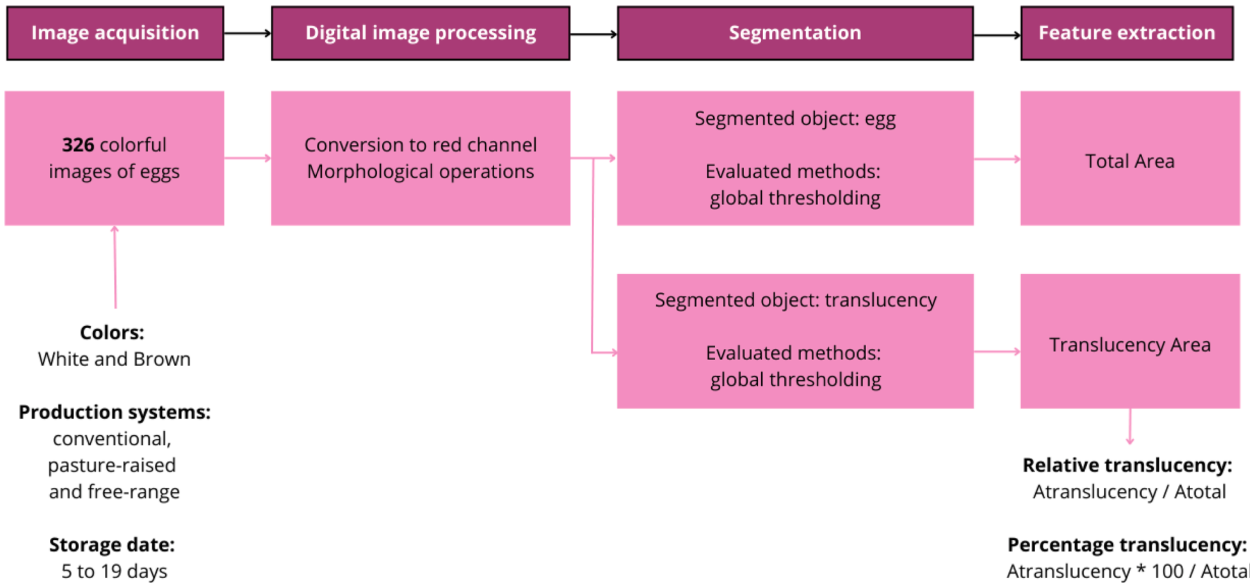

Fig. 1. Flowchart of the automated system for eggshell translucency extraction and calculation.

environment with no variation in lighting, background, or egg positioning; therefore, global thresholding was adopted for its simplicity and reliable performance under these conditions. The threshold values used for image segmentation were determined empirically through preliminary testing and visual validation. This process involved analyzing a representative subset of images with varying degrees of translucency and manually adjusting the threshold values to maximize the contrast between translucent regions and the surrounding shell. Thresholds were selected based on their ability to consistently isolate regions of interest across samples without including background noise or excluding relevant areas.

In this step, all pixels with intensity values above 0.51 (on a normalized scale from 0 to 1) were considered part of the object of interest—the egg—while all others were classified as background. The same thresholds were applied for both brown and white eggshells. The resulting binary image was then processed with a region-filling algorithm based on neighborhood connectivity to ensure the integrity of the segmented objects. This correction was essential to eliminate thresholding artifacts and ensure that the computed area accurately represented the entire egg structure (Grift et al., 2017). With the corrected binary mask, the total egg area, A_{total}, was estimated by counting the number of pixels classified as part of the object.

The identification of translucent regions—presumably associated with pores or structural imperfections in the shell—was carried out through a second segmentation step with a higher threshold. From the same grayscale image, a threshold of 0.91 (white-shelled eggs) and 0.88 (brown-shelled eggs) was applied, based on preliminary tests and visual observation, to highlight only the pixels with high light intensity, i.e., those that allowed greater light transmission. Pixels with intensity above this threshold were considered part of the translucent regions and were used to calculate the translucent area, $A_{translucency}$.

Based on these two extracted areas, the relative translucency (T_r) was defined as the ratio between the area of the translucent regions and the total egg area, as shown in Equation 1:

$$T_r = \frac{A_{translucency}}{A_{total}} \quad \text{(Eq. 1)}$$

Additionally, this value was converted into a percentage, resulting in the percent translucency ($T_{\%}$), as shown in Equation 2:

$$T_{\%} = \frac{A_{translucency} * 100}{A_{total}} \quad \text{(Eq. 2)}$$

For visual validation and qualitative analysis, an overlay image was generated by combining the original egg image with the binary mask of the translucent regions, with those areas highlighted in artificial color. This visualization step allowed verification of whether the segmentation effectively corresponded to the regions perceived as translucent in the original image, as recommended in morphological analysis systems for segmentation validation (Gonzalez & Woods, 2010).

Automated metrics

To evaluate the qualitative aspects of the experimental eggs, the measured variables were categorized into two groups. Non-invasive measurements (collected before breaking the eggs): weight (g), maximum egg length (mm), maximum egg width (mm), translucency (score). Invasive measurements (collected after breaking the eggs): liquid weight (g), shell weight (g), yolk color (score), yolk diameter (mm), yolk height (mm), albumen height (mm), shell thickness (mm).

The total egg weight, liquid weight, and shell weight were measured using a precision electronic balance (Gehaka, model BG 2000, Brazil), factory-calibrated. The maximum egg length, maximum width, albumen height, and yolk diameter and height were measured using a high-precision digital caliper (Digimess, model 100.174BL, Brazil). During the measurements, the eggs and internal contents were placed on a flat surface to avoid distortion due to tilt. Weight and size measurements followed standard methodologies presented in previous studies (Almeida et al., 2021; Nyalala et al., 2021).

Yolk color was manually evaluated using the YolkFan™ colorimetric scale (dsm-firmenich), which classifies yolk color on a scale from 1 (light yellow) to 16 (deep orange). This is a widely accepted method for yolk color characterization and is strongly correlated with the carotenoid content in the hens' diet (Ortiz et al., 2021).

Shell translucency was also visually assessed under standardized lighting in a low-light environment. The evaluation followed the protocol described by Orellana et al. (2023), in which eggs are classified into three categories (A, B, and C) based on the presence, size, and distribution of translucent or mottled regions on the shell surface. To minimize subjectivity and ensure consistency, a preliminary calibration session was conducted with an expert in egg quality evaluation, and the classification strictly adhered to the sample illustrations provided in the original protocol (Orellana et al., 2023).

To ensure accurate shell thickness measurements, a preparation protocol was adopted based on the methodology adapted from Carter

(1968). First, the eggshells were carefully washed under running water to remove internal residues. The samples were then air-dried at room temperature (~25°C) for 48 hours in a protected environment. After complete drying, shell thickness was measured using a high-precision digital micrometer (Dasqua, model 417.0028, Brazil) with 0.001 mm resolution. For greater reliability, three measurements were taken in different regions of the egg — the broad end, narrow end, and equatorial region — and the average of these values was considered the representative thickness of the sample.

Based on the collected data, the yolk index (YI) was calculated using Equation 3, and the Haugh Unit (HU) using Equation 4:

$$YI = \frac{Yolk\ Height}{Yolk\ Diameter} \quad \text{(Eq. 3)}$$

$$HU = 100\ x\log\left(Albumen\ Height - 1,7 * \left(Egg\ Weight^{\ 0,37}\right) + 7,6\right) \quad \text{(Eq. 4)}$$

Validation and classification

This study aimed to address two main questions regarding the analysis of eggshell translucency: (1) Can translucency be automated and measured quantitatively? and (2) Can translucency replace variables traditionally measured through invasive methods? To investigate these questions, a two-step methodological approach was adopted. First, a comparison was conducted between the visual (manual) classification of translucency and its numerical versions extracted through digital image processing. Next, the potential of translucency measurements to serve as substitutes for invasive variables was assessed.

Automated Quantification of Translucency. The first step consisted of assessing the feasibility of quantitatively and automatically measuring eggshell translucency. For this purpose, the visual classification of eggs into three categories (A, B, and C), based on the presence and distribution of spots on the shell, was compared with values obtained from two numerical metrics: relative translucency and percentage translucency.

Initially, an exploratory data analysis was performed to visualize the distribution of numerical translucency measurements within each manual category. This visualization allowed for the identification of overlaps, central tendencies, and dispersions associated with each group — a fundamental step to evaluate class separability.

Subsequently, supervised classification models were applied to predict the visual class (A, B, or C) based on the numerical measurements. The input variables (features) were the translucency measures, while the target variable was the manual classification. The models employed were: K-Nearest Neighbors (KNN); Support Vector Machine (SVM); and Random Forest. All tests and statistical analyses were conducted using the R language via RStudio version 2024.12.1+563. For all tests, the dataset was randomly and representatively split into training (75 %) and testing (25 %) sets. To preserve the original class distribution during model training and evaluation, the dataset was split into training and testing subsets using stratified random sampling.

The K-Nearest Neighbors (KNN) method was implemented with k = 5, meaning the algorithm classified a new observation based on the majority labels among its five nearest neighbors, calculated using Euclidean distance in the translucency variable space (Henderi et al., 2021). Prior to model application, the numerical variables were standardized (mean zero and standard deviation one) to ensure equal contribution to the distance calculation.

The Support Vector Machine (SVM) method was used as a model aiming to find optimal hyperplanes separating classes in the translucency variable space, even in high-dimensional contexts. Initially, the numerical variables were standardized to ensure comparability and good algorithm performance. The target variable, representing the visual classification of samples, was converted to a factor type with levels "A", "B", and "C", preparing the dataset for classification. The classifier was conFig.d as "C-classification" with a "linear" kernel, aiming to maximize the margin between class boundaries.

The Random Forest model is an ensemble learning algorithm that combines results from multiple decision trees built on random samples of data and predictor variables, promoting greater stability and predictive accuracy (Parmar et al., 2018). Here, the target variable was also treated as a factor, a necessary condition for classification tasks. The classifier was trained with 10 trees using the standardized numerical translucency variables as predictors.

Model performance was evaluated and compared based on confusion matrices and classification performance metrics. In this study, the following metrics were considered: accuracy, precision, recall, and F1-score, which together provide a comprehensive view of each model's predictive quality.

Replacement of Intrusive Variables. The second stage of data analysis aimed to investigate whether translucency measurements, obtained non-invasively, could replace variables traditionally collected through intrusive methods, such as shell thickness, yolk height, albumen height, and shell weight. This analysis was conducted in two complementary approaches: identifying the relevance of translucency via Principal Component Analysis (PCA) and building regression models to predict intrusive variables solely based on non-intrusive features. Again, all analyses were performed using the R language in version 2024.12.1+563 of RStudio.

In the first approach, the correlation matrix among the dataset variables was analyzed to identify potential associations between non-invasively obtained features—such as percentage translucency—and traditionally measured intrusive variables, including shell thickness, shell weight, albumen height, and yolk height. Spearman's correlation coefficient was employed for this analysis, a non-parametric measure that assesses monotonic relationships even in the absence of strict linearity between variables (Song et al., 2022).

The second approach consisted of constructing predictive models using supervised regression algorithms. The objective was to verify whether it is possible to predict quantitative variables based on translucency measures, specifically percentage translucency.

Two distinct models were utilized. The first was Multiple Linear Regression, which seeks to establish a linear relationship between predictor variables and the response variable (Uyanik & Guler, 2013). The second model used was the Support Vector Machine (SVM) algorithm in regression mode (epsilon-regression) with a radial kernel function, enabling the capture of nonlinear relationships between variables (Parreño & Anter, 2024). The model was trained with all available data, and predictions were generated from the non-invasive variables.

Both models were evaluated and compared based on performance metrics: R^2 (coefficient of determination); ME (mean error); RMSE (root mean square error); SSR (sum of squares due to regression); SSE (sum of squared errors); and SST (total sum of squares). The comparison of model performances allowed identification of whether including translucency significantly improves predictive capability, providing evidence that this variable can, in fact, replace or complement intrusive measurements.

Results and discussion

Digital processing

Fig. 3 illustrates the main steps of the digital processing applied to the images of white (A) and red (B) eggshells, visually highlighting the transformation flow from the original image to the final segmentation of the regions of interest.

Initially, the process started from a color image in RGB format (Fig. 2.1), acquired through a standardized capture system. To facilitate segmentation and reduce computational complexity, the image was decomposed into its three basic channels (red, green, and blue), and only the red channel (R) was used, as illustrated in Fig. 2.2. The choice of the

R channel is justified by its ability to maximize the contrast between the egg and the dark background, favoring the separation of the object of interest — the egg — from external elements and visual artifacts. This approach is frequently reported in the literature as an effective technique in image analysis contexts with controlled artificial lighting (Gonzalez & Woods, 2010).

Next, a thresholding step was applied, converting the intensity matrix into a binary image based on a predefined threshold value. This thresholding allowed isolating the complete contour of the egg (Fig. 2.3), classifying it as the main region of interest in the image. The appropriate selection of the threshold value was essential to avoid both the inclusion of unwanted noise and the exclusion of significant parts of the shell, especially in cases with shadows or non-uniform lighting. As noted by Wang et al. (2020), the segmentation effectiveness is directly related to the precise choice of the intensity threshold.

To isolate the areas of higher translucency — interpreted as imperfections in the shell structure — a more restrictive thresholding was applied, resulting in the identification of regions with higher luminance intensity in the red channel. These regions are shown in Fig. 2.4. In both shell types, the method proved sensitive to the presence of these structural variations.

After segmenting the imperfections, the extracted regions were overlaid onto the original image, resulting in a visual fusion that allowed qualitative inspection of the algorithm's performance. In Fig. 2.5, the imperfections are highlighted in blue over the original egg image, showing the correspondence between the segmented regions and the points of higher translucency detected.

This process enabled the extraction of morphometric attributes such as the total shell area and the area corresponding to the translucent regions. Using these data, it was possible to calculate the relative and percentage proportion of translucency concerning the total egg area, providing a novel and objective metric for the quantitative analysis of shell quality.

Can translucency be automated and measured quantitatively?

Table 1 presents descriptive statistics of the percentage translucency values (%) calculated per image, segmented by manual translucency categories (A, B, and C) and shell type (white and brown). In class A, representing eggs with low translucency, the mean percentage translucency values are the lowest in the dataset, with 3.21 % for white eggs and 2.99 % for brown eggs. Maximum values remain below 9 %, and standard deviations are relatively low, indicating uniformity within samples of this class.

In class B, there is a noticeable increase in mean values, with 5.69 % and 5.83 % for white and brown shells, respectively. Standard deviations remain around 1 %, suggesting that class B has greater variability than class A but still presents a relatively compact distribution. In class C, there is a marked increase in average translucency, especially for brown eggs, reaching 12.21 %, compared to 10.14 % for white eggs. The standard deviation for brown eggs (4.51 %) indicates a wide dispersion, also reflected in the maximum translucency value (25.52 %). This higher variability may be explained by more pronounced differences in shell structure or by greater sensitivity of the automated technique in capturing subtle variations in eggs with high translucency.

Table 1
Descriptive statistics of percentage translucency (%) obtained by digital image processing, according to manual classification (A, B, and C) and shell type (white and brown).

Translucency (Score)	Shell	Percentage translucency (%)			
		Mean	Std. Dev.	Min	Max
A	White	3.2122	0.8937	1.4504	4.9102
	Brown	2.9908	1.1129	0.6379	8.6023
B	White	5.6861	0.9944	3.5400	8.6368
	Brown	5.8279	1.0262	3.1470	9.4947
C	White	10.1386	1.8971	7.4208	13.9067
	Brown	12.2099	4.5054	7.0698	25.5183

Fig. 3 shows a boxplot comparing the percentage translucency values automatically calculated from images with the manually assigned translucency categories (A, B, and C) for white and brown eggs. Supporting the results presented in Table 1, there is a clear trend of increasing translucency (%) as the manual classification progresses from A to C, suggesting good correspondence between the visual scores and the values obtained through digital image processing.

In class A, representing eggs with the lowest visual translucency, percentage values remain concentrated below 5 %, with little variation between white and brown eggs. In class B, translucency values increase, with a median around 5 to 6 %, remaining relatively consistent across the two shell types. The largest difference appears in class C, where there is greater data dispersion and both mean and maximum translucency values increase significantly, surpassing 10 % in both groups and reaching nearly 20 % in brown eggs, with an outlier close to 26 %.

The consistent increasing trend and the spacing between quartiles reinforce the validity of the automated methodology to quantify eggshell translucency. Additionally, the similarity in behavior between white and brown eggs indicates that the automated classification is robust to variation in shell pigmentation.

Given these promising exploratory analysis results, Table 2 presents a comparison of the KNN, SVM, and Random Forest models regarding their performance in classifying eggshell translucency. Overall, the Support Vector Machines (SVM) model showed the best performance, achieving the highest overall accuracy (93.06 %) and the best F1-scores for classes A and B, demonstrating a balance between precision and recall. The perfect precision (1.000) of SVM for class A is notable, indicating that the model made no false positives in this category during testing.

The Random Forest model also showed robust results, with an overall accuracy of 91.43 % and competitive performance across the three classes. Although slightly behind the SVM in classes A and B, Random Forest achieved the highest F1-score for class C (0.750), suggesting an advantage in correctly identifying eggs classified with higher translucency. This result is especially relevant since class C generally tends to present greater data variability and lower relative frequency, which can challenge its correct classification.

The KNN model presented the lowest performance among the three, with overall accuracy of 88.89 % and lower F1-scores across the classes, especially in class C (0.667), where both precision and recall were the lowest. This outcome may indicate greater sensitivity of KNN to data distribution and the number of neighbors chosen, which can impair its performance in contexts with less represented classes or with more overlap between categories. Other comparative studies in different areas have also reported inferior KNN performance compared to other methods (Islam et al., 2022; Kutlay et al., 2019; Oliveira-Boreli et al., 2023; Raghuwanshi et al., 2022).

It is noteworthy that all models performed worse on class C, with recall only 66.7 % in all cases, indicating a common difficulty in correctly identifying eggs with higher translucency. This highlights the need for additional strategies, such as weight adjustment or balancing techniques, to improve model sensitivity regarding this class.

Finally, Fig. 4 presents specific classification cases that are worth highlighting. In images A, B, and C, there is a correct match between the automatic method and the manual classification, demonstrating the system's ability to accurately identify different levels of eggshell translucency. In contrast, images D and E show disagreement between the methods. In the case of image D, the automatic method overestimated the translucent area by mistakenly interpreting the air cell as a translucent region, which led to classifying the egg as Class B, whereas manual analysis correctly assigned it to Class A. On the other hand, image E represents an atypical case involving a rotten egg, in which the dark internal content interfered with segmentation (as seen in Step 3 of

Table 2
Performance of translucency classification models based on automated measures (numerical translucency).

Model	Overall Accuracy	Precision			Recall			F1-Score		
		A	B	C	A	B	C	A	B	C
KNN	0.8889	0.914	0.903	0.667	0.970	0.848	0.667	0.941	0.875	0.667
SVM	0.9306	1.000	0.912	0.667	0.969	0.939	0.667	0.985	0.925	0.667
Random Forest	0.9143	0.914	0.867	0.857	0.941	0.897	0.667	0.927	0.882	0.750

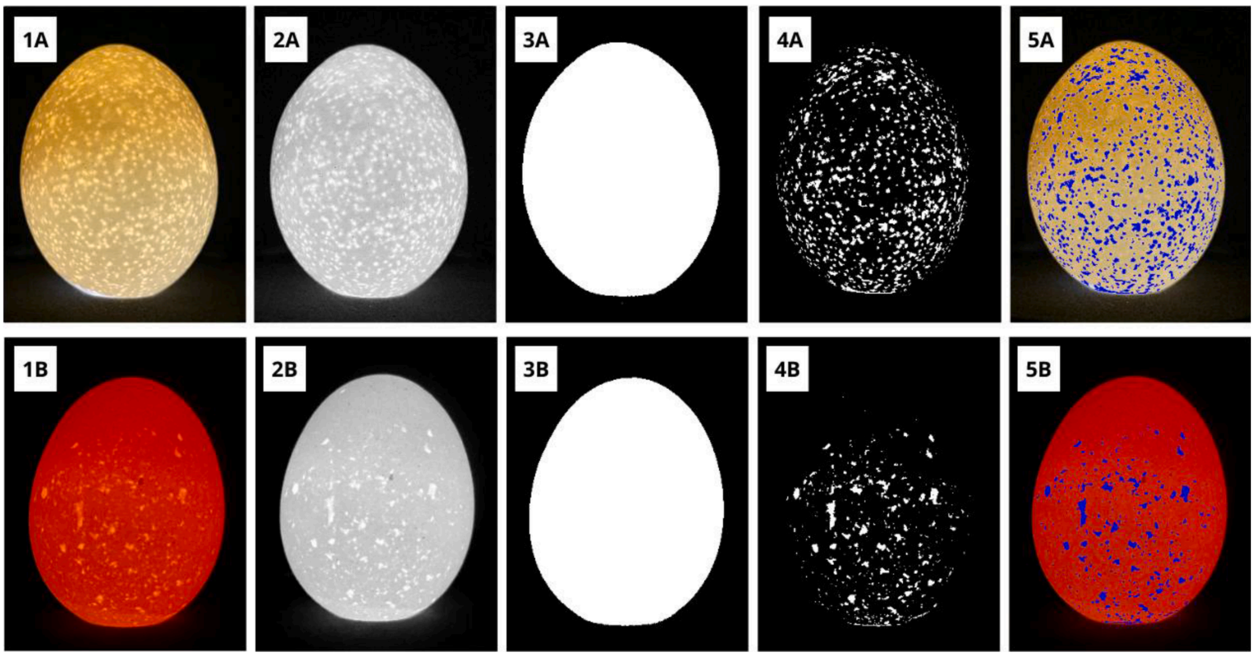

Fig. 2. Steps of the digital processing of a white eggshell sample (A) and a red eggshell sample (B). 1: original RGB image; 2: image with the R channel; 3: segmented image of the eggs; 4: segmented image of the imperfections; 5: original image overlaid with imperfections (in blue).

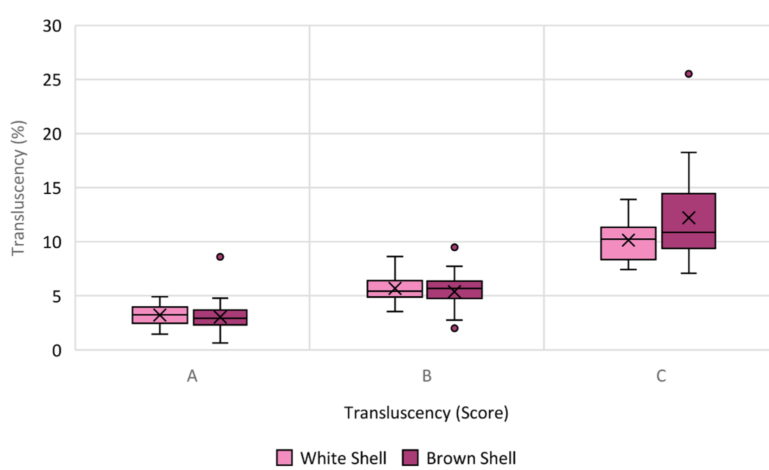

Fig. 3. Boxplots of translucency metrics by visual class (A, B, and C).

Fig. 2). In this scenario, the algorithm underestimated the translucent area, since a significant portion of the egg's interior was interpreted as background, reducing the region considered in the analysis. To address these errors, it is recommended to evaluate alternative thresholding methods, such as adaptive thresholding techniques that dynamically adjust to variations in lighting and contrast. Furthermore, the algorithm should be revised to handle anomalous cases more effectively, such as rotten or fertile eggs, by incorporating anomaly detection mechanisms or specialized pre-processing steps for such conditions.

These case analyses complement the broader findings of this study, which align closely with prior research on quantitative translucency assessment. Wang et al. (2019) proposed a grayscale recognition method combined with colorimetry, identifying relative translucent area values (RSS) ranging from approximately 1.3 % to 11.9 % across different translucency levels. Similarly, our results showed increasing percentage translucency values from Class A to Class C, with averages and dispersion patterns that reflect progressive intensities of the phenomenon, especially in brown-shelled eggs. While the grayscale and colorimetric

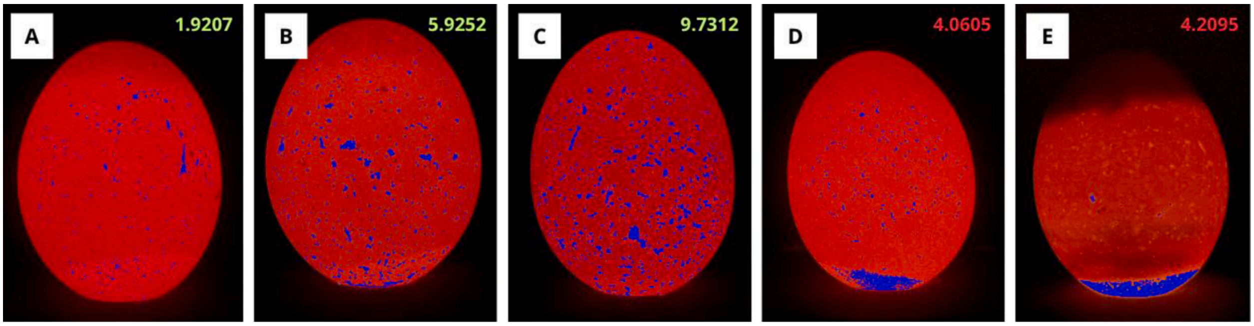

Fig. 4. Sample images of red-shelled eggs. The values in the top right corner indicate the percentage translucency (%); green values represent correct classification by the automatic method compared to the manual method, while red values indicate disagreement between the two methods tested. Image A was classified as Class A (low translucency); images B, D, and E were classified as Class B; and image C was classified as Class C (high translucency).

techniques introduced by Wang et al. (2019) provided an important foundation for quantifying translucency with greater objectivity, the present study builds upon these advances by implementing a fully automated workflow. In particular, the use of red-channel segmentation and morphological analysis offers a simplified and scalable alternative that retains strong correspondence with manual classification. Complementary to this, Wang et al. (2020) demonstrated the feasibility of using machine vision to detect and quantify dark spots related to translucency through techniques such as K-means clustering and unsharp masking. Their system achieved high processing speeds and accuracy, reinforcing the potential of automated approaches. The methodology proposed here aligns with that objective, offering a robust and flexible pipeline that can also be integrated with machine learning models and extended to investigate correlations with internal quality parameters, expanding the practical applications of automated translucency analysis in egg grading systems.

Although the proposed image acquisition setup, which was conducted in a controlled dark environment with fixed lighting and positioning, ensured high consistency and image quality, its direct implementation in commercial production lines may be challenging. Real-world environments are subject to variations in lighting, vibration, egg positioning, and equipment constraints. To facilitate deployment in industrial settings, future adaptations should consider integrating the system into existing candling or grading stations, using enclosed imaging chambers with diffuse LED lighting and mechanical guides to standardize egg orientation. Additionally, real-time calibration algorithms and adaptive segmentation techniques could be employed to compensate for environmental variability, enabling robust performance without requiring fully controlled conditions.

Can translucency predict other qualitative parameters?

The correlation matrix analysis (Table 3) revealed that relative shell translucency exhibited weak to moderate positive associations with a few variables, most notably average shell thickness (correlation coefficient = 0.258) and shell weight (r = 0.192). These findings suggest that eggs with thicker or heavier shells may tend to show higher translucency values, potentially due to structural or compositional differences. This may be explained by the multifactorial nature of translucency, which is influenced not only by one specific shell characteristic but also by internal microstructural features and membrane properties not captured in this study. However, since no hypothesis testing was conducted, these coefficients should be interpreted as descriptive indicators of monotonic relationships, rather than statistically significant parameters.

This result partially corroborates the findings of Wang et al. (2017), who observed that translucent eggs had significantly thicker shells than opaque ones, especially in brown-egg laying hen lines. Furthermore, in the same study, the shell membrane thickness was significantly lower in translucent eggs, which may indicate a microstructural reorganization responsible for the formation of translucent areas in the shell. Orellana et al. (2023) also reported a positive association between translucency and shell thickness in fertile eggs from broiler breeder hens. Eggs with high translucency exhibited significantly thicker shells compared to less translucent eggs ($P < 0.0001$). However, the initial egg weight (prior to incubation) did not differ significantly among the different translucency levels. Although the genetic lines and purposes of the eggs used in those studies differ from the present work, the results offer relevant indications. This reinforces the need for further investigation into the relationship between translucency and other egg quality parameters.

Table 4, in turn, presents the performance metrics of two predictive models for estimating shell thickness and shell weight — variables selected based on the correlation analysis. The predictive variables

Table 3
Spearman correlation matrix between relative shell translucency (T) and morphometric and qualitative egg variables.

	T	TW	EH	EW	IW	YC	YD	AH	YH	SW	YI	HU	ST
T	1.000	0.069	0.037	0.015	0.049	-0.031	-0.048	0.135	0.057	0.192	0.064	0.103	0.258
TW		1.000	0.835	0.883	0.972	-0.126	0.678	-0.048	0.011	0.665	-0.367	-0.296	0.115
EH			1.000	0.628	0.803	-0.146	0.645	-0.094	-0.065	0.596	-0.398	-0.302	0.019
EW				1.000	0.873	-0.047	0.630	-0.090	-0.054	0.589	-0.394	-0.311	0.094
IW					1.000	-0.096	0.653	-0.003	0.032	0.522	-0.340	-0.248	0.041
YC						1.000	-0.018	-0.208	-0.395	-0.015	-0.237	-0.174	-0.021
YD							1.000	-0.147	-0.297	0.510	-0.739	-0.319	0.221
AH								1.000	0.366	-0.141	0.328	0.9618	0.058
YH									1.000	-0.039	0.838	0.346	-0.061
SW										1.000	-0.305	-0.305	0.400
YI											1.000	0.411	-0.157
HU												1.000	0.022
ST													1.000

Notes: T – Relative translucency; TW – Total weight; EH – Egg height; EW – Egg width; IW – Internal weight; YC – Yolk color; YD – Yolk diameter; AH – Albumen height; YH – Yolk height; SW – Shell weight; YI – Yolk index; HU – Haugh unit; ST – Average shell thickness.

Table 4
Average performance of regression models.

Models	R^2	ME	RMSE	RSS	SSE	TSS
Target variable: Shell Thickness						
Multiple Linear Regression	0.122	0.048	0.219	0.216	1.548	1.765
ANN (Deep Learning)	0.192	-0.019	0.070	0.294	1.426	1.765
Target variable: Shell Weight						
Multiple Linear Regression	0.354	0.632	0.795	173.18	315.76	488.94
ANN (Deep Learning)	0.463	-0.093	0.954	262.36	170.34	448.94

Notes: R^2 - coefficient of determination; ME - mean error; RMSE - root mean square error; RSS - regression sum of squares; SSE - sum of squared errors; TSS - total sum of squares.

focused on non-invasive parameters: relative translucency, total weight, egg height, and egg width.

In the analysis of the shell thickness variable, the results indicate that the Multiple Linear Regression model obtained an R^2 of 0.122, suggesting a limited capacity to explain the variability of shell thickness based on the chosen predictor variables. This is reinforced by the mean error value, which was 0.048, indicating that the model has a relatively high average prediction error.

In comparison, the Artificial Neural Network (Deep Learning) model showed slightly better performance, with an R^2 of 0.192, indicating a greater capacity to explain shell thickness variability. The root mean square error for the ANN was 0.070, significantly lower than the value obtained by linear regression, indicating that the ANN is more efficient in terms of prediction error. Although the regression sum of squares is higher for the ANN, the model still presents a lower sum of squared errors, suggesting that the ANN is more effective at minimizing prediction error.

For the shell weight variable, the models' performance was more consistent. Multiple Linear Regression obtained an R^2 of 0.354, reflecting a more significant explanation of the variability of shell weight compared to the shell thickness model. However, the mean error was 0.632, indicating that despite reasonable variability explanation, the model still presents considerable error in predicting shell weight values.

The ANN (Deep Learning) outperformed Multiple Linear Regression, with an R^2 of 0.463, demonstrating a substantial improvement in model explanatory power. Additionally, the ANN's RMSE of 0.954 was lower than that of linear regression, suggesting that the neural network model had a more robust performance in predicting shell weight. The RSS and SSE values for the ANN also indicate that the neural network model is more effective in minimizing both explained variability and prediction error, with an TSS of 448.94 compared to 488.94 for the linear regression model.

Therefore, eggshell translucency stands out as a unique attribute with its own characteristics that provide valuable information about egg quality. It is important to note that translucent regions may arise from a range of underlying causes, including uneven shell thickness, localized pigment concentration, differences in mineralization, or membrane structure, rather than exclusively from defects such as pores or microcracks. Thus, translucency should be understood as an optical manifestation of multiple shell characteristics.

However, although it is a relevant variable by itself, the use of translucency to directly estimate other parameters, such as shell thickness or shell weight, is not recommended. This is because translucency, despite being correlated with certain aspects of egg quality, does not directly reflect all involved variables, such as the physical shell structure or internal egg composition, which are determined by distinct biological processes. Moreover, relying on predictive models to estimate these parameters based on translucency may lead to a loss of precision, since other invasive variables (such as actual shell thickness) provide more direct and reliable data. Thus, the recommendation of this article is that translucency should be valued as a complementary, not substitutive, measure for comprehensive egg quality assessment.

Limitations and future research

Despite the positive results obtained in this study, some limitations must be considered to ensure the applicability and generalization of the automated eggshell translucency analysis system in real-world production contexts.

Firstly, although the sample included eggs with different shell types, production systems, and weight ranges, it remains limited by unknown factors such as hen lineage, age, and feeding management. Literature indicates that genetics, nutrition, and layer age strongly influence the morphometric properties of the shell, including its thickness, strength, and permeability (Abdelqader et al., 2013; Elnesr et al., 2024; Santos et al., 2024). Therefore, future research should expand the dataset both qualitatively and quantitatively to include eggs from broiler breeders, alternative breeds, and different laying stages, aiming to develop more robust and generalizable models.

Moreover, the image acquisition in this study was conducted under controlled conditions, with no ambient light interference and using standardized equipment, which favored consistency in digital processing. However, such conditions are rarely replicated in commercial environments, such as automated farms or egg grading units, where light variability, motion, and egg positioning can compromise the system's accuracy (Ahmed et al., 2023; Wu et al., 2025). Thus, validation of the method under real operational conditions is recommended, along with technical adaptations to handle noise and visual interference commonly found in such settings. In future developments, the evaluation of adaptive or hybrid thresholding techniques may also prove beneficial to enhance the robustness of the segmentation process under variable lighting conditions.

Another critical issue lies in the reliance on manual labeling for training supervised models. While visual classification of translucency is widely used, it carries a degree of subjectivity—particularly in intermediate categories—that may affect the quality of training data (Orellana et al., 2023; Wang et al., 2019). Future studies could adopt semi-supervised or active learning strategies to reduce the need for continuous human labeling and make the models more adaptive to new usage conditions, as suggested by the methodologies presented by Ouali et al. (2020).

From a technical standpoint, the predictive models used in this study showed only moderate performance in estimating variables such as shell thickness and shell weight, with relatively low coefficients of determination ($R^2 < 0.5$). This indicates that, although translucency is associated with structural aspects of the shell, it does not fully replace intrusive measurements, as it reflects an optical phenomenon and does not directly measure attributes such as mineral composition or crystalline structure. Therefore, its application should be considered a complementary quality indicator, rather than a direct substitute for more specific structural variables.

In conclusion, the automated system developed represents a significant innovation in egg quality assessment, but it requires further validation and technological refinement to be established as a practical and reliable tool within the poultry production chain.

Conclusion

This study demonstrated that the application of computer vision and machine learning can serve as a viable, objective, and non-destructive alternative for analyzing eggshell translucency, showing a high degree of agreement with traditional visual evaluation. The proposed system was able to accurately quantify translucent regions and classify them with high performance, especially through the SVM model, which achieved an accuracy above 90 %. Although the regression models indicated moderate correlations between translucency and intrusive variables such as shell thickness and shell weight, the results suggest that translucency should be treated as a complementary rather than a substitutive parameter. The approach presented is promising for modernizing quality control processes in the poultry production chain, contributing to automation, standardization, and increased operational efficiency. Finally, further studies are recommended with a more diverse sample set and under real-world production conditions in order to consolidate its use on a commercial scale.

Declaration of AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used CHAT GPT in order to improve language, with caution. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Disclosures

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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