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Advanced Analytical Techniques for Egg Quality and Safety: From Colorimetry to Chemometrics

Maneysha Rajavel Viji[1], Vakalapudi Sanjani[2], Monica V[3], Kirthika Suresh[2]*

[1]Department of Food Process Technology, National Institute of Food Technology, Entrepreneurship and Management, Thanjavur, Tamilnadu, India, maneysharv@gmail.com, ORCID: 0009-0000-6691-1374
[2] Department of Biotechnology, Anna University, Chennai, Tamilnadu, India, vakalapudisanjani@gmail.com, ORCID: 0009-0008-7471-555
[3]Department of Food Technology, Rajalakshmi Engineering College, Chennai, Tamilnadu, India, monikala152000@gmail.com, ORCID: 0009-0004-3543-3102

**Corresponding author: suresh.kirthika1@gmail.com, ORCID: 0009-0000-3319-8699*

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Abstract

Egg quality remains a major concern in the poultry sector, where postharvest losses affect food security and economic returns. Conventional assessment methods such as candling, yolk index, and Haugh units, although prevalent, are subjective, destructive, and inefficient for extensive grading systems, motivating reliable, non-destructive, and rapid alternatives. This review examines emerging analytical techniques such as colorimetry, spectroscopy (NIR, VIS, Raman, FTIR), acoustic and sensor-based systems that enable real-time, non-invasive, and multi-parametric assessments of freshness, shell integrity, microbial contamination, and chemical residues with high accuracy. Machine vision, electronic nose, electronic tongue, and IoT-enabled smart detection systems which improve automation and objectivity are also discussed alongside chemometric tools and artificial neural network (ANN) models supporting advanced data interpretation, pattern recognition, and prediction of egg quality parameters. This review traces the progression from traditional to contemporary analytical methods, highlighting their benefits, challenges, and future directions of non-destructive quality evaluation in the poultry industry.

Keywords: *Egg quality assessment, Non-destructive techniques, Spectroscopy, Colorimetry, Sensors, Acoustics, Chemometrics.*

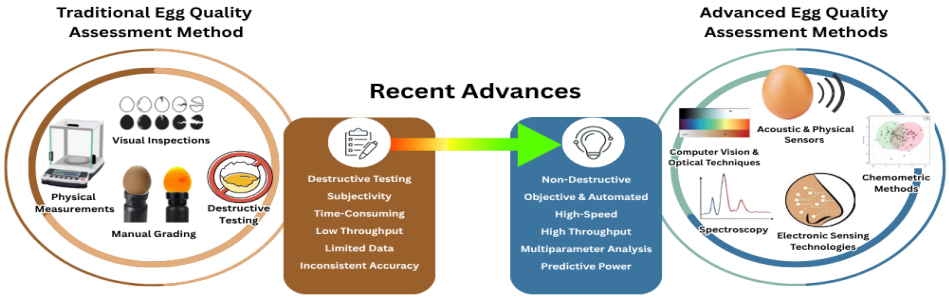

Figure 1.- Graphical abstract highlighting the evolution of conventional egg quality assessment methods to modern analytical instrumentation techniques

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1. Introduction

Since the prehistoric era, eggs from birds including chicken, duck, geese, and quails have been the most widely consumed and adaptable food item. In many countries around the world, eggs are a cheap and nutritious food source that is well-balanced [1]. Egg proteins are known for their high nutritional quality, essential amino acid composition and digestibility [2]. Additionally, in the contemporary food sector, poly-functional qualities including foaming, emulsification coagulation, colourant, and anti-crystallizing capabilities are commercially significant [1]. The structure of the egg is generally classified into an outer calcium rich egg shell, lipid containing egg yolk and protein rich egg white. The eggshell has about 10,000 pores for the exchange of water and gases [3]. Detailed accounts of chicken egg structure, composition, and formation have been compiled in the poultry science literature [4], and both traditional selection and modern genomic breeding approaches have been shown to influence key egg quality traits such as shell strength and albumen quality [5]. Egg yolks are incredibly rich in lipids, making up 33% of their total content [6]. The main components of egg yolk are phospholipids and triacylglycerols [7]. Egg white is composed of four layers: chalky, thin, thick, and chalky record. The thin outer layer connects to the inner eggshell membrane, while the thin inner layer is attached to the chalaziferous layer. The thick, viscous layer constitutes the majority of egg white. Major egg proteins like ovalbumin, ovotransferrin, ovomucin, ovomucoid, and lysozyme are studied extensively [8]. Egg white is rich in antibacterial lysozyme, which is widely used as a food preservative [9]. Eggs intended for human consumption must adhere to stringent quality standards established by modern industrial poultry practices. Egg quality encompasses the attributes that influence consumer acceptance and preference, focusing on both shell and interior egg quality. For eggs intended for further processing, the interior quality is particularly crucial. Factors such as handling, storage conditions, temperature, humidity, and the age of the egg all play significant roles in preserving its quality**.** Fig.2 highlights the various factors affecting the quality of whole egg**.** The Food and Agriculture Organization indicates that an estimated 30% of all eggs produced globally millions of metric tons go to waste every year, with developing nations losing almost two-thirds of such losses.

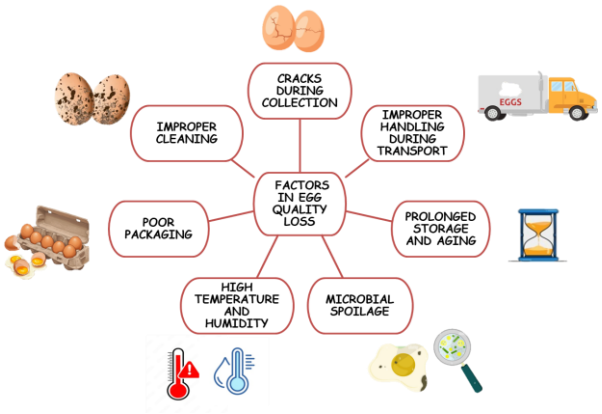

Figure 2. - Factors influencing the loss in quality and freshness of whole egg

This wastage happens at several stages: 45% at the production and handling stage, 30% at the distribution and storage stage, and 25% at retail and consumption stages [10]. The significant loss of egg quality throughout the supply chain is due to moisture evaporation and carbon dioxide diffusion through eggshell pores that leads to thinning of albumen, enlargement of air cell and weakening of vitelline membrane [11]. In addition, changes in the storage temperature and relative humidity cause physicochemical deterioration and microbial infestation, particularly by pathogenic organisms like Salmonella spp. Mechanical damage that occurs during handling, transportation, and distribution also affects quality and results in economic loss. Rapid, reliable and non-destructive technologies for quality assessment are required to maintain the quality and safety of eggs throughout the supply chain [12]. Nigeria experiences even greater losses of 20-30%, where Agbaje *et al*. (2021) revealed 60% is damage during loading/unloading, while microbial spoilage represents 25% of total loss, mainly caused by temperature changes in excess of 30°C during storage [13]. Developed countries show improved but still substantial wastage trends. Gustavsson *et al*. (2011) found that the EU and North America waste 5-10% of eggs (an estimated 7-14 billion eggs per year), and 65% of these wastes are lost at retail due to stringent grading requirements rejecting eggs with slight shell damage (≤0.5mm cracks) [14]. Jones *et al*. (2018) found that temperature abuse during retail storage increases Salmonella risk by 40-60% when eggs are stored above 7°C, contributing to additional losses through precautionary recalls [15]. In Ghana's Bono Region, Mensah *et al*. (2022) estimated these microbial losses at 18% of production, and of spoiled

eggs due to fungal contamination, 62% during rainy periods (humidity >85%) [16]. The financial effects are significant. Egg losses worldwide amount to $7-10 billion in direct value every year [10], with developing nations taking up 70% of those costs. In certain instances such as Ghana, losses per week equal 31,440 eggs valued at $2,287 in a single region [16], while US food retailers lose $400 million annually in egg downgrades [15]**.** These figures highlight the pressing requirement for standardized protocols for handling, enhanced cold chain infrastructure and intelligent packaging techniques to mitigate this worldwide problem. Recent advances in molecular spectroscopy with chemometric and machine learning strategies have improved food quality monitoring in recent years through rapid, accurate, and non-destructive analysis of complex biological systems. Spectroscopic techniques together with artificial intelligence algorithms can help identify the subtle physicochemical changes that take place to monitor the freshness and spoilage, contamination, and authenticity of the product. Also, Zuo *et al*. (2023) indicates that the combination of hyperspectral imaging and prediction model has showed great potential to evaluate quality characteristics in a nondestructive manner for food [17]. In addition, Zuo *et al*. (2024) indicates that the combination of transfer learning using spectroscopy methods has improved the accuracy and robustness of spoilage detection model, portraying the growing role of intelligent analytical systems in food quality monitoring [18]. This review comprehensively examines egg quality assessment methods, from traditional techniques like candling and Haugh units to advanced approaches including colorimetric analysis, sensor-based detection, spectroscopic methods, acoustic techniques, and chemometric analysis, highlighting their applications and innovations in non-destructive egg quality evaluation.

2. Traditional Egg Quality Assessment Methods

The external and internal quality parameters include egg shape, egg length, egg width, shell thickening, yolk index, yolk colour, yolk width, high albumin and egg weight**.** A digital vernier calliper is used to measure the length and width of the egg in centimetres; the weight of each egg is determined utilizing a sensitive scale, and the weight of the oven-dried egg shell was used to determine the egg's shell weight; the thickness of the dried shell of the egg is measured using a micrometre screw gauge which calculates the mean of the narrow, middle and broad points [19]**.** Other important external characteristics include shell colour, shell crack detection and shell index. Consumers often judge the quality of eggs based on their appearance, with a preference for those with pure, consistent colors though the colour and texture of an egg's shell have no bearing on its nutritional content [20, 21]. Chicken eggshells are delicate and brittle, and are prone to cracking when handled. These fissures raise the possibility that bacteria, including salmonella, will seep in and contaminate the eggs' contents. Visible cracks appear in the shell when a force is applied that is higher than the strength of the shell. Conversely, any impact that is less than the strength of the shell produces tiny cracks, known as micro-cracks, that are difficult to see with the unaided eye [21]. The egg shape index, defined as the ratio of an egg's width to its length, is an important parameter in evaluating egg quality. Deviations from the standard shape include excessively round or elongated eggs, which are generally considered undesirable, as they not only affect the aesthetic appeal but also reduce compatibility with conventional egg packaging systems, making them considerably more prone to break during transportation [22]. The shape index (SI) is determined using the formula [1].

$$\text{Shape Index \%} = \left[\frac{Width\ of\ egg\ (mm)}{Length\ of\ egg\ (mm)} \right] \times 100$$

In commercial poultry production, eggs having a shape index of about 72 to 76% are considered normal and acceptable. Eggs that have values below this range will be excessively elongated, while those with higher values will be rounder [22]. To assess the internal quality attributes of the eggs including albumen width, albumen height, yolk width, yolk height, albumen index and yolk index. The eggs are gently cracked and the albumen height, albumen width, and yolk width are measured using a vernier caliper. The albumen is then separated from the yolk and yolk height is measured with a tripod micrometer. The yolk's color is assessed using a Yolk Fan, which provides a color scale from 1 to 16. Finally, each separated albumen and yolk was weighed individually using a digital scale [23]. Yolk index: The yolk height divided by the yolk width (in centimetres) is yolk index and albumen height to egg width ratio is the Albumen index [19]. The Haugh unit (HU) has become incredibly popular for determining the quality of the contents of chicken eggs [24]. It is measured using the weight of the egg

and the height of the thick albumen. HU is calculated using the following formula [25]:

$$HU = 100 \times log\,[H + 7.57 - 1.7\,W^{0.35}]$$

where, HU is the Haugh Unit
H is the height of the thick albumen (mm)
W is the egg weight (grams)

3. Recent Advances in Quality Assessment of Egg

Traditional egg quality testing methods such as chemical analysis, physical measurements or sensory evaluation, can be destructive and affect the integrity of the egg sample [12]. Conventional egg-quality testing includes visual grading, candling, and Haugh unit testing, which are subjective, destructive, and time-consuming. A large proportion of flaws are missed by human graders (up to 30 %) and there is much inter-operator variation, whereas candling only detects apparent cracks and not albumen viscosity or yolk integrity. Since Haugh units involve breaking the shell, standard sampling means that the majority of eggs are never tested and undetected issues can still reach consumers [26,27]. Spectroscopic and imaging non-destructive technologies bridge these gaps by recovering rich, quantitative data from each egg in real-time. Hyperspectral imaging, near-infrared, and Raman spectroscopy, electronic noses, and deep-learning classifiers combine to identify hairline cracks, incipient microbial contamination, freshness indicators like pH or CO_2 changes, and volatile spoilage volatiles with > 95 % accuracy while analyzing thousands of eggs per hour [28,29]. Such systems convert quality control from a labor-intensive, single-parameter process to a multi-parameter, automated process whose outputs track effortlessly into digital traceability systems. Subsumed within the larger Industry 4.0 transformation, intelligent grading lines now combine imaging, vibrational spectroscopy, cloud analytics, and AI to provide real-time, end-to-end quality information. They not only mark defects but predict shelf life, initiate early-warning food-safety notifications, and offer producers and retailers a clear quality record for each egg moving through the supply chain. Digital, impartial, and complete, this method obliterates the principal flaws of traditional methods while opening up new avenues for data-based quality management and consumer confidence [28]).

4. Colorimetric Method For Egg Quality Analysis

Colorimetry is a widely used method for quantitatively estimating color in a sample solution, such as water or biological samples, at visible light wavelengths (380–780 nm). The intensity of the color is directly proportional to the concentration of the colored compound in the sample [30]. A significant increase in the use of colorimetric techniques for quality control of eggs is due to its cost effectiveness, sensitivity, ease of operation and real time monitoring. Following the remarkable surge in their use, many colour detection modes have been developed [31]. In order to determine colour values between reference black (0%) and white (100%) photoelectric colorimetry records reflected light at red, green, and blue wavelengths. Table 1 consolidates the recent research findings with relevance to colorimetry for assessing egg quality. Most studies associate yolk and eggshell colours as quality indicators influencing consumer preference.
Compared with spectroscopic and sensor-based methods, colorimetry offers the lowest instrument cost and simplest operation, making it attractive for routine grading, but it is largely limited to surface-level or single-parameter (e.g., colour) assessment and cannot resolve internal defects such as microcracks or microbial contamination.

5. Spectroscopic Methods For Egg Quality Analysis

Spectroscopic methods offer a reliable and non destructive solution for rapid assessment of egg quality. Various spectroscopic techniques such as microwave, visible, near infra-red (NIR), ultraviolet (UV), Fourier-transform infrared (FTIR), Raman spectroscopy and hyperspectral imaging are studied for quality analysis [26]. Commercial table eggs have either a brown, white, or coloured shell. Protoporphyrin-IX, biliverdin-IX, and zinc chelates are the sources of the brown hue. Eggs that are too pale or have uneven coloring are frequently rejected by customers. Using VIS/NIR spectroscopy, the transmission colour value (TCV), which is utilised for brown eggs, is calculated and reported as the ratio T643/T610. Higher TCV values denote lower shell pigmentation intensity [15]. This TCV concept was originally introduced as a means of using shell colour to monitor the stress and health status of brown-egg-laying flocks [40]. The major spectroscopic methods used for egg quality assessment are summarized in Table 2.

Spectroscopic methods determine egg quality through the effect of electromagnetic radiation on constituents of eggs. NIR spectroscopy recognizes the changes in moisture, protein, and fat content by assessing the overtone and combination vibrations of molecules [41]. FTIR spectroscopy reveals the changes in chemical functional groups and composition due to storage and degradation processes [42]. Raman spectroscopy measures the vibrational spectra of molecules induced by inelastic light scattering, thus enabling to detect the changes related to freshness, adulteration, and alterations in egg structure [43]. Microwave spectroscopy measures changes in the dielectric properties associated with the composition and aging of an egg [44]. Spectroscopic methods have many advantages, including fast determination, no need for sample preparation, sensitivity, and applicability in a non-destructive manner. However, these advantages come at a higher instrument cost than colorimetry or acoustic methods, and techniques such as FTIR and Raman typically require more specialized operator training, which can limit adoption in smaller processing facilities despite their superior accuracy and multi-parameter capability.

Table 1. Colorimetric Approaches for Egg Quality Evaluation and Consumer Perception

No.	Parameter	Method of analysis	Interpretation
1.	Yolk colour of the egg [32]	Subjective Evaluation by assessment using Roche Yolk Colour Fan and objective Evaluation using colorimeter to get Lab* colour space values	Colorimetric measurements were consistent and reliable. Deeper yolk colour is associated with greater customer perceptions of quality.
2.	Yolk colour enhancement using Curcuma domestica [33]	Fresh Egg yolk reflectance colorimetry values L* (lightness), a* (redness), and b* (yellowness) was measured using Colorimeter ZE 2000. Weekly colour stability checks were conducted on the collected eggs between weeks 23 and 28.	Curcumin at a dose of 3 ml/100 ml enhanced the yolk colour which was also stable on storage thus improving the perceived quality of eggs
3.	Egg shell colour [34]	Egg's blunt, equatorial, and sharp portions- Values for the parameters L* (lightness), a* (redness), and b* (yellowness) were measured using portable colorimeter $E = \sqrt{(L^2 + a^2 + b^2)}$	Darker eggshells are indicated by a lower E_{whole} egg value, and consumers tend to connect darker eggshells with higher quality.
4.	Water Dilution in liquid egg [35]	Liquid egg colour measured using colorimeter with 30 seconds stabilisation period	Colorimetry with Linear fitting ($R^2 \geq 0.984$) and exponential fitting ($R^2 \geq 0.992$) for colour and opacity of the broiler and country eggs was observed
5.	Eggshell color and translucency [36]	Portable colorimeter (L, A, B values at the sharp, middle, and blunt ends of the egg) for opacity	Effective in distinguishing between opaque and highly translucent eggshells. Provides objective assessment Recommended for extreme translucency differentiation
6.	Egg yolk index [37]	Color and index measurement by CIELAB colorspace dimensions a* and b*	Egg yolks salted in 16% solution had the highest egg yolk index and CIELAB a* and b* values.
7.	Salted Egg quality [37]	Colorimetric sensor array based on Silver nanoprisms (AgNPRs) etching and hyperspectral imaging were	High coefficients of determination indicate

		predicted using Partial least squares regression (PLSR)	strong predictive performance for predicting moisture, lipid, and salt content in salted duck eggs
8.	Albumen transparency [38]	Colorimetric assessment using the visible/near-infrared (VIS/NIR) transmission spectroscopy in the range of 350–2,500 nm to quantify light transmission through albumen. Partial least squares (PLS) predictive models were developed to correlate spectral data with egg freshness indicators.	Increased albumen turbidity corresponds to protein denaturation and reduced freshness. Transparent albumen indicates a fresher egg with intact protein structure. The method allows non-destructive prediction of Haugh unit (HU), albumen pH, and storage duration.
9.	Yolk colour response to natural/chemical colorant supplementation [39]	Laying hens fed natural vs. chemical colorants; yolk colour scored and correlated with fatty-acid profile and blood parameters	Colorant type affected yolk pigmentation intensity and fatty-acid composition, linking dietary intervention to consumer-perceived yolk quality

Table 2. Spectroscopic Techniques for Non-Destructive Egg Quality and Freshness Assessment

No.	Spectroscopic Technique	Methodology	Interpretation
1.	Egg classification based on aging by microwave spectroscopy [45]	A rectangular waveguide along with a network analyzer, assessed shell egg quality by measuring scattering parameters in the 0.9-1.7 GHz range and calculating microwave spectra.	ANN regression models accurately predicted air cell height, yolk coefficient, Haugh unit, thick albumen height and its pH. SIMCA and ANN classification methods achieved 100% accuracy in classifying eggs based on storage time.
2.	Haugh unit and Ph by Visible transmission spectroscopy [46]	Transmission spectra (570-750 nm) of 600 white-shelled eggs, measured at intervals up to 18 days were used to predict the Albumen pH and Haugh units.	Partial least squares (PLS) model showed high correlation coefficients of 0.842 for Haugh units and 0.867 for pH between predicted and measured values.
3.	Freshness indices by Visible - Near infrared spectroscopy [26]	Freshness indices- yolk index, egg shape index, albumen pH, Haugh unit, air cell diameter, and eggshell thickness were determined from 91 White Leghorn eggs and Pearson correlation and PLS regression (480 to 960 nm)was used.	The comprehensive freshness indicator showed better prediction accuracy than individual freshness measures, with a predictive correlation coefficient of 0.891.
4.	Water adulteration detection by Fourier-transform infrared (ATR-FTIR), near	Liquid and dry samples (n=50) of whole egg, egg white, egg yolk, and egg containing extra egg white and water were prepared and ATR-FTIR	Adulterated egg samples can be qualitatively detected with the best classification achieved for dry (100%)

	infrared (NIR) spectroscopy [47]	and NIR measurements were done for creation of Principal Component Analysis (PCA) models.	against liquid (80%) samples.
5.	Fake eggs detection by Raman spectral analysis [48]	Fake eggs made with sodium alginate, gypsum powder, tartrazine dye, and paraffin wax identified by Raman spectroscopic and imaging data(1800–600 cm^{-1}) with multivariate analysis methods and Raman hyperspectral imaging (1500–390 cm^{-1}) with waveband optimization optimization.	Both techniques could differentiate fake eggs from actual eggs.
6.	Freshness assessment by Raman spectroscopy technique [43]	Raman spectra were obtained from upper, middle, and lower regions of 125 eggs' shell surface for 60 days, Partial least squares regression 100–3000 cm−1 was applied.	The model with spectra of egg top was the best. Quality indices such as Haugh unit, albumen pH, air cell diameter had correlation coefficient above 0.9 confirming strong correlation between the Raman spectrum of the egg shell surface and the freshness.
7.	S-Ovalbumin quantification by NIR spectroscopy [49]	NIR spectrometer(900–1700 nm) coupled along with multivariate analysis was used to track changes in S-ovalbumin content in eggs during storage. Higher S-ovalbumin indicates longer storage.	NIR Spectra with Partial least squares regression (PLSR) model preprocessed by wavelet threshold denoising and multiplicative scatter correction can be used to monitor S-ovalbumin content in eggs without damaging them.
8.	Classification of fresh and stale eggs byNIR spectroscopy [50]	Spectral data obtained for fresh and stale eggs were preprocessed and correlated with the Haugh unit. Classification achieved by PLS-DA and SVM-C in the spectral region of 1300–1690 nm	PLS-DA gave better classification results than SVM-C for distinguishing fresh and stale eggs, achieving 87.0% accuracy and showing higher sensitivity in detecting stale eggs.

6. Sensor Based Methods For Egg Quality Analysis

The old-fashioned manual techniques of sorting eggs by candling is labour intensive and time consuming. When exposed to light, high-quality eggs usually appear bright, while low-quality or rotting eggs typically appear dark because their internal contents are obstructing the light. An automated egg detection system has been developed to precisely assess the quality of eggs as depicted in Fig.3. This system integrates sensors for weight and light that are linked to a microprocessor. Using Firebase and Fuzzy Logic for processing and storing data in real-time, the system can discern between bad and good eggs with accuracy. Using the processed data as a basis, actuators then sort the eggs. This method is further improved with the incorporation of Internet of Things (IoT) technologies. The procedure is managed by a microcontroller that provides real-time information on egg quality through the use of fuzzy logic. In comparison to tests using simply

the sensors without Fuzzy Logic, which produced 5 errors out of 20 eggs, tests using this approach demonstrated a 75% accuracy rate with only 1 error out of 20 eggs. Thus, accuracy can be increased by up to 20% using the optimisation strategy [51].

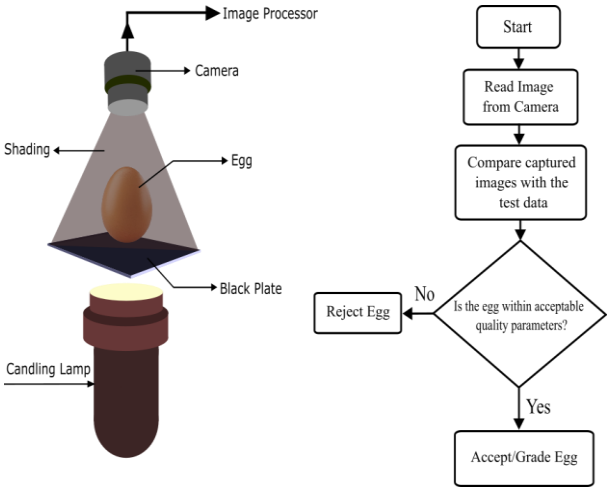

Figure 3. - Automated Egg Candling System for Quality Control and Grading

Two of the most reliable techniques for determining the freshness of agricultural items based on density are water displacement and flotation. These techniques, however, are inappropriate for eggs since they are invasive and may have an impact on the outcome because of water absorption. Machine vision and weighing sensors are new, non-invasive, low-cost, real-time technology that is used for density detection to grade and evaluate the freshness of eggs. Three components make up the measuring system - load cell's weight, volume using machine vision and calibration provided by the Eureka can. The egg density is computed using the formula $\rho = m/v$ and the following elements are displayed - picture, weight, length, width, volume, density, size classification number, and percentage of freshness of the egg. The system's accuracy in weight, volume, and density measurements was 99.88%, 98.26%, and 99.02%, respectively [52]. Incorporating Industry 4.0 concepts, a system for inspecting eggshell cracks using image processing techniques was created to reduce the need for manual coordination during the egg manufacturing process. These image processing methods provide great computing performance and detect eggshell cracks with over 98% accuracy [53].

6.1 Freshness and sensorial assessment of eggs using e-tongue and e-nose

The goal of the poultry industry nowadays is to develop faster ways to gauge quality characteristics. Freshness, weight loss, air cell size, albumen and yolk indices, Haugh units (HUs) and albumen and yolk pH are the main quality criteria that are important. After laying, time and temperature conditions cause freshness, the trait most frequently linked to egg quality, to decrease. Using electronic noses (e-noses) to detect the organic volatiles released by eggs is an alternate method of determining the freshness of eggs. An electronic nose, or e-nose, is a device that uses a variety of sensors to gather chemical signals for the purpose of detecting volatile compounds. These signals are then processed and interpreted using a pattern recognition approach utilising multivariate statistical techniques, which replicates the sensory evaluation of a human nose [54]. The electronic nose (e-nose) for fast gas chromatography (GC) is a very selective and sensitive specialty gas chromatograph that can test hydrocarbons at low concentrations in field/ laboratory settings very quickly. Its new characteristics, which give superior throughput when compared to more conventional gas chromatographs, include adaptability and faster analysis speeds. Using a fast GC e-nose, the two goals were highlighted: 1) to use multivariate chemometric techniques to differentiate the freshness of egg samples stored for varying amounts of time, and 2) to construct freshness prediction models based on Correlation analysis between electronic nose responses and sensory evaluation scores (Odour and Overall score), the HUs, and egg storage times using the partial least squares (PLS) model. According to the study [55], electronic nose (e-nose) signals may accurately predict quality indices for eggs, including freshness. Correlation coefficients (R^2) for e-nose signals were 0.9441, 0.9511, 0.9725, and 0.9530, and training errors were 1.24, 0.626, 0.629, and 0.887, respectively. The ANOVA findings indicate that there is no significant difference ($P > 0.05$) between the PLS model results and the reference values. This suggests that the rapid GC electronic nose can be used to forecast numerous freshness indices and evaluate the freshness of eggs at different stages of the supply chain. In another study, the alterations in the organoleptic characteristics of eggs derived from Lohmann Brown-Classic chickens fed diets with varying

concentrations of Zincoppyeast (ZP): ZP 2.5%, ZP 5.0%, and Control (0%) was studied. Eggs were collected from two batches: Batch 1 after a 30-day feeding period and Batch 2 after a 60-day feeding period.They were subjected to e-tongue, chemical, microbiological, and human sensory investigations. Using linear discriminant analysis (LDA), the e-tongue, an Alpha Astree (AlphaMOS) equipped with seven food-grade sensors, correctly identified the groups for batches 1 and 2. The eggs were crushed, beaten, and homogenised as part of the sample preparation process a 16-position auto-sampler was utilized for analysis. The accuracy was found to be 95.9% and 100% for batch 1 and batch 2 respectively [56].

6.2.Biosensors for chemical residues detection

Bio-based colorimetric sensors are increasingly used in food safety testing owing to their ease of use, portability, and potential for providing speedy, visible results without the expense of complex equipment. To determine egg quality, sensors employ biological recognition molecules such as aptamers, antibodies, and naturally occurring enzymes together with nanomaterials including gold nanoparticles (AuNPs) or magnetic composites to sense contaminants, chemical residues, and freshness markers. These sensors have been shown to offer a cost-effective and sensitive platform for on-site screening of antibiotic residues (e.g., florfenicol and tobramycin), veterinary medicines (e.g., toltrazuril), and bacterial toxins (e.g., staphylococcal enterotoxins). Further, colorimetric films incorporated with pH indicators also find use as freshness indicators by monitoring CO_2 content and pH changes during storage. These approaches provide very good specificity, low limits of detection (LOD), and fast response time, which are suitable for real-time quality control in eggs, and are in line with today's food safety legislation and consumer openness requirements. Recent studies linked to biobased sensing technologies for egg quality evaluation is presented in Table 3.

Table 3. Bio-Based Colorimetric Sensing Methods for Egg Safety and Freshness Evaluation

No.	Bio-based sensor	Methodology	Interpretation
1.	Determination of staphylococcal enterotoxins B (SE-B) [57]	Colorimetric assay using Fluorescent Eggshell Membrane- Templated Gold Nanoclusters (Au-ESM) and Gold Nanoparticles (GNPs)	Detects SE-B at concentration range of 0.4–20 ng/mL with Limits of detection (LOD) of 0.12 ng/mL based on the catalytic activity of Au-ESM
2.	Florfenicol (FF) Detection in Eggs [57]	Colorimetric aptasensor with Au@Fe3O4 nanoparticles detects the presence of FF residues in eggs which produces a colour change. The optimisation settings are 2:1 aptamer to Au ratio, 3-hour incubation period and 15-minute reaction time.	Detect FF within a range of 10–40 Mm and a limit of detection (LOD) of 10 μM. The sensor exhibits high sensitivity and stability
3.	Toltrazuril (Tol) and its metabolites detection [58]	An antiprotozoal agent, Toltrazuril detected using a paper-based colorimetric sensor containing monoclonal antibody (mAb) against Toltrazuril and its metabolites.	Detection Time is 15 min. LOD <2.60 μg/kg for Tol and its metabolites in eggs and sensitivity meets European Union requirements
4.	Tobramycin (TOB) detection in egg [59]	Colorimetric aptasensors were created using single-strand DNA (ssDNA) and unaltered gold nanoparticles (AuNPs). The aptamer attaches to TOB and separates from the AuNPs, causing AuNP aggregation and a noticeable shift from red colour to purple-blue.	These aptasensors, which had a linear range of 40–200 nM and a detection limit of 23.3 nM, demonstrated excellent sensitivity and selectivity for TOB detection in chicken egg

5.	Quantification of egg freshness (pH measurement) [60]	pH-indicator dye incorporated in a colorimetric film	Color shift corresponds to CO_2 release and pH increase over time; provides a visual indicator of egg freshness

Relative to spectroscopic instruments, e-nose/e-tongue and biosensor platforms are generally more portable and lower cost, and biosensors in particular achieve very low limits of detection for specific residues, but each sensor is typically analyte or application specific, whereas spectroscopy can assess multiple quality parameters simultaneously.

7. Acoustic Techniques For Egg Quality Analysis

Ultrasound is an emerging, rapid and versatile technology that can be used to replace thermal processing techniques. Ultrasound may often be applied to eggs in two steps: detection and disinfection. The food sector is in great demand for the assessment of egg freshness, which is linked to the amount of proteins, minerals, and vitamins in them. Research indicates that the physical and mechanical characteristics of the egg determine the ultrasonic phase's speed, making ultrasound a useful and non-destructive method for evaluating egg quality. When it comes to disinfection, ultrasound technology is also highly useful and effective [61]. The two methods that were most frequently researched for finding cracks were acoustic analysis and computer vision [21]. In a current study, an excitation device that impacts an egg to produce acoustic signals was produced using a solenoid. Features from the time and frequency domains were retrieved and examined, drawing on earlier studies. Each feature's ability to differentiate between sound and broken eggs was assessed using the F-ratio; features with low F-ratios and couples with strong correlations were ignored. An accuracy of 99.2% was obtained in the classification process by using a neural network with feature reduction. This feature reduction lowers the computing demands on online systems and streamlines recognition algorithms [62]. Acoustic methods rival spectroscopy in accuracy for crack detection specifically (up to ~99%) at comparatively low equipment cost, but they are narrower in scope than spectroscopic or imaging techniques, which can also capture compositional and freshness information.

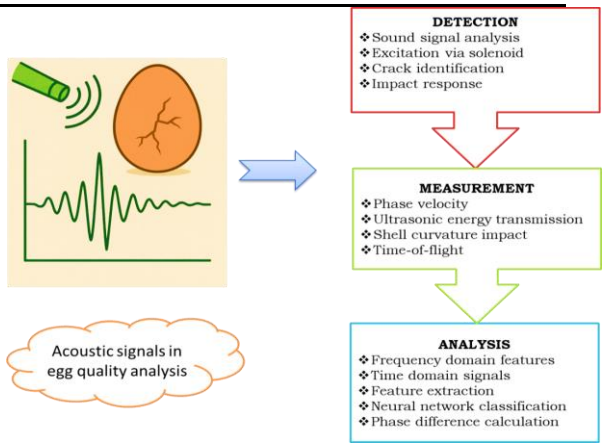

Figure 4. - Schematic Representation of Acoustic Signal Detection to Analysis in Egg Quality Evaluation

As shown in Figure 4, the acoustic measurement technique comprises an excitation mechanism, egg-holding device, signal collection system, and signal processing system. The excitation mechanism is responsible for delivering a deliberate mechanical stimulus that causes vibrations in the egg. These vibrations travel through the eggshell and contents and are captured by acoustic sensors or microphones. Signal processing is used to convert the signal measurements into frequency domain and time domain attributes [62]. Changes in resonant frequency, damping effects, and attenuation are highly dependent on the shell properties, internal content, and state of freshness of the egg. Consequently, acoustic measurement offers an effective method of detecting cracks or defects in the egg non-destructively.A study compared four methods (dial gauge, ultrasound, micrometer, and photometer) for measuring eggshell thickness, with dial gauge as the control. Ultrasound demonstrated the lowest measurement error (7.1%) compared to the control, while the photometer had the highest (15.7%). Regression equations were established between measurement methods and shell strength. The study concluded that ultrasound is a non-destructive, accurate, and efficient method for measuring eggshell thickness, making it a suitable alternative to destructive methods for quality grading [63]. Correlating the characteristics of ultrasonic signals with the egg material's composition is the basis of the ultrasonic analysis of egg quality. The findings of the

experiment show that the thickness and curvature of the eggshell affect the transmitted ultrasound's energy. On the other hand, this physical feature has no effect on the more stable parameter which is the phase velocity of sound within the egg. This phase velocity is a crucial sign for determining the freshness of eggs and can be connected to the composition of eggs. It is essential to comprehend how ultrasonic interacts with the eggshell in order to use it successfully. Significant changes can be seen between the phase velocities of signals from fresh and old eggs. In order to create a mathematical model for calculating the phase velocity of ultrasound inside the shell of the egg, it is crucial to comprehend how ultrasound interacts with the eggshell. Next, using the phase difference as a base, phase velocity was calculated as follows [64]

$$\frac{1}{Cegg} = (1 - \frac{\Delta D}{Din})\ \frac{1}{Cw} + \frac{\Delta \varphi}{2\pi f . Din}$$

where C_{egg} - the phase velocity of sound within the egg liquid

D_{in} - inside diameter of the egg in the direction of transmission of wave

ΔD/Cw - difference between flight time of signal passing through eggshell filled with water and through the same in a normal situation

Δφ - phase difference between the signals from the control eggshell and normal egg.

The study (Aboonajmi *et al*., 2010) showed a strong correlation with the ultrasonic phase velocity and several established detrimental indicators of egg quality, including yolk index, air cell size, albumen height, and Haugh unit [65]. The phase velocity of eggs kept at room temperature declined more quickly than that of eggs kept in a refrigerator, indicating the impact of temperature on the preservation of egg quality. According to the study's findings, ultrasound technology may be used successfully as a non-invasive method of assessing egg quality in commercial settings, eliminating the need for risky testing techniques and offering precise evaluations of quality during storage. Even though advanced techniques offer a significant improvement in accuracy, speed, and automation of assessing egg quality, each technique has its specific advantages and disadvantages that will affect the decision whether to apply it industrially [26]. Factors including costs, complexity of operation, calibration, environmental conditions, and data analysis have to be accounted for. The advantages and disadvantages of new analytical technologies applied to assessing egg quality are discussed in Table 4.

Table 4. Advantages and Limitations of Emerging Egg Quality Assessment Techniques

Technique	Advantages	Limitations
NIR Spectroscopy	Rapid, non-destructive, high throughput	Requires calibration models and expensive instrumentation
Raman Spectroscopy	High molecular specificity, detects freshness and adulteration	Fluorescence interference, high equipment cost
FTIR Spectroscopy	Chemical fingerprinting capability	Sensitive to moisture variation
Hyperspectral Imaging	Simultaneous spatial and spectral information	Large data volume and complex analysis
Electronic Nose	Rapid freshness assessment	Sensor drift and environmental sensitivity
Electronic Tongue	Objective sensory analysis	Requires calibration and sample preparation
Acoustic Techniques	Effective crack detection, non-destructive	Sensitive to background noise
Machine Vision	Automated inspection and grading	Dependent on illumination conditions
Biosensors	High sensitivity and portability	Limited shelf life of biological recognition elements

8. Chemometric Methods For Egg Quality Analysis

8.1. Overview of Chemometrics

Chemometrics is a term that has in the past described chemical data [66]**.** All aspects of data collection and analysis are now included in the comprehensive definition of chemometrics. The global data structure is underutilised and only partially represented by the traditional univariate approach, which considers one variable at a time. Multivariate techniques, on the other hand, enable a more thorough analysis of the data and the utilisation of the information [67]. Automation in data collection and processing are crucial for in-line and real time monitoring of food quality [66]**.** In recent years, spectroscopic methods coupled with chemometric techniques have emerged as powerful non-invasive tools for real-time and in situ monitoring of eggs' quality and their freshness. Advanced chemometrics functions, among other things, enable the processing and interpretation of voluminous and intricate datasets. In the case of NIR, the spectral data consists of many wavelengths. It may be hard to extract information from this data immediately, however, once chemometric techniques like PCA or PLSR are employed, such data can be transformed into significant characteristics such as egg moisture content, egg protein levels, egg freshness and other quality attributes[68]. Egg mislabeling is a common issue in the market, leading to the sale of expired eggs as fresh, despite their low cost. Unlike the traditional egg freshness measures like air cell height and Haugh Unit, the ages of the eggs were tracked in a study using chemometrics techniques such as pH, colour characteristics, fluorescence spectroscopy, and UV-Visible (UV-Vis) spectra [69].

8.2. Data Pre-processing and Calibration Techniques

Preprocessing techniques, such as spectral corrections, outlier control, and sophisticated imaging and statistical processing, improve the accuracy of evaluating the quality of eggs overall and allow for more dependable and effective analysis. Unwanted variance in data produced by analytical devices can arise from the method of measurement, the condition of the sample, and additional external physical, chemical, and environmental elements. In order to enhance data quality, efficiency and accuracy, pre-processing is necessary [70]. In order to refine Near-Infrared (NIR) spectra for the purpose of determining the moisture content of powdered eggs without the need for extra sample preparation, spectral preprocessing techniques such as Multiplicative Scatter Correction (MSC), Standard Normal Variate (SNV), detrending, and smoothing are essential [71]. Before using analytical algorithms like the competitive adaptive reweighted sampling (MPA-CARS), spectral data is preprocessed using sophisticated methods like SNV and Savitzky-Golay first derivatives to ensure greater accuracy [49]. Artificial neural networks and Principal Component Analysis (PCA) are commonly used to assess how environmental factors affect egg quality [72,73]. In image-based egg quality analysis, preprocessing consists of segmentation using splitting and merging algorithms, edge identification using Sobel operators, and denoising with median filters. By further synthesising segmented pictures, image fusion approaches enhance the evaluation process [74]. In exploratory investigations, scatter correction techniques like MSC and SNV, as well as derivation methods like Savitzky–Golay, are useful because they reinforce the linear relationship between spectral signals and analyte concentrations. Methods like PCA, stepwise discriminant canonical analysis, and multicollinearity analysis are used to eliminate redundant variables and comprehend differences among egg genotypes in order to optimise datasets [75]. An organised method for enhancing data quality is offered by a six-step preprocessing framework that addresses standardisation, analysis, and errors in data gathering. These approaches can be modified for the analysis of egg quality, especially when it comes to managing and analysing complicated data [76].

Table 5. Advanced Spectroscopic and Chemometric Techniques for Egg Freshness and Quality

Instrumental method	Chemometric Method	Interpretation
UV–Visible (UV-Vis) Spectroscopy [69]	Partial Least-Squares (PLS)	UV–Vis and fluorescence spectra with PLS presented high accuracy in the prediction of the age of eggs stored at 35°C.
NIR Spectroscopy [76]	Standard Normal Variate (SNV), Multiplicative Scatter Correction (MSC), Predictive Modeling	SNV preprocessing enhances the reliability of NIR spectral data for freshness detection. MSC preprocessing contributes to the accuracy of predictive models based on Haugh Units with high accuracy
NIR Spectroscopy [77]	Multiplicative scatter correction and principal component analysis (MSC-PCA), Linear Discriminant Analysis (LDA)	MSC-PCA-LDA achieved over 95% identification rate for egg freshness categories and their mark date of lay of eggs in cold and ambient storage
Solid-Phase Micro Extraction Gas Chromatography (SPME-GC-MS) [78]	Chemometric Modeling, Orthogonal Partial Least Squares Discriminant Analysis (OPLS-DA)	The model with OPLS-DA demonstrates high accuracy in classifying based on aging of eggs. Identification of specific markers related to thermal degradation supports the assessment of egg freshness and quality
High-Resolution Mass Spectrometry (HRMS) [78]	Cross-Validation, High-Resolution Mass Spectrometry (HRMS)	Detection of multiple sets of metabolites related to microbial growth over time.This method ensures that the model is not overfitting and maintains its predictive power across different samples.
Electronic nose [80]	Support Vector Machine (SVM), Back Propagation Neural Networks (BPNN), Independent Component Analysis (ICA) and Local Linear Embedding (LLE)	SVM outperforms BPNN, indicating its effectiveness in predicting yolk index and egg freshness. Dimensionality reduction techniques significantly enhance the predictive performance of SVM models.
Transmittance spectroscopy [81]	Fuzzy C-means Algorithm, Artificial Neural Networks (ANN) and RELIEF Algorithm	Fuzzy C-means algorithm effectively categorizes eggs into freshness groups based on quality indicators; significant increase in S-ovalbumin concentration over storage. The RELIEF algorithm highlights key wavelength (228 and 280 nm) for non-invasive assessment of egg quality.

8.3. Application of chemometrics in egg quality analysis

Chemometrics has emerged as a crucial instrument for analysing the quality of eggs, providing sophisticated ways to handle and decipher intricate datasets gathered from a variety of analytical approaches. Chemometrics makes it possible to accurately evaluate important quality criteria such as freshness, yolk colour, shell strength, and nutrient content by combining statistical and mathematical approaches. Data from Near-Infrared (NIR) spectroscopy, imaging, and hyperspectral sensors are frequently analysed using methods like Partial Least Squares Regression (PLSR), Principal Component Analysis (PCA), and machine learning models (Fig.5). In addition to increasing forecast accuracy, these techniques make it easier to assess egg quality in real time and without causing damage while it is being produced, stored, and transported. Additionally, chemometric techniques have demonstrated efficacy in detecting minute changes in quality that are impacted by processing techniques, storage time, and environmental variables. The specific uses of chemometric approaches in egg quality analysis are compiled in the following Table 5, which also highlights the methods' applicability in other fields. While modern techniques offer great opportunities in terms of accuracy and automation, their effectiveness mainly relies on correct data pretreatment and model calibration and validation.

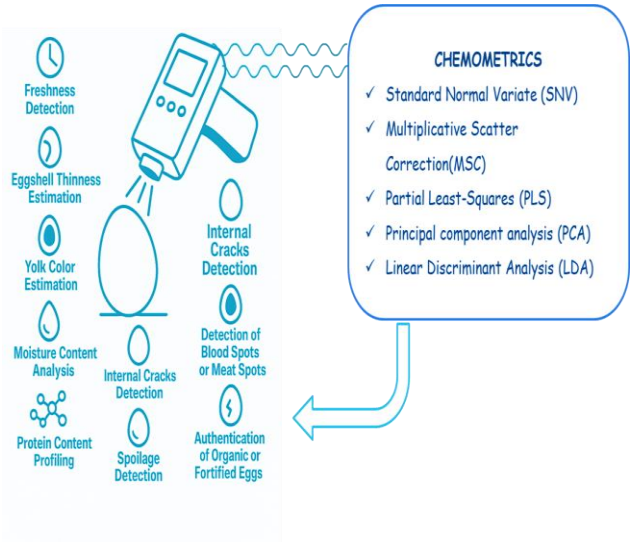

Figure 5. - Near-infra red spectrometry with chemometrics for egg quality analysis

Chemometrics are used to analyze spectral, acoustic, and sensor-based data in order to estimate the quality indicators of the product. However, there is a question concerning the transferability of models obtained in one laboratory or under one set of environmental conditions for another set of eggs. Overall, colorimetry and acoustic methods offer the best cost to simplicity ratio for single-parameter industrial screening, spectroscopic and imaging techniques provide the greatest analytical depth and multi-parameter capability at higher capital cost, and sensor/biosensor platforms fill a niche for rapid, low cost, analyte specific residue detection; chemometric modelling is what ultimately makes the richer spectroscopic and imaging datasets industrially actionable in real time.

9. Conclusion

In conclusion, egg quality assessment techniques have progressed from traditional visual inspections to non-destructive advancements. Various spectroscopic techniques including UV/Visible, NIR, FTIR, Raman and hyperspectral imaging have shown great promise in assessing shell colour, integrity, yolk index, and Haugh unit without disintegrating the shell. Acoustic and ultrasonic methods have great potential in assessing microcrack and internal quality, while IOT-based sensors, colorimetric biosensors and films offer potential uses for real-time monitoring of chemical residues and detection of spoilage. Automated visual inspection and AI-based classification models lead to notable reduction in human error and enhance grading efficiency. Moreover, chemometrics has become crucial for multivariate data analysis which facilitates real-time quality monitoring and predictive analytics. Despite these advancements, certain limitations such as affordability, portability, and ease of operation require enhanced consideration. Future research should incline towards developing portable affordable devices for field-level implementation, integrating sensor data into centralized cloud based platforms for traceability, blockchain integration for robust supply chain management and training AI models with varied datasets to improve performance across various species of egg varieties and geographic variations. Such measures will ensure egg quality and safety, minimize postharvest losses, and promote sustainability in poultry industries worldwide.

Author Contributions
Conceptualization: MRV, VS; Methodology: MRV, VS, KS; Data curation: MRV, VS; Formal analysis: KS; Validation: MV, KS; Writing—original draft: MRV, VS; Writing—review and editing: MV, KS; Supervision: MV, KS.
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References

1. 1. Wijedasa, W. M. R. M., Wickramasinghe, Y. H. S. T., Vidanarachchi, J. K., & Himali, S. M. C. (**2020**). Comparison of egg quality characteristics of different poultry species. *Journal of Agricultural Science*, *12*(11), 331–342. https://doi.org/10.5539/jas.v12n11p331
2. Kuang, H., Yang, F., Zhang, Y., Wang, T., & Chen, G. (**2018**). The impact of egg nutrient composition and its consumption on cholesterol homeostasis. *Cholesterol*, *2018*, Article 6303810. https://doi.org/10.1155/2018/6303810
3. Sharaf Eddin, A., Ibrahim, S. A., & Tahergorabi, R. (**2019**). Egg quality and safety with an overview of edible coating application for egg preservation. *Food Chemistry*, *296*, 29–39. https://doi.org/10.1016/j.foodchem.2019.05.182
4. Chambers, J. R., Khalid, Z., Akhtar, H., & Abdel-Aal, E.-S. M. (**2017**). Chicken eggs. In P. Y. Hester (Ed.), *Egg innovations and strategies for improvements* (pp. 1–9). Academic Press. https://doi.org/10.1016/B978-0-12-800879-9.00001-9
5. Dunn, I. (**2011**). Poultry breeding for egg quality: Traditional and modern genetic approaches. In Y. Nys, M. Bain, & F. Van Immerseel (Eds.), *Improving the safety and quality of eggs and egg products: Egg chemistry, production and consumption* (Vol. 1, pp. 245–260). Woodhead Publishing. https://doi.org/10.1533/9780857093912.3.245
6. Abeyrathne, E. D. N. S., Nam, K.-C., Huang, X., & Ahn, D. U. (**2022**). Egg yolk lipids: Separation, characterization, and utilization. *Food Science and Biotechnology*, *31*(10), 1243–1256. https://doi.org/10.1007/s10068-022-01138-4
7. Juneja, L. R. (**2018**). Egg yolk lipids. In T. Yamamoto, L. R. Juneja, H. Hatta, & M. Kim (Eds.), *Hen eggs: Basic and applied science* (pp. 73–98). CRC Press. https://doi.org/10.1201/9780203752081-6
8. Guha, S., Majumder, K., & Mine, Y. (**2019**). Egg proteins. In L. D. Melton, F. Shahidi, & P. Varelis (Eds.), *Encyclopedia of food chemistry* (pp. 74–84). Elsevier. https://doi.org/10.1016/B978-0-08-100596-5.21603-X
9. Réhault-Godbert, S., Guyot, N., & Nys, Y. (**2019**). The golden egg: Nutritional value, bioactivities, and emerging benefits for human health. *Nutrients*, *11*(3), Article 684. https://doi.org/10.3390/nu11030684
10. Food and Agriculture Organization of the United Nations. (**2019**). *The state of food and agriculture 2019: Moving forward on food loss and waste reduction*. https://doi.org/10.4060/CA6030EN
11. Atwa, E. M., Xu, S., Rashwan, A. K., Abdelshafy, A. M., ElMasry, G., Al-Rejaie, S., Xu, H., Lin, H., & Pan, J. (**2024**). Advances in emerging non-destructive technologies for detecting raw egg freshness: A comprehensive review. *Foods*, *13*(22), Article 3563. https://doi.org/10.3390/foods13223563
12. Rho, T.-G., & Cho, B.-K. (**2024**). Non-destructive evaluation of physicochemical properties for egg freshness: A review. *Agriculture*, *14*(11), Article 2049. https://doi.org/10.3390/agriculture14112049
13. Agbaje, M., Ayo-Ajayi, P., Kehinde, O., Omoshaba, E., Dipeolu, M., & Fasina, F. O. (**2021**). Salmonella characterization in poultry eggs sold in farms and markets in relation to handling and biosecurity practices in Ogun State, Nigeria. *Antibiotics*, *10*(7), Article 773. https://doi.org/10.3390/antibiotics10070773
14. Gustavsson, J., Cederberg, C., Sonesson, U., van Otterdijk, R., & Meybeck, A. (**2011**). *Global food losses and food waste: Extent, causes and prevention*. Food and Agriculture Organization of the United Nations. https://www.fao.org/4/mb060e/mb060e00.htm
15. Jones, D. R., Ward, G. E., Regmi, P., & Karcher, D. M. (**2018**). Impact of egg handling and conditions during extended storage on egg quality. *Poultry Science*, *97*(2), 716–723. https://doi.org/10.3382/ps/pex351
16. Mensah, E. P., Bannor, R. K., Oppong-Kyeremeh, H., & Kyire, S. K. C. (**2022**). An assessment of postharvest losses to support innovation in the egg value chain in Ghana.

African Journal of Science, Technology, Innovation and Development, 14(4), 947–959. https://doi.org/10.1080/20421338.2021.1920679

17. Zuo, J., Peng, Y., Li, Y., Zou, W., Chen, Y., Huo, D., & Chao, K. (**2023**). Nondestructive detection of nutritional parameters of pork based on NIR hyperspectral imaging technique. *Meat Science, 202*, Article 109204. https://doi.org/10.1016/j.meatsci.2023.109204
18. Zuo, J., Peng, Y., Li, Y., Chen, Y., Yin, T., & Chao, K. (**2025**). Integrating transfer learning and spectroscopy for enhanced pork spoilage assessment using correlation analysis. *Food Chemistry, 465*(Pt. 2), Article 142117. https://doi.org/10.1016/j.foodchem.2024.142117
19. Sati, N. M., Oshibanjo, D. O., Emennaa, P. E., Mbuka, J. J., Haliru, H., Ponfa, S. B., Abimiku, O. R., & Nwamo, A. C. (**2020**). Egg quality assessment within day 0 to 10 as affected by storage temperature. *Asian Journal of Research in Animal and Veterinary Sciences, 3*(4), 306–316. https://doi.org/10.9734/ajravs/2020/v3i4137
20. Lukanov, H., Genchev, A., & Pavlov, A. (**2015**). Colour traits of chicken eggs with different eggshell pigmentation. *Trakia Journal of Sciences, 13*(2), 149–158. https://doi.org/10.15547/tjs.2015.02.007
21. Botta, B., Gattam, S. S. R., & Datta, A. K. (**2022**). Eggshell crack detection using deep convolutional neural networks. *Journal of Food Engineering, 315*, Article 110798. https://doi.org/10.1016/j.jfoodeng.2021.110798
22. Duman, M., Şekeroğlu, A., Yıldırım, A., Eleroğlu, H., & Camcı, O. (**2016**). Relation between egg shape index and egg quality characteristics. *European Poultry Science, 80*, 1–9. https://doi.org/10.1399/eps.2016.117
23. Anene, D. O., Akter, Y., Thomson, P. C., Groves, P., & O'Shea, C. J. (**2020**). Variation and association of hen performance and egg quality traits in individual early-laying ISA Brown hens. *Animals, 10*(9), Article 1601. https://doi.org/10.3390/ani10091601
24. Narushin, V. G., Romanov, M. N., & Griffin, D. K. (**2021**). A novel Egg Quality Index as an alternative to Haugh unit score. *Journal of Food Engineering, 289*, Article 110176. https://doi.org/10.1016/j.jfoodeng.2020.110176
25. Yakubu, A., Ogah, D. M., & Barde, R. E. (**2008**). Productivity and egg quality characteristics of free range naked neck and normal feathered Nigerian indigenous chickens. *International Journal of Poultry Science, 7*(6), 579–585. https://doi.org/10.3923/ijps.2008.579.585
26. Loffredi, E., Grassi, S., & Alamprese, C. (**2021**). Spectroscopic approaches for non-destructive shell egg quality and freshness evaluation: Opportunities and challenges. *Food Control, 129*, Article 108255. https://doi.org/10.1016/j.foodcont.2021.108255
27. Nasiri, A., Omid, M., & Taheri-Garavand, A. (**2020**). An automatic sorting system for unwashed eggs using deep learning. *Journal of Food Engineering, 283*, Article 110036. https://doi.org/10.1016/j.jfoodeng.2020.110036
28. Hassoun, A., Jagtap, S., Garcia-Garcia, G., Trollman, H., Pateiro, M., Lorenzo, J. M., Trif, M., Rusu, A. V., Aadil, R. M., Šimat, V., Cropotova, J., & Câmara, J. S. (**2023**). Food quality 4.0: From traditional approaches to digitalized automated analysis. *Journal of Food Engineering, 337*, Article 111216. https://doi.org/10.1016/j.jfoodeng.2022.111216
29. Yao, K., Sun, J., Chen, C., Xu, M., Zhou, X., Cao, Y., & Tian, Y. (**2022**). Non-destructive detection of egg qualities based on hyperspectral imaging. *Journal of Food Engineering, 325*, Article 111024. https://doi.org/10.1016/j.jfoodeng.2022.111024
30. Shrestha, Y. K., & Shrestha, S. K. (**2023**). Fundamentals of colorimetry. In *Advances in colorimetry*. IntechOpen. https://doi.org/10.5772/intechopen.112344
31. Fernandes, G. M., Silva, W. R., Barreto, D. N., Lamarca, R. S., Gomes, P. C. F. L., Petruci, J. F. da S., & Batista, A. D. (**2020**). Novel approaches for colorimetric measurements in analytical chemistry: A review. *Analytica Chimica Acta, 1135*, 187–203. https://doi.org/10.1016/j.aca.2020.07.030
32. Milovanovic, B., Tomović, V., Djekic, I., Sołowiej, B. G., Lorenzo, J. M., Barba, F. J., & Tomasevic, I. (**2021**). Color assessment of the eggs using computer vision system and Minolta colorimeter. *Journal of Food Measurement and Characterization, 15*, 5097–5112. https://doi.org/10.1007/s11694-021-01085-4
33. Nuningtyas, Y. F., Chang, H. L., Lin, M. J., & Widodo, E. (**2020**). Evaluation of curcumin as an additive on egg yolk pigmentation of white laying hens. *IOP Conference Series: Earth and Environmental Science, 478*(1), Article 012050. https://doi.org/10.1088/1755-1315/478/1/012050
34. Djokić, N., Suvajdžić, B., Vićić, I., Grković, N., Karabasil, N., & Čobanović, N. (**2023**). Quality of table eggs in relation to shell colour. *Veterinarska stanica, 54*(2), 171–184. https://doi.org/10.46419/vs.54.2.5
35. Yang, S., Yang, F., Dou, W., Chi, Y., & Chi, Y. (**2024**). Testing adulterated liquid-egg: Developing rapid detection techniques based on colorimetry, electrochemistry, and interfacial fingerprinting. *Food Chemistry, 444*, Article 138674. https://doi.org/10.1016/j.foodchem.2024.138674
36. Wang, D.-H., Chen, H., Zhou, R.-Y., Huang, C.-

X., Gao, H.-X., Fan, B.-L., Liu, G.-J., & Ning, Z.-H. (**2019**). Study of measurement methods on phenotype of translucent eggs. *Poultry Science, 98*(12), 6677–6683. https://doi.org/10.3382/ps/pez539

37. Xu, F., Huang, X., Tian, X., Yu, S., Zhang, X., & Zareef, M. (**2024**). Application of hyperspectral imaging and colorimetric sensor array coupled with multivariate analysis for quality detection during salted duck eggs processing. *Journal of Food Process Engineering, 47*(3), Article e14589. https://doi.org/10.1111/jfpe.14589
38. Abdel-Nour, N., Ngadi, M., Prasher, S., & Karimi, Y. (**2011**). Prediction of egg freshness and albumen quality using visible/near infrared spectroscopy. *Food and Bioprocess Technology, 4*, 731–736. https://doi.org/10.1007/s11947-009-0265-0
39. Saleh, A. A., Gawish, E., Mahmoud, S. F., Amber, K., Awad, W., Alzawqari, M. H., Shukry, M., & Abdel-Moneim, A. E. A.-M. (**2021**). Effect of natural and chemical colorant supplementation on performance, egg-quality characteristics, yolk fatty-acid profile, and blood constituents in laying hens. *Sustainability, 13*(8), Article 4503. https://doi.org/10.3390/su13084503
40. Mertens, K., Vaesen, I., Löffel, J., Kemps, B., Kamers, B., Perianu, C., Zoons, J., Darius, P., Decuypere, E., De Baerdemaeker, J., & De Ketelaere, B. (**2010**). The transmission color value: A novel egg quality measure for recording shell color used for monitoring the stress and health status of a brown layer flock. *Poultry Science, 89*(3), 609–617. https://doi.org/10.3382/ps.2009-00261
41. Zhao, Q., Lv, X., Jia, Y., Chen, Y., Xu, G., & Qu, L. (**2018**). Rapid determination of the fat, moisture, and protein contents in homogenized chicken eggs based on near-infrared reflectance spectroscopy. *Poultry Science, 97*(6), 2239–2245. https://doi.org/10.3382/ps/pey070
42. Li, L., Ren, S., Yang, H., Liu, J., & Zhang, J. (2023). Study of the molecular structure of proteins in eggs under different storage conditions. *Journal of Food Processing and Preservation, **2023***, Article 4754074. https://doi.org/10.1155/2023/4754074
43. Liu, Y., Ren, X., Yu, H., Cheng, Y., Guo, Y., Yao, W., & Xie, Y. (**2020**). Non-destructive and online egg freshness assessment from the egg shell based on Raman spectroscopy. *Food Control, 118*, Article 107426. https://doi.org/10.1016/j.foodcont.2020.107426
44. Ragni, L., Al-Shami, A., Mikhaylenko, G., & Tang, J. (**2007**). Dielectric characterization of hen eggs during storage. *Journal of Food Engineering, 82*(4), 450–459. https://doi.org/10.1016/j.jfoodeng.2007.02.063
45. Akbarzadeh, N., Mireei, S. A., Askari, G., & Mahdavi, A. H. (**2019**). Microwave spectroscopy based on the waveguide technique for the nondestructive freshness evaluation of egg. *Food Chemistry, 277*, 558–565. https://doi.org/10.1016/j.foodchem.2018.10.143
46. Dong, X., Zhang, B., Dong, J., Lu, B., Hu, C., & Tang, X. (**2020**). Egg freshness prediction using a comprehensive analysis based on visible near infrared spectroscopy. *Spectroscopy Letters, 53*(7), 512–522. https://doi.org/10.1080/00387010.2020.1787455
47. Uysal, R. S., & Boyaci, I. H. (**2020**). Authentication of liquid egg composition using ATR-FTIR and NIR spectroscopy in combination with PCA. *Journal of the Science of Food and Agriculture, 100*(2), 855–862. https://doi.org/10.1002/jsfa.10097
48. Joshi, R., Lohumi, S., Joshi, R., Kim, M. S., Qin, J., Baek, I., & Cho, B. (**2020**). Raman spectral analysis for non-invasive detection of external and internal parameters of fake eggs. *Sensors and Actuators B: Chemical, 303*, Article 127243. https://doi.org/10.1016/j.snb.2019.127243
49. Yao, K., Sun, J., Cheng, J., Xu, M., Chen, C., & Zhou, X. (**2023**). Monitoring S-ovalbumin content in eggs during storage using portable NIR spectrometer and multivariate analysis. *Infrared Physics & Technology, 131*, Article 104685. https://doi.org/10.1016/j.infrared.2023.104685
50. Cruz-Tirado, J. P., da Silva Medeiros, M. L., & Barbin, D. F. (**2021**). On-line monitoring of egg freshness using a portable NIR spectrometer in tandem with machine learning. *Journal of Food Engineering, 306*, Article 110643. https://doi.org/10.1016/j.jfoodeng.2021.110643
51. Mahesa, I., Putrada, A. G., & Abdurohman, M. (**2019**). Egg quality detection system using fuzzy logic method. *Kinetik, 4*(3). https://doi.org/10.22219/kinetik.v4i3.839
52. Harnsoongnoen, S., & Jaroensuk, N. (**2021**). The grades and freshness assessment of eggs based on density detection using machine vision and weighing sensor. *Scientific Reports, 11*, Article 16640. https://doi.org/10.1038/s41598-021-96140-x
53. Purahong, B., Chaowalittawin, V., Krungseanmuang, W., Sathaporn, P., Anuwongpinit, T., & Lasakul, A. (**2022**). Crack detection of eggshell using image processing and computer vision. *Journal of Physics: Conference Series, 2261*(1), Article 012021. https://doi.org/10.1088/1742-6596/2261/1/012021
54. Chilo, J., Pelegrí Sebastiá, J., Cupane, M., & Sogorb Devesa, T. C. (**2016**). E-nose application to food industry production. *IEEE Instrumentation & Measurement Magazine,*

19(1), 27–33. https://doi.org/10.1109/MIM.2016.7384957

55. Yimenu, S. M., Kim, J. Y., & Kim, B. S. (**2017**). Prediction of egg freshness during storage using electronic nose. *Poultry Science*, *96*(10), 3733–3746. https://doi.org/10.3382/ps/pex193
56. Aguinaga Bósquez, J. P., Kovacs, Z., Gillay, Z., Bázár, G., Palkó, C., Hingyi, H., Csavajda, É., Üveges, M., Jókainé Szatura, Z., Barbulescu, I. D., Begea, M., & Tóth, T. (**2021**). Evaluating the effect of a brewery by-product as feed supplementation on the quality of eggs by means of a human panel and e-tongue and e-nose analysis. *Chemosensors*, *9*(8), Article 213. https://doi.org/10.3390/chemosensors9080213
57. Wang, Q., Huang, L., Pei, K., Sun, H., & Wang, X. (**2022**). A magnetic relaxation switching and colorimetric dual-mode aptasensor for the rapid detection of florfenicol and florfenicol amine in eggs. *Analytica Chimica Acta*, *1208*, Article 339849. https://doi.org/10.1016/j.aca.2022.339849
58. Wang, Z., Zhang, J., Liu, L., Wu, X., Kuang, H., Xu, C., & Xu, L. (**2019**). A colorimetric paper-based sensor for toltrazuril and its metabolites in feed, chicken, and egg samples. *Food Chemistry*, *276*, 707–713. https://doi.org/10.1016/j.foodchem.2018.10.047
59. Ma, Q., Wang, Y., Jia, J., & Xiang, Y. (**2018**). Colorimetric aptasensors for determination of tobramycin in milk and chicken eggs based on DNA and gold nanoparticles. *Food Chemistry*, *249*, 98–103. https://doi.org/10.1016/j.foodchem.2018.01.022
60. Liu, D., Zhang, C., Pu, Y., Chen, S., Liu, L., Cui, Z., & Zhong, Y. (**2022**). Recent advances in pH-responsive freshness indicators using natural food colorants to monitor food freshness. *Foods*, *11*(13), Article 1884. https://doi.org/10.3390/foods11131884
61. Hamidy Isfahani, Z., & Naderi, L. (**2021**). Investigation of the ultrasound effects on assessing the freshness of egg and egg processing as a new and advanced processing method. *Journal of Vibration and Sound*, *10*(19), 162–181.
62. Wang, H., Mao, J., Zhang, J., Jiang, H., & Wang, J. (**2016**). Acoustic feature extraction and optimization of crack detection for eggshell. *Journal of Food Engineering*, *171*, 240–247. https://doi.org/10.1016/j.jfoodeng.2015.10.030
63. Amini, S., Mohamadzamani, D., & Javidan, S. M. (**2022**). Investigation of the relationship between egg shell strength and thickness using non-destructive ultrasound method. *Journal of Biosystems Engineering*, *47*(3), 263–269. https://doi.org/10.1007/s42853-022-00144-y
64. Aboonajmi, M., Setarehdan, S. K., Akram, A., Nishizu, T., & Kondo, N. (**2014**). Prediction of poultry egg freshness using ultrasound. *International Journal of Food Properties*, *17*(9), 1889–1899. https://doi.org/10.1080/10942912.2013.770015
65. Aboonajmi, M., Akram, A., Nishizu, T., Kondo, N., Setarehdan, S. K., & Rajabipour, A. (**2010**). An ultrasound based technique for the determination of poultry egg quality. *Research in Agricultural Engineering*, *56*(1), 26–32. https://doi.org/10.17221/18/2009-RAE
66. Burgard, D. R. (**2018**). *Chemometrics: Chemical and sensory data*. CRC Press. https://doi.org/10.1201/9781351070607
67. Oliveri, P., Malegori, C., & Casale, M. (**2020**). Chemometrics: Multivariate analysis of chemical data. In Y. Picó (Ed.), *Chemical analysis of food* (2nd ed., Vol. 2, pp. 33–76). Academic Press. https://doi.org/10.1016/B978-0-12-813266-1.00002-4
68. Workman, J., Jr., & Mark, H. (**2023**). Artificial intelligence in analytical spectroscopy, Part II: Examples in spectroscopy. *Spectroscopy*, *38*(6), 10–15. https://doi.org/10.56530/spectroscopy.js8781e3
69. Çiftçi, H. G., Bilge, G., & Aytaç, E. (**2024**). Monitoring the quality changes and freshness assessment of eggs based on chemometrics method. *Journal of Food Process Engineering*, *47*(3), Article e14591. https://doi.org/10.1111/jfpe.14591
70. Mishra, P., Biancolillo, A., Roger, J. M., Marini, F., & Rutledge, D. N. (**2020**). New data preprocessing trends based on ensemble of multiple preprocessing techniques. *TrAC Trends in Analytical Chemistry*, *132*, Article 116045. https://doi.org/10.1016/j.trac.2020.116045
71. Watanabe, L. S., Bovolenta, Y. R., Acquaro Junior, V. R., Barbin, D. F., Madeira, T. B., & Nixdorf, S. L. (**2018**). Investigation of NIR spectra pre-processing methods combined with multivariate regression for determination of moisture in powdered industrial egg. *Acta Scientiarum. Technology*, *40*(1), Article 30133. https://doi.org/10.4025/actascitechnol.v40i1.30133
72. Malfatti, L. H., Zampar, A., Galvão, A. C., Robazza, W. da S., & Boiago, M. M. (**2021**). Evaluating and predicting egg quality indicators through principal component analysis and artificial neural networks. *LWT*, *148*, Article 111720. https://doi.org/10.1016/j.lwt.2021.111720

73. Sharma, R., Sandhu, J., & Bharti, V. (**2024**). Experimental analysis of a multimodal biometric system using preprocessing and feature extraction techniques and their impact on analytical results. In *2024 Sixth International Conference on*

74. *Computational Intelligence and Communication Technologies (CCICT)* (pp. 212–219). IEEE. https://doi.org/10.1109/CCICT62777.2024.00043
75. Soltani, M., Omid, M., & Alimardani, R. (**2015**). Egg volume prediction using machine vision technique based on Pappus theorem and artificial neural network. *Journal of Food Science and Technology*, *52*(5), 3065–3071. https://doi.org/10.1007/s13197-014-1350-6
76. González Ariza, A., Arando Arbulu, A., Navas González, F. J., León Jurado, J. M., Delgado Bermejo, J. V., & Camacho Vallejo, M. E. (**2022**). Data mining-based discriminant analysis as a tool for the study of egg quality in native hen breeds. *Scientific Reports*, *12*, Article 15873. https://doi.org/10.1038/s41598-022-20111-z
77. Patil, P. P., & Patil, V. N. (**2024**). NIR spectroscopy for freshness detection and classification of chicken eggs. In *2024 11th International Conference on Computing for Sustainable Global Development (INDIACom)*. IEEE. https://doi.org/10.23919/INDIACom61295.2024.10498863
78. Akowuah, T. O. S., Teye, E., Hagan, J., & Nyandey, K. (**2020**). Rapid and nondestructive determination of egg freshness category and marked date of lay using spectral fingerprint. *Journal of Spectroscopy*, *2020*, Article 8838542. https://doi.org/10.1155/2020/8838542
79. Cavanna, D., Zanardi, S., Dall'Asta, C., & Suman, M. (**2019**). Ion mobility spectrometry coupled to gas chromatography: A rapid tool to assess eggs freshness. *Food Chemistry*, *271*, 691–696. https://doi.org/10.1016/j.foodchem.2018.07.204
80. Cavanna, D., Catellani, D., Dall'Asta, C., & Suman, M. (**2018**). Egg product freshness evaluation: A metabolomic approach. *Journal of Mass Spectrometry*, *53*(9), 849–861. https://doi.org/10.1002/jms.4256
81. Li, J., Zhu, S., Jiang, S., & Wang, J. (**2017**). Prediction of egg storage time and yolk index based on electronic nose combined with chemometric methods. *LWT*, *82*, 369–376. https://doi.org/10.1016/j.lwt.2017.04.070
82. Rouhollahi, G., Mollazade, K., & Nourbakhsh, H. (**2024**). Predicting the S-ovalbumin content and determining the freshness of chicken eggs via transmittance spectroscopy. *Scientific Reports*, *14*, Article 28405. https://doi.org/10.1038/s41598-024-79975-y