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Spectroscopic approaches for non-destructive shell egg quality and freshness

evaluation: opportunities and challenges

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Abstract:	<p>Shell egg quality and freshness are traditionally assessed by destructive laboratory-level methods, thus restricting the possibilities to be easily guaranteed in the industrial chain. Non-destructive techniques are therefore of paramount importance, giving accuracy, speed, and instantaneous results. Among these techniques, spectroscopy is promising because it would allow the development of on-line applications for shell egg grading, with clear benefits for both industries and consumers. However, there are still few works in the literature about this topic. Thus, this review presents recently published (years 2015-2020) applications of spectroscopy methods (i.e., VIS-NIR, NIR, Raman, microwaves, hyperspectral imaging, pulsed IR thermography) to the non-destructive assessment of shell egg quality and freshness, with the aim of boosting the research in this field giving some directions for the fulfilment of industrial needs. Indeed, spectroscopic techniques have been proven to be useful tools for the evaluation of shell egg quality and freshness. The advances in instrumentation and data analysis allow to predict shell egg quality by non-destructive, fast, and environmentally friendly approaches. However, the industrial implementation still requires robust calibration transfer to simplified hand-held systems for low-cost and easy use.</p>
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Dear Editor,

Please find a copy of the manuscript "Spectroscopic approaches for non-destructive shell egg quality and freshness evaluation: opportunities and challenges" by Eleonora Loffredi, Silvia Grassi, and Cristina Alamprese we would like to submit for publication in Food Control, as suggested by the Article Transfer Service.

Due to the high perishability of eggs, food industries need fast, reliable, and non-destructive methods for the evaluation of shell egg quality and freshness. Thus, the review presents recently published (years 2015-2020) applications of spectroscopy techniques (i.e., VIS-NIR, NIR, Raman, microwaves, hyperspectral imaging, pulsed IR thermography) to the non-destructive assessment of shell egg quality and freshness, with the aim of boosting the research in this field, giving some directions for the fulfilment of industrial needs.

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Looking forward to hearing from you soon, I remain sincerely yours.

Cristina Alamprese

1 **Spectroscopic approaches for non-destructive shell egg quality and freshness evaluation:**
2 **opportunities and challenges**

3

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10

11 **Abstract**

12 Shell egg quality and freshness are traditionally assessed by destructive laboratory-level
13 methods, thus restricting the possibilities to be easily guaranteed in the industrial chain. Non-
14 destructive techniques are therefore of paramount importance, giving accuracy, speed, and
15 instantaneous results. Among these techniques, spectroscopy is promising because it would
16 allow the development of on-line applications for shell egg grading, with clear benefits for
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25 friendly approaches. However, the industrial implementation still requires robust calibration
26 transfer to simplified hand-held systems for low-cost and easy use.

27

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29 thermography.

30

31 **1. Introduction**

32 Eggs are extremely important in human diet because they represent a cheap source of high-
33 quality proteins and easily digestible fats, besides representing important ingredients for the
34 food industry thanks to their technological properties (i.e., foaming, gelling, emulsifying).
35 Unfortunately, eggs are highly perishable and quality deterioration occurs during storage,
36 distribution, sale, and processing, altering physical, chemical, nutritional, and sensory
37 properties. Egg quality is a general term including all the characteristics that can affect
38 consumers' acceptability and preference. For egg grading, both external and internal
39 parameters are commonly considered, such as shell features (e.g., cleanliness, strength,
40 texture, and shape), albumen viscosity, and yolk shape and firmness. The interior egg quality
41 begins to deteriorate just after laying through many complex changes, including albumen
42 thinning, pH increasing, weakening and stretching of the vitelline membrane, and increase in
43 water content of yolk. Thus, freshness plays a major role in the quality perception and
44 consumers usually perceive variability in freshness as a lack of quality (Hisasaga et al., 2020;
45 Karoui et al., 2006). Therefore, the determination of specific parameters for the evaluation of
46 egg freshness and quality has been the major challenge of the last century (Stadelman &
47 Cotterill, 1995).

48 Several methods have been developed for the assessment of egg quality and a distinction can
49 be made between destructive and non-destructive methods. Among destructive methods, the
50 most widely used parameters for the determination of egg quality are the shell strength and
51 thickness, the internal air cell size, the albumen/yolk ratio, the albumen viscosity, height, and
52 pH, the yolk colour and shape, and the strength of the vitelline membrane (Karoui et al., 2006;
53 Sharaf Eddin et al., 2019; Stadelman & Cotterill, 1995). Shell strength and thickness are
54 significantly correlated and associated to egg viability during carriage and storage. These
55 quality parameters are mainly affected by hen breed, age, and nutrition. Fragile eggs not only

56 lead to economic loss, but also increase the risk of cracking with subsequent bacterial
57 contamination (Sharaf Eddin et al., 2019). Air cell is formed by the separation of the shell
58 membrane (i.e., the inner and the outer) at the blunt end of an egg, because of the egg content
59 shrinkage during cooling after laying. It enlarges continuously during storage, due to water
60 evaporation and carbon dioxide escape through the eggshell (Stadelman & Cotterill, 1995). It
61 is affected by egg weight and storage conditions. Air cell height is the only quantitative egg
62 freshness parameter considered by the European Union regulation (Commission Regulation
63 No 589/2008; Karoui et al., 2006). A visible sign of internal quality loss is the albumen
64 thinning mainly due to changes in the ovomucin-lysozyme complex. Albumen freshness is
65 usually measured in Haugh Units (HU), an index proposed in 1937 that consists in measuring
66 the height of the thick albumen at 1 cm from the yolk, avoiding chalazae, by means of a
67 micrometre mounted on a tripod. A suitable equation allows then the conversion in HU, also
68 considering the egg weight. HU decrease with storage time as a consequence of albumen
69 thinning (Stadelman & Cotterill, 1995). Another index related to egg freshness is pH. The
70 albumen pH of newly laid eggs ranges between 7.6 and 8.5. During storage, it increases as a
71 function of environmental conditions due to a loss of carbon dioxide through the shell pores
72 (Karoui et al., 2006). Several changes occur also in the yolk, such as colour modification and
73 shape deformation. Colour is an important acceptability factor to consumers and colour
74 preferences are different across countries (Sharaf Eddin et al., 2019). Changes in shape of the
75 yolk are mainly related to weakening of the vitelline membrane and they can be assessed
76 through the Yolk Index (YI), calculated as the ratio between the yolk height and width
77 (Stadelman & Cotterill, 1995), or by the Yolk Coefficient (YC), expressed as the ratio
78 between the yolk weight and height (Abdanan Mehdizadeh et al., 2014).
79 The advantage of destructive analyses is that the measurements are directly performed on the
80 egg fraction of interest, thus providing more reliable data, but they are time-consuming,

81 require skilled operators, and can only be applied at laboratory level, thus disregarding the
82 industrial urgent need for fast and reliable methods for the egg quality assessment.

83 Several studies have been recently focused on the evaluation of different non-destructive
84 techniques for the rapid and reliable determination of quality and freshness of intact food
85 products. One of the most researched field has been the dairy sector, for which Karoui & De
86 Baerdemaeker (2007) presented an overview of different spectroscopic applications including
87 Near Infrared (NIR), Mid Infrared (MIR), and Front Face Fluorescence (FFF) spectroscopy,
88 as well as stable isotope and Nuclear Magnetic Resonance (NMR). Indeed, these
89 spectroscopic methods guarantee null/low sample preparation and reduce analysis time and
90 costs. Since a huge amount of data is usually generated by these techniques, multivariate
91 statistical methods (i.e., chemometrics) are fundamental for signal elaboration, in order to
92 extract the interesting information (Chen et al., 2019).

93 NIR spectroscopy has been extensively applied for rapid quality assessment in diverse food
94 product chains. Recent comprehensive reviews report success of this technique in assessing
95 quality parameters in meat (Berri et al., 2019; Dixit et al., 2017), fish (Cheng & Sun, 2017),
96 and dairy (Pu et al., 2020) products. In the horticultural field, NIR spectral range is often
97 associated with visible spectral region (i.e., VIS-NIR), leading to successful applications for
98 the in-line inspection of agro-food products under semi-industrial conditions (Cortés et al.,
99 2019). Furthermore, technological advances facing size miniaturization, cost reduction, and
100 data analysis are making NIR spectroscopy easily applicable on process lines (Antequera et
101 al., 2021). Raman spectroscopy struggles in food quality applications, due to the presence of
102 many interfering artefacts created by the complex matrices. However, new strategies, such as
103 the Surface Enhanced Raman spectroscopy, improved sensitivity, selectivity, and
104 reproducibility in the determination of quality parameters and contaminants (Lin & He, 2019).
105 Terahertz spectroscopy, covering a very small range of the electromagnetic spectrum between

106 the microwave and infrared regions, has been widely used in the medical field, but novel
107 applications have been recently discussed for quality control both in the agricultural and food
108 industries, as well described in the review by Afsah-Hejri et al. (2019). Similarly, microwave
109 dielectric spectroscopy demonstrated how low-power analytical methodology, based on
110 electromagnetic field in the 0.3–300 GHz frequency range, could be useful for different
111 applications in the food industry thanks to the capability of differentiating materials of
112 different composition (Blakey & Morales-Partera, 2016).

113 Analyses of intact foods have been promoted also by coupling spectral and spatial
114 information using Hyperspectral Imaging (HSI) systems. A relevant number of works has
115 been published about the application of HSI systems for food quality evaluation, considering
116 meat (Antequera et al., 2021), fish (Cheng & Sun, 2017), dairy (Dufour, 2011), and
117 horticultural products (Lu et al., 2020). In most cases, HSI demonstrated to be a reliable tool
118 also for industrial applications. Infrared thermography has been less implemented in food
119 studies, but active thermography, i.e., the generation of a thermal contrast between target and
120 background by an energy source, is drawing attention in food quality control. The few
121 published works in the field have been recently discussed in the review by Ferreira (2020).

122 Based on the above-mentioned promising applications, researchers have evaluated potential
123 of spectroscopic techniques also in the egg field, considering both shell eggs and egg products
124 (Grassi et al., 2018). The main challenge is of course the possibility to unravel shell egg
125 characteristics without breaking the eggs. Thus, this review discusses the recent works about
126 spectroscopy applications for the non-destructive evaluation of shell egg freshness and
127 quality. The considered papers (published in 2015-2020) are summarized in Table 1 and
128 commented hereafter following a technique-wise scheme.

129

130 **2. VIS-NIR and NIR spectroscopy**

131 Interesting applications of transmission VIS-NIR spectroscopy (from 300 to 1100 nm; Fig. 1)
132 for the non-destructive assessment of egg quality and freshness were proposed by Dong et al.
133 (2017a, 2017b, 2018a, 2018b). Spectra were acquired with a fibre probe placed directly on the
134 equatorial region of eggs, reduced in the range 480-960 nm, and pretreated with different
135 methods including Savitzky-Golay smoothing (SG), Multiplicative Scatter Correction (MSC),
136 and Standard Normal Variate (SNV). Partial Least Square Regression (PLSR) was used to
137 build prediction models for eggshell thickness, air chamber diameter, and pH of albumen and
138 whole egg. In the case of eggshell thickness (Dong et al., 2017b), 70 intact, white-shelled
139 eggs were analysed, including 52 samples in the calibration set and 18 samples in the
140 prediction set. The best correlation coefficients obtained in calibration (r_c) and prediction (r_p)
141 (MSC-treated spectra) were 0.86 and 0.84, respectively, with a Root Mean Square Error in
142 Calibration (RMSEC) and Prediction (RMSEP) of 0.01 mm, over a 0.270-0.378 mm range of
143 shell thickness measured by a vernier calliper in the equatorial region. For the air chamber
144 diameter (Dong et al., 2018b), 90 brown-shelled eggs were considered, split into a calibration
145 set of 68 eggs and a prediction set of 22 samples. The air chamber diameter, measured by a
146 vernier calliper after shelling, ranged from 15.82 to 35.32 mm. The best PLSR model was
147 obtained with MSC-treated spectra, with a r_c value of 0.87 and a RMSEC value of 2.13 mm,
148 and r_p , RMSEP values of 0.85 and 2.14 mm, respectively. Albumen and whole egg pH are
149 considered freshness markers. Indeed, albumen pH increases during egg storage because of
150 the gaseous exchanges with ambient air through shell pores, and the water and mineral
151 migration between albumen and yolk through vitelline membrane. Prediction models were
152 built by Dong et al. (2017a) on 178 white-shelled eggs stored for different periods (up to 3
153 weeks) under controlled temperature and Relative Humidity (RH) conditions (30°C, 65%
154 RH). During storage, pH changed from 8.08 to 10.11 for albumen and from 7.06 to 8.76 for
155 whole egg. In this case, the reduced spectral range was 550-850 nm. For albumen pH, the

156 PLSR model developed with SNV-preprocessed spectra got the best correlation coefficient in
157 prediction ($r_p = 0.923$), with a RMSEP of 0.17. The whole egg pH model yielded a lower
158 prediction accuracy, with a r_p of 0.752 and a RMSEP of 0.27, maybe due to the smaller
159 variation in pH data.

160 Similar results for the air chamber height prediction were obtained by Aboonajmi et al.
161 (2016), applying VIS-NIR spectroscopy to 300 eggs stored in different conditions
162 (temperatures of 25 and 5 °C, with RH of 40% and 75% respectively, up to 30 days). Spectral
163 data were corrected for both multiplicative and additive effects due to scattering, reduced in
164 dimension by applying the Principal Component Analysis (PCA), and then elaborated by an
165 Artificial Neural Network (ANN) algorithm (i.e., radial basis function) internally validated by
166 cross-validation (CV). Values of coefficient of determination (R^2) in CV were 0.844 and
167 0.835 for the eggs stored at 5 and 25 °C, respectively. No information about predictive errors
168 were reported. The authors also measured the HU, obtaining R^2 of 0.767 and 0.745 in CV.
169 The observed differences between the room and cold temperature datasets were ascribed to
170 the albumen viscosity change, which can have affected the results. Thus, potential of the
171 spectroscopic technology for a rough screening was demonstrated, but further research on the
172 optic fibre used are suggested. Of course, also the combination of data in a single model and
173 an external validation can contribute to a higher robustness of the proposed procedure.

174 Indeed, Akowuah et al. (2020) encouraged the development of a predictive model for HU and
175 marked date of lay considering different storage conditions, because they observed that HU of
176 eggs stored at low temperature were not directly correlated with storage time (at least in the
177 limited period of their measurements). Thus, in order to provide consumers with the real
178 length of storage, information about the environment conditions is important. In their study,
179 120 brown-shelled eggs were used, stored under cold (4 °C) and ambient temperature (28 °C)
180 up to 20 days and analysed with a handheld NIR device working in the range 740-1070 nm.

181 After MSC pretreatment, classification models were developed for the two storage
182 temperatures applying the Linear Discriminant Analysis (LDA) and dividing samples in four
183 classes based on storage duration. An average correct classification rate in prediction of 96%
184 and 100% was obtained for cold and ambient storage, respectively. For predicting the storage
185 duration, the authors developed also a PLS model, reaching r_p values of 0.89 and 0.91 for
186 ambient and cold storage, respectively, with RMSEP of 3 and 2.5 days.

187 The same handheld NIR spectrometer was already used by Coronel-Reyes et al. (2018) for the
188 determination of egg storage time (up to 21 days), considering only room temperature (23 °C,
189 90% RU) and a total of 30 eggs. Several preprocessing methods and ANN algorithms were
190 tested and cross-validated. The best model was obtained by SG preprocessing and an ANN
191 with ten neurons in one hidden layer, achieving in prediction a R^2 of 0.873 and a RMSECV of
192 1.97 days. Even if the considered number of samples was very small, the work showed the
193 potential of a portable and low-cost NIR device that can be even connected to a smartphone
194 for a rapid response about egg freshness.

195 The potential of VIS-NIR spectroscopy in investigating shell egg internal quality was studied
196 also for the evaluation of yolk viscosity. Apparent yolk viscosity in lightly heated shell eggs
197 was targeted in the study of Kuroki et al. (2017) as this parameter is an important quality
198 attribute related to textural preference and usage suitability to several dishes. The egg
199 albumen begins denaturing at a lower temperature than the yolk, thus increasing turbidity and
200 possibly masking the variation in transmittance spectra due to increment in yolk viscosity. In
201 this study, 88 white-shelled eggs were cooked by far-infrared heating, under seven different
202 conditions identified with levels from 1 to 7 as a function of the heat intensity. Then, the
203 samples were stored overnight at 20 °C and the transmittance spectra were acquired in three
204 points along the equatorial region by an optic fibre in the 588-1084 nm range. After spectra
205 acquisition, the samples were broken and the apparent yolk viscosity was measured with a

206 portable falling-needle viscometer, registering a range of approximately 200-600000 mPa s.
207 Before multivariate analysis, spectra were pretreated using SG and the second derivative (d2).
208 A PCA was used to investigate the relations between the spectral variation of whole shell
209 eggs and the degree of cooking. It was demonstrated that 85% of the spectral variation of the
210 heated shell eggs resulted from change in the interaction between water and ovotransferrin in
211 egg white. A model for the prediction of yolk viscosity was subsequently developed by PLSR,
212 obtaining a R^2_{CV} value of 0.81 with a RMSECV of 0.49 log mPa·s. The model was then
213 judged as “usable for sample screening”. A variable selection was then performed by applying
214 the Martens uncertainty test, obtaining an “excellent predictive model” with $R^2_{CV} = 0.89$ and
215 $RMSECV = 0.37$ log mPa·s. The selected wavelengths were in the range 600-850 nm, and the
216 authors demonstrated that those features did not contain the information about thermal
217 gelation of egg albumen. Thus, the model obtained after variable selection was considered
218 robust and independent from the egg white gelation status. However, an external validation of
219 the model was not carried out.

220 Any change in specific instrument or sample orientation/variety/colour used for model
221 development might influence predictive abilities and results. For instance, Dong et al. (2018a)
222 evaluated the egg orientation effect during non-destructive measurements by means of VIS-
223 NIR spectroscopy. For this purpose, transmission spectra (340-1030 nm) were acquired from
224 both the equatorial and blunt region of 91 white-shelled eggs before the destructive evaluation
225 of HU, YI, and albumen pH. A PLSR was employed for modelling the freshness parameters,
226 after SG, MSC, SNV, first and second derivative pretreatments on the spectra. The results
227 obtained from the equatorial region showed higher correlation coefficients in prediction
228 compared to those of the blunt end (i.e., 0.881 vs. 0.813 for HU, 0.855 vs. 0.848 for YI, and
229 0.888 vs. 0.857 for albumen pH), with lower RMSEP (i.e., 7.720 vs. 9.576 for HU, 0.034 vs.
230 0.039 for YI, and 0.147 vs. 0.126 for albumen pH). These results might be explained by the

231 presence of the air chamber in the blunt end, which may affect spectra collection; moreover,
232 the eggshell has more homogeneous texture and thickness in the equatorial region.
233 Eggshell colour can also play an important role in spectral results, mainly when the visible
234 region is included in the analysis. For this reason, many studies on egg freshness evaluation
235 involve only white-shelled eggs, possibly because brown-shelled eggs have limitations due to
236 the interference of spectral bands. However, it could be advisable to consider both the shell
237 egg types to assess spectroscopic method reliability on a larger scale. Eggshell colour is
238 mainly related to the hen breeds and the main pigment comes from protoporphyrin IX in
239 haemoglobin. Eggs with different colours can show no obvious differences in nutritional
240 value or composition. Thus, some authors tried different approaches to manage differences
241 linked to shell colour. For instance, Dong et al. (2019) developed predictive models for
242 albumen pH considering both white- and brown-shelled eggs. A total of 192 eggs, 96 from
243 White Leghorns hens and 96 from Bantam hens, were purchased and then stored under
244 controlled conditions (30 °C, 60% RH) up to three weeks, in order to promote pH changes
245 (from 8.24 to 9.76). Eggs were sampled every two days, carrying out both non-destructive
246 VIS-NIR (340-1030 nm) analysis and destructive measurements of albumen pH. After
247 combining the Mahalanobis distance with PCA in order to eliminate outliers, the 167
248 remaining spectra were pretreated with different methods (SG, MSC, SNV, first and second
249 derivatives), and PLSR models were developed separately or jointly for the eggs of the two
250 hen breeds. For the White Leghorn eggs, the best prediction model was obtained with MSC
251 pretreatment, resulting in $r_p = 0.907$ and $RMSEP = 0.123$. Similar results were obtained also
252 for Bantam eggs, with $r_p = 0.947$ and $RMSEP = 0.115$. However, prediction of albumen pH
253 for the eggs obtained by the two hen breeds exchanging predictive models was not reliable,
254 resulting in low r_p (0.6-0.7) and high $RMSEP$ (0.5-0.8), maybe related to the different
255 eggshell colour. The issue was solved by an updated global calibration considering all the

256 eggs together and applying a slope/bias correction, thus obtaining a r_p of 0.908 and a RMSEP
257 of 0.133. The work demonstrated that the variability related to different egg types should be
258 considered in the model calibration to obtain good prediction ability.

259 NIR spectroscopy can also be applied to authenticity issues. For instance, Chen et al. (2019)
260 explored the combination of NIR spectroscopy, Joint Mutual Information (JMI) variable
261 selection, and Data Driven-based Class-Modelling (DDCM) for non-destructive
262 discrimination of eggs laid by hens reared in a natural environment (named “native eggs”)
263 from eggs obtained in two different industrial systems (“feed eggs”). A total of 122 samples
264 were considered and analysed by NIR spectroscopy ($10000\text{--}4000\text{ cm}^{-1}$), using an optic fibre
265 probe in reflectance mode. After SNV pretreatment, the variable selection based on JMI
266 algorithm picked out 20 informative variables over the 1557 original wavenumbers. The
267 DDCM algorithm was then applied for class-modelling, dividing samples in calibration and
268 test sets. The results showed that when “native eggs” were the target class, sensitivity in
269 calibration was 93.3%, while sensitivity and specificity in prediction were 100% and 98.8%,
270 respectively. The authors considered the model satisfactory. However, due to the limited
271 number of analysed samples that can strongly affect classification model performance, they
272 suggested further research in the field of egg authentication.

273

274 **3. Raman spectroscopy**

275 Raman spectroscopy (Fig. 2) has found limited applications in non-destructive evaluation of
276 egg freshness and quality. Liu et al. (2020) proposed Raman spectroscopy to detect in a
277 simple, fast, and non-destructive way cuticle modifications, correlated to freshness
278 parameters. Indeed, the egg cuticle is a protein layer covering eggshell surface, which
279 deteriorates with storage time and can thus indicate egg freshness. Raman spectra ($100\text{--}3000$
280 cm^{-1}) of 125 Hy-Line Brown eggs stored under controlled conditions ($20\text{ }^\circ\text{C}$, 40% RH) up to

281 59 days were collected on the top (pointed area), bottom (blunt area), and equatorial regions,
282 with a 6 mm distance between the probe and the eggshell surface. HU, YI, albumen pH, and
283 air chamber height and diameter were analysed by the common destructive methods. Different
284 preprocessing algorithms were applied to Raman spectra: SG, normalization (NL), first and
285 second derivatives, baseline correction (BL), SNV, MSC, and denoise. Afterwards, PLSR
286 models were developed for all the freshness indicators, using 80% of the samples as the
287 calibration set and 20% as the prediction set. Good results were obtained for HU, albumen
288 pH, and air chamber dimensions, with r_p ranging from 0.807 to 0.895. YI was not
289 satisfactorily predicted, reaching a maximum value of r_p of 0.540 with spectra transformed in
290 second derivative. This result can be due to a weak relationship between the changes in
291 eggshell surface and yolk. Moreover, an evaluation of the best acquisition area was carried
292 out, demonstrating that the prediction performance of the PLSR model established by the top
293 Raman spectrum was relatively better for the considered freshness parameters, increasing
294 values of r_p (0.830-0.935). This can be due to the absence of an air chamber in the top of the
295 egg, leading to a constant contact of the egg content with the eggshell. In order to increase the
296 adaptability of the models and maximize Raman spectroscopy application, other influencing
297 factors should be considered, such as breed, hen age, and rearing systems.

298

299 **4. Dielectric spectroscopy**

300 Few attempts to apply dielectric methods (Fig. 3) for non-destructive measurement of various
301 quality indices of shell eggs have been recently published (Akbarzadeh et al., 2019; Soltani et
302 al., 2015; Soltani & Omid, 2015). Akbarzadeh et al. (2019) aimed to develop a microwave
303 spectroscopy approach based on a waveguide and network analyser instrument for the non-
304 destructive prediction of several egg freshness indices, including air chamber height, thick
305 albumen height, HU, albumen pH, and YC. White-shelled eggs (244 samples) were used,

306 stored at room temperature (25 °C) up to 24 days. The average reflection and transmission
307 spectra were obtained in the 0.9-1.7 GHz microwave range, immediately before the
308 destructive evaluation of freshness parameters. Then, regression and classification models
309 were developed and validated, applying different chemometric methods. Generally, the return
310 loss reflection spectra gave the best predictive models for all quality indices, except for
311 albumen pH, with a Residual Prediction Deviation (RPD) over 2. In particular, RPD was
312 close to 3 for the air chamber height. RPD is the ratio of standard deviation to RMSEP and it
313 is used as a performance index of the developed models. Higher RPD values represent strong
314 calibration models since they are obtained with RMSEP lowering and standard deviation
315 increasing. Hence, RPD values higher than 2 or 3 indicate good or excellent calibrations,
316 respectively. When ANN was used for regression purposes, the best predictive models were
317 obtained considering different input spectra. Anyway, also with this algorithm, RPD values
318 were higher than 2 for all the freshness parameters, except for pH albumen (RPD = 1.83).
319 Good results were obtained also in classification by applying the Soft Independent Modelling
320 of Class Analogy (SIMCA) or the ANN algorithm. Considering six different classes of
321 freshness, the best discrimination power was provided by the return loss reflection spectra,
322 with a total accuracy of 100%. In conclusion, despite the good results obtained, the authors
323 highlighted the necessity to develop a more economical system, since the network analyser
324 used was expensive, and to implement the technique for on-line applications.

325 The range of radio frequency (40 kHz-20 MHz) was investigated by Soltani & Omid (2015)
326 and Soltani et al. (2015) in order to build a robust model for non-destructive classification of
327 eggs based on freshness. In the work by Soltani & Omid (2015), several machine learning
328 techniques were coupled with dielectric spectroscopy, including ANN, Support Vector
329 Machine (SVM), Bayesian Networks (BN), and Decision Tree (DT). Moreover, a
330 Correlation-based Feature Selection (CFS) was applied to spectra, thus reducing the size of

331 feature vector from 387 to 24. A total of 150 white-shelled eggs were used (i.e., 110 samples
332 in the calibration set and 40 samples in the prediction set), stored for different periods (up to
333 24 days) at 20 °C and 35% RH. All the machine learning techniques resulted in 100%
334 classification accuracy, except for DT that reached 87.5%. ANN, SVM, and DT were applied
335 also in regression, in order to predict the air cell height. Good performances were calculated
336 for all the developed models, but the lowest errors were obtained with a Meta-Super-Peer DT
337 (RMSEP = 1.043 mm).

338 In the work by Soltani et al. (2015), a Multilayer Perceptron Feedforward Neural Network
339 was applied, combined with Levenberg-Marquardt algorithm for error minimization.

340 Considering HU, YI, yolk/albumen ratio, and yolk weight as quality factors of eggs (287
341 white-shelled eggs, stored at 20 °C and 35% RU up to 24 days) the following R^2 in validation
342 were achieved: 0.998, 0.998, 0.998, and 0.994, respectively. In prediction mode, the mean
343 absolute percent errors obtained were 5.41, 6.84, 8.79, and 4.24% for HU, YI, yolk/albumen,
344 and yolk weight, respectively.

345

346 **5. Hyperspectral Imaging**

347 Coupling spectral and spatial information can be a successful strategy for non-destructive
348 evaluation of food quality on industrial lines. Different works recently demonstrated the
349 potential of HSI (Fig. 4) as a rapid online system for the egg classification based on freshness.
350 Yao et al. (2020) proposed a solution implementing VIS-NIR-HSI for egg classification based
351 on HU. They measured 188 eggs at three freshness grades, acquiring images in the 400–1000
352 nm spectral range and using a Region of Interest (ROI) of 32×32 pixel from the centre of the
353 samples. An average spectrum was then calculated for each sample and different variable
354 selection strategies were adopted. Among them, the iteratively retains informative variables
355 algorithm, based on binary matrix shuffling filter, in combination with genetic algorithm gave

356 the most promising classification accuracy for the classification models developed by SVM.
357 Indeed, the calibration and prediction classification accuracies were 99.29 and 97.87%,
358 respectively.

359 Similarly, Suktanarak & Teerachaichayut (2017) proposed the use of reflectance NIR-HSI for
360 prediction of HU. The samples (91 eggs) were divided into 7 groups as a function of storage
361 time (up to 21 days) at 25 °C. NIR-HSI data were acquired in reflectance mode (wavelength
362 range, 900-1700 nm), considering a ROI of 50 x 90 pixel at the centre of each egg image. An
363 average spectrum was calculated for each sample and used for PLSR modelling. The model
364 was calibrated considering 58 eggs and tested for prediction by using the other 33 samples.

365 An excellent performance in prediction was reached by SNV spectral pretreatment, with a R^2_p
366 of 0.85, a RMSEP of 6.29 HU, and a RPD of 3.07. Furthermore, the authors proposed a pixel
367 by pixel distribution maps of HU, thus giving the possibility to evaluate egg freshness by a
368 simple visual inspection according to an intensity scale.

369 Different factors can affect HSI results, such as the incident light angle and the number of
370 wavelengths. Dai et al. (2020) studied the influence of incident angles on the accuracy of egg
371 HU prediction. Evaluating 350 eggs, and considering scattering, transmission, and mixed
372 hyperspectral images, they found that the accuracy was higher (up to 100%) with scattering
373 images and inversely proportional to the incident angle. In particular, the best classification
374 model for egg freshness prediction was developed by merging multiple weak classifiers (i.e.,
375 Discriminant Analysis Classifier, K-Nearest Neighbour and Random Forest) into a strong
376 classifier by Stacking Ensemble Learning. The model was based on feature wavelengths
377 extracted by Successive Projections Algorithm (SPA) from spectra collected with 0° incident
378 light and transformed by MSC. Also Zhang et al. (2015) applied a wavelength optimization
379 by SPA, thus selecting only thirteen features in the range 380–1010 nm to predict HU based
380 on a Support Vector Regression model. Wavelength selection increased R^2_p from 0.85 to 0.87,

381 while reducing RMSEP from 4.33 to 4.01 HU. Although only a small improvement was
382 obtained, the reduction of the wavelengths paves the way to the construction of simpler and
383 cheaper NIR-HSI systems, suitable also for industrial applications. Moreover, the authors
384 demonstrated that HSI can be useful in discovering internal defects, such as scattered yolk
385 and the presence of air bubbles, with an accuracy in prediction of 90.0 and 96.3%,
386 respectively.

387 NIR-HSI was proposed also to predict S-ovalbumin content (Fu et al., 2019), which is highly
388 correlated with storage time and has low natural variability. It is a promising and significant
389 shell egg freshness index, generated during storage from ovalbumin, the most abundant
390 protein of eggs. The conversion of ovalbumin into the more heat stable S-ovalbumin is
391 affected by pH and temperature, but it does not change depending on breed, hen age, and
392 nutritional status, thus showing high repeatability (Huang et al., 2012). A total of 108 brown-
393 shelled eggs stored up to 41 days at 22 °C and 65% RH were analysed in transmission mode
394 with a wavelength range of 300–1100 nm (Fu et al., 2019). In this case, an average spectrum
395 was calculated considering as ROI the entire egg area. Spectra were pretreated by a min-max
396 normalisation. Furthermore, a variable selection strategy was implemented by SPA in order to
397 consider a reduced number of wavelengths (i.e., 12) related to S-ovalbumin content. The
398 PLSR and Multiple Linear Regression (MLR) models were developed using two-thirds of the
399 samples (i.e., 72 eggs), selected using the joint x-y distance method, for calibration, and the
400 remaining samples (i.e., 36 eggs) for the prediction step. The S-ovalbumin fraction analysed
401 by the classical chemical method had a range of about 20-100%. The best PLSR model gave a
402 r_p of 0.87, a RMSEP of 0.14%, and a RPD of 1.87. Even better model performances were
403 obtained by MLR with a r_p of 0.91, a RMSEP of 0.12%, and a RPD of 2.35. Furthermore, a
404 visualisation of S-ovalbumin fraction distribution was proposed by a distribution map.

405 Raman Hyperspectral Imaging (RHSI) has been also applied to the non-destructive evaluation
406 of egg quality. In particular, a recent study by Joshi et al. (2020) applied Raman spectroscopy
407 and RHSI to the identification of “fake eggs”. Cases of imitation or “fake food” materials are
408 a major economic fraud for both the food industry and the final consumer. These products are
409 obtained by the incorporation of lower quality or cheaper alternative ingredients that in some
410 cases are not edible nor safe for consumption. The case of fake eggs is only one of the major
411 food frauds of the last few years, prepared using harmful additives, with no nutritional value
412 and difficult to identify by eye. Raman spectroscopy in the 1800-600 cm^{-1} range and RHSI in
413 the 1500-390 cm^{-1} range were able to identify differences linked to the materials used in the
414 preparation of fake eggs (i.e., sodium alginate, tartrazine dye, calcium chloride, gypsum
415 powder, and paraffin wax). In addition, RHSI had the advantage of speed, because a large
416 number of samples can be scanned at one time. In this study, 40 samples (20 real and 20 fake)
417 of shell eggs, albumen, and yolk were analysed and divided in calibration set (24 samples)
418 and validation set (16 samples). A PLS-Discriminant Analysis (PLS-DA) was used for a
419 classification after MSC preprocessing. For all the types of sample considered, a perfectly
420 accurate (100%) discrimination between real and fake samples was obtained. Moreover, the
421 fluorescence corrected egg images, generated by selecting in the acquired RHSI images a
422 single band of the chemical of interest (i.e., the Raman peak at 1295 cm^{-1}), provided a simple
423 visualization method for the distinction of real and fake samples.

424 In conclusion, the different approaches indicated that hyperspectral imaging technology could
425 be a feasible solution for the detection of freshness and quality of shell eggs, offering the
426 possibility to develop rapid and simple visualization methods for online screening.

427

428 **6. Pulsed infrared thermography**

429 Pulsed infrared thermography (Fig. 5) is another approach that merges spatial and spectral
430 information. Freni et al. (2018) proposed a methodology for eggs freshness assessment based
431 on active thermography by means of pulsed thermal stimulation in reflection. The authors
432 irradiated samples by means of a xenon flash, which raised up the temperature of the egg of
433 less than 1 °C. The generated thermograms were recorded by means of an IR camera working
434 in the 36000-51000 nm range and equipped with a synchronization unit that permitted to
435 trigger the acquisition with the generated pulse. Eighteen eggs were stored up to 20 days in a
436 climatic chamber (28 ° C, 30% RH) and tested every day by acquiring the heating and cooling
437 profiles. Two thermograms were recorded, corresponding to the two orthogonal sides of the
438 eggs (i.e., frontally and laterally to the dull pole). The IR images clearly showed the air
439 chamber at the dull pole; moreover, they allowed to immediately identify possible anomalies
440 in the egg structure that are not visible to the naked eye, thus providing a powerful tool for
441 checking egg quality. The thermal images were then preprocessed to reach a proper air
442 chamber segmentation by applying the Wiener filter and the top hat operator followed by
443 morphological opening and closure calculations. From the processed images it was possible to
444 calculate the relative increment of air chamber size during storage. The soundness of the
445 approach relies on the difference in thermal propagation, so that the air chamber appears as an
446 area of different temperature with respect to the liquid part of the egg. However, as suggested
447 also by the authors, a higher number of samples considering higher variability should be
448 tested to validate the reliability of the approach; moreover, prediction models should be
449 developed based on multivariate approaches.

450

451 **7. Conclusions**

452 This review demonstrates that spectroscopic techniques, combined with chemometrics, are
453 useful tools for the evaluation of shell egg quality and freshness. The recent advances in

454 instrumentation and data analysis allowed to develop non-destructive, fast, and
455 environmentally friendly approaches. However, all the reviewed studies were carried out at a
456 laboratory level and sometimes only a limited number of samples were analysed. Moreover,
457 many studies did not validate the predictive models with an external test set, thus not
458 confirming the robustness of the calibration. Therefore, there are still some challenges to face
459 for an industrial implementation, such as the use of a large number of samples considering as
460 many sources of variation as possible (e.g., hen breed, hen age, rearing systems, storage
461 conditions), a robust calibration transfer to simplified handheld systems for low-cost and easy
462 use, a reliable on-line set-up of the proposed approaches overcoming possible issues related to
463 the fastness of the industrial lines. Thus, much research work is still needed in order to
464 develop non-destructive methods for the shell egg quality evaluation able to satisfy industrial
465 requirements and this can be done only with a strict cooperation of the scientific and
466 industrial world.

467

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469

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475

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619

620 **Figure Legends**

621 **Fig. 1.** Block scheme of VIS-NIR spectroscopy.

622

623 **Fig. 2.** Block scheme of Raman spectroscopy.

624

625 **Fig. 3.** Block scheme of dielectric spectroscopy.

626

627 **Fig. 4.** Block scheme of hyperspectral imaging systems.

628

629 **Fig. 5.** Block scheme of pulsed infrared thermography.

Table 1.

Spectroscopy techniques applied to the evaluation of quality and freshness of shell eggs.

Analytical technology	Egg parameter	Number of samples (eggs)	Predictive algorithm	Accuracy of the best models obtained for each algorithm	Reference
VIS-NIR spectroscopy	Eggshell thickness	70 (52, C; 18, P)	PLSR	$r_C = 0.86, r_P = 0.84$	Dong et al. (2017b)
	Air chamber diameter	90 (68, C; 22, P)	PLSR	$r_C = 0.87, r_P = 0.85$	Dong et al. (2018b)
	Air chamber height Haugh Units	300 (no test set)	ANN (RBF)	Air chamber height: $R^2_C = 0.941, R^2_{CV} = 0.844$ (5 °C) $R^2_C = 0.918, R^2_{CV} = 0.835$ (25 °C) Haugh Units: $R^2_C = 0.898, R^2_{CV} = 0.767$ (5 °C) $R^2_C = 0.871, R^2_{CV} = 0.745$ (25 °C)	Aboonajmi et al. (2016)
	Haugh Units Yolk index Albumen pH	91 (68, C; 23, P)	PLSR	Equatorial region: Haugh Units: $r_C = 0.897; r_P = 0.881$ Yolk Index: $r_C = 0.903; r_P = 0.855$ Albumen pH: $r_C = 0.936; r_P = 0.888$	Dong et al. (2018a)
	Albumen pH	80 White Leghorns (53, C; 27, P) 87 Bantam (58, C; 29, P)	PLSR	White Leghorns $r_C = 0.918, r_P = 0.907$ Bantam $r_C = 0.955, r_P = 0.947$	Dong et al. (2019)
	Albumen pH Whole egg pH	178 (133, C; 45, P)	PLSR	Albumen pH: $r_C = 0.943, r_P = 0.923$ Whole egg pH: $r_C = 0.776, r_P = 0.752$	Dong et al. (2017a)
	Apparent yolk viscosity	88 (no test set)	PLSR	$R^2_C = -, R^2_{CV} = 0.89$	Kuroki et al. (2017)

NIR spectroscopy	Marked day of lay	120 (90, C; 30, P)	PLSR	$r_C = 0.83$; $r_P = 0.89$ (28 °C) $r_C = 0.86$; $r_P = 0.91$ (4 °C)	Akowuah et al. (2020)		
			LDA	Accuracy P = 100% (28 °C) Accuracy P = 96% (4 °C)			
	Egg storage time	30 (21, C; 9, P)	ANN	$R^2_C = 0.865$, $R^2_{CV} = 0.873$	Coronel-Reyes et al. (2018)		
Raman spectroscopy	Native eggs/feed eggs	112	DDCM	Sensitivity P = 100% Specificity P = 98.8%	Chen et al. (2019)		
			PLSR	Air chamber height: $r_C = 0.828$, $r_P = 0.830$ Air chamber diameter: $r_C = 0.903$, $r_P = 0.915$ Haugh Units: $r_C = 0.944$, $r_P = 0.925$ Albumen pH: $r_C = 0.945$, $r_P = 0.935$	Liu et al. (2020)		
Dielectric spectroscopy	Air chamber height Thick albumen height Haugh Units Albumen pH Yolk Coefficient	244 (196, C; 48, P)	SIMCA	Air chamber height: $R^2_C = 0.900$, $R^2_P = 0.893$ Thick albumen height: $R^2_C = 0.839$, $R^2_P = 0.826$ Haugh Units $R^2_C = 0.814$, $R^2_P = 0.804$ Albumen pH $R^2_C = 0.787$, $R^2_P = 0.779$ Yolk Coefficient $R^2_C = 0.883$, $R^2_P = 0.869$	Akbarzadeh et al. (2019)		
				Freshness		244 (196, C; 48, P)	Accuracy P = 100%
				Air cell height		150 (110, C; 40, P)	$r_{P\ ANN} = 0.817$ $r_{P\ SVM} = 0.920$ $r_{P\ DT} = 0.906$
	Haugh Units Yolk/Albumen Yolk weight Yolk Index	287 (124, C; 163, P)	FFNN	Haugh Units: $R^2_C = 0.998$, $R^2_P = 0.998$ Yolk/Albumen: $R^2_C = 0.996$, $R^2_P = 0.998$	Soltani et al. (2015)		

Yolk weight
 $R^2_C = 0.994$, $R^2_P = 0.994$
 Yolk Index:
 $R^2_C = 0.994$, $R^2_P = 0.998$

VIS-NIR-HSI	Haugh Units	188 (141, C; 47, P)	IRIV-GA-SVM	Accuracy P = 97.87%	Yao et al. (2020)
	Haugh Units	350 (200, C; 150, P)	SPA-SEL	Accuracy up to 100%	Dai et al. (2020)
	Haugh Units Scattered yolk Air bubbles	645 (200, C; 150, P)	SPA-SVR	Haugh Units: $R^2_C = 0.89$, $R^2_P = 0.87$ Scattered yolk: Accuracy = 90% Air bubbles: Accuracy = 96.3%	Zhang et al. (2015)
	S-ovalbumin content	108 (72, C; 36, P)	PLSR MLR	PLSR: $r_C = 0.929$, $r_P = 0.875$ MLR: $r_C = 0.922$, $r_P = 0.911$	Fu et al. (2019)
NIR-HSI	Haugh Units	91 (58, C; 33, P)	PLSR	$R^2_C = 0.91$, $R^2_P = 0.85$	Suktanarak & Teerachaichayut (2017)
RHSI	Identification of fake eggs	120 (72, C; 48, P)	PLS-DA	Accuracy = 100%	Joshi et al. (2020)
Pulsed infrared thermography	Air chamber	18 (no test set)	-	-	Freni et al. (2018)

VIS-NIR, Visible and Near-Infrared; NIR, Near-Infrared; NIR-HIS, Near-Infrared Hyperspectral Imaging; VIS-NIR-HIS, Visible and Near-Infrared Hyperspectral Imaging; RHSI, Raman Hyperspectral Imaging; C, calibration; P, prediction; PLSR, Partial Least Squares Regression; LDA, Linear Discriminant Analysis; RBF, Radial Basis function; ANN, Artificial Neural Network; SVM, Support Vector Machine; DT, Decision Tree; DDCM, Data Driven-based Class-Modelling; FFNN, Feedforward Neural Network; SIMCA, Soft Independent Modelling of Class Analogy; SPA-SEL, Successive Projection Algorithm-Stacking Ensemble Learning; SPA-SVR, Successive Projection Algorithm-Support Vector Regression; MLR, Multiple Linear Regression; r, coefficient of correlation; CV, Cross-Validation; RPD, Residual Prediction Deviation; R^2 , coefficient of determination.

Figure 1

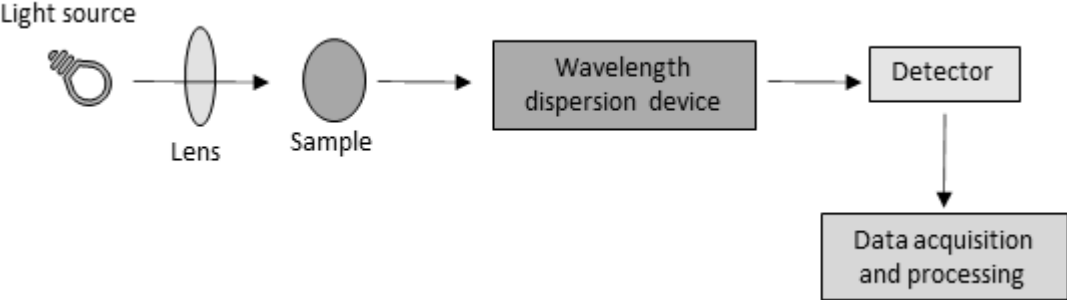


Figure 1 - Color version for online only

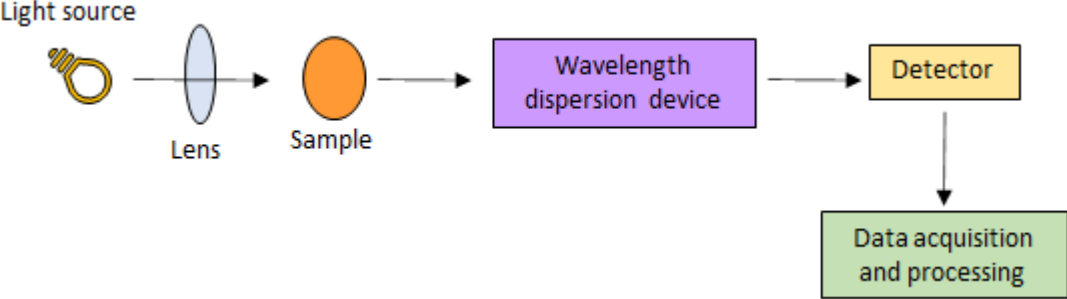


Figure 2

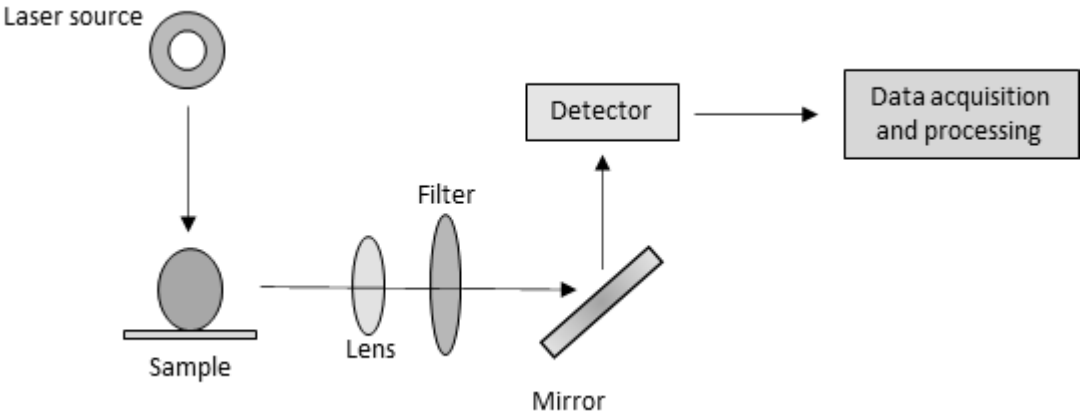


Figure 2 - Color version for online only

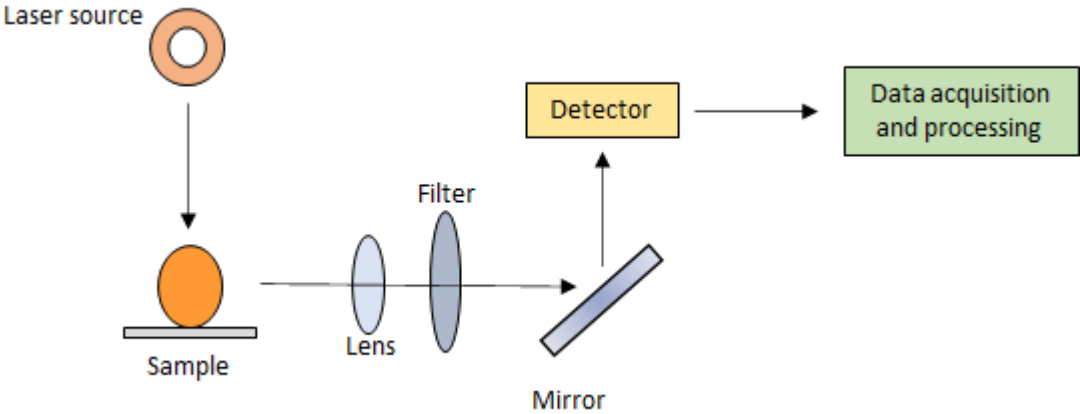


Figure 3

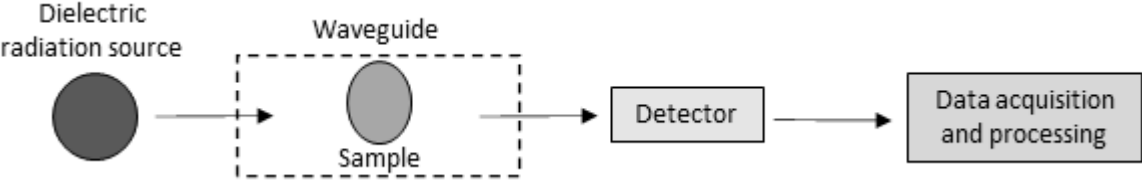


Figure 3 - Color version for online only

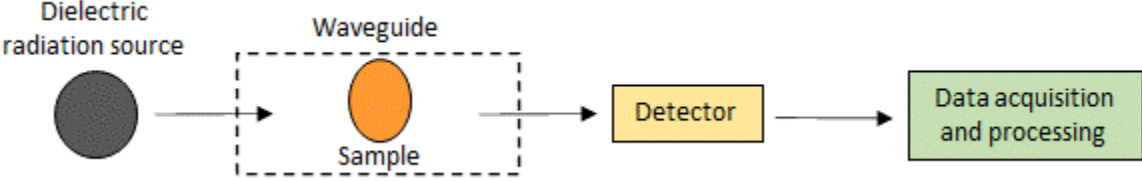


Figure 4

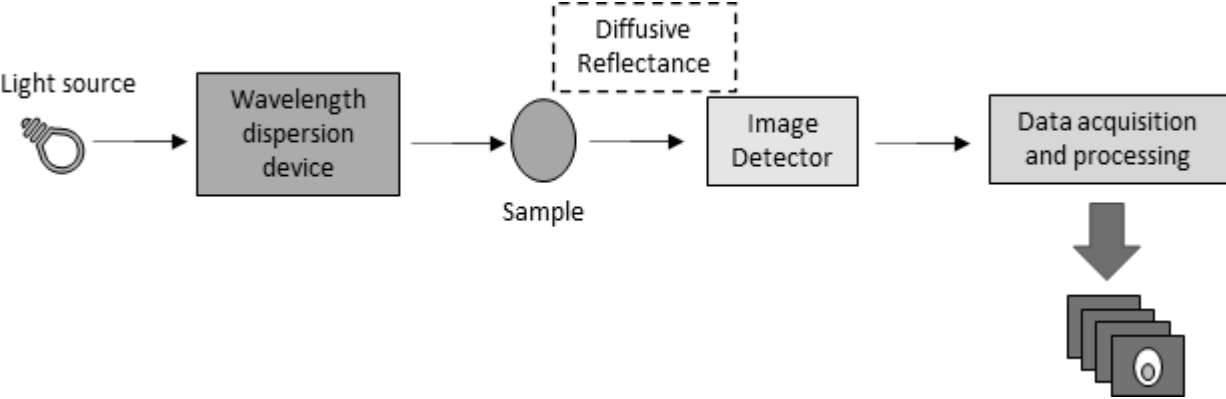


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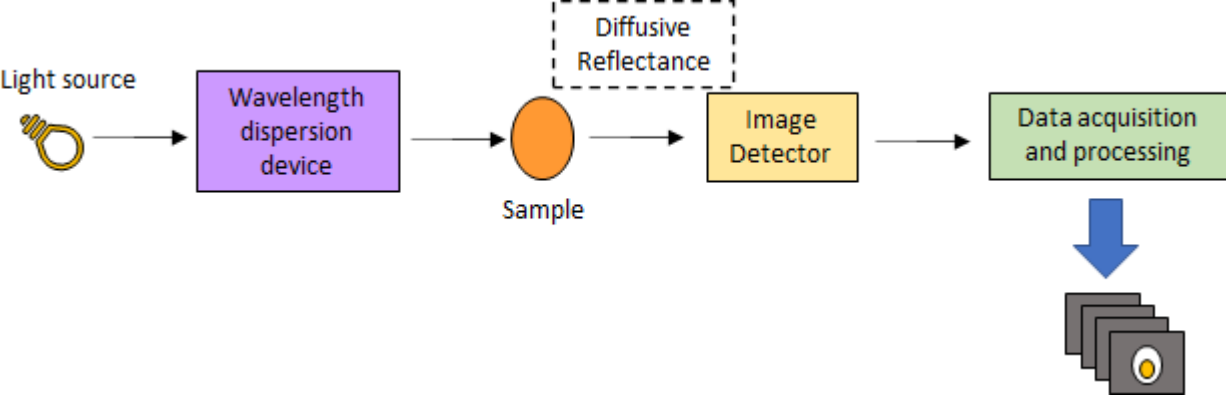


Figure 5

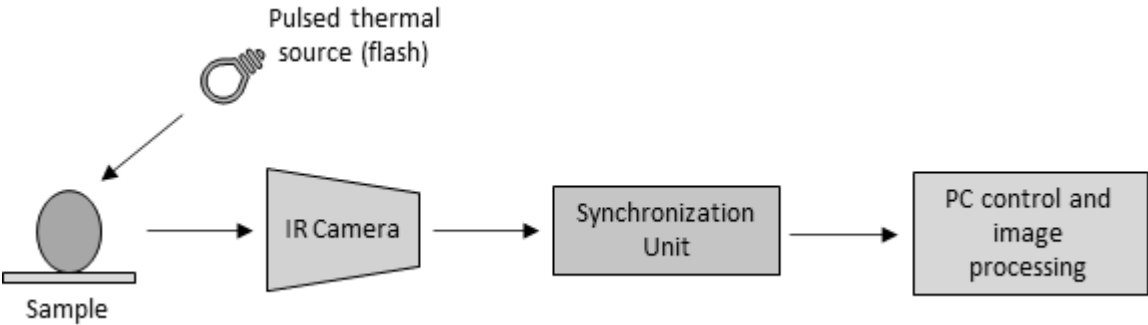
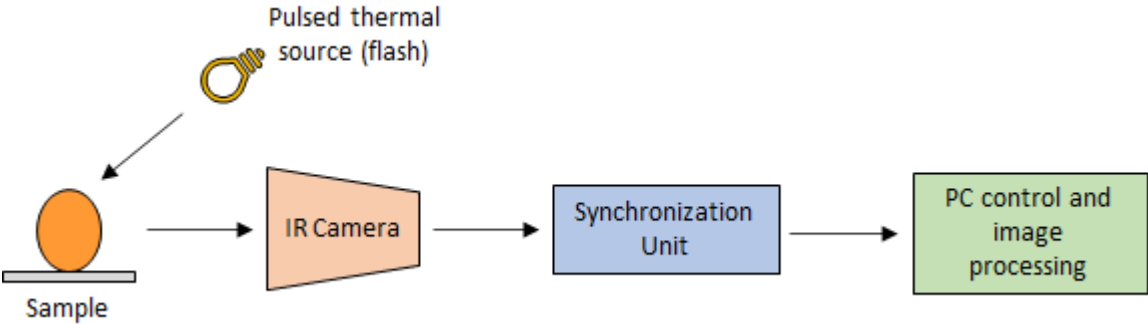


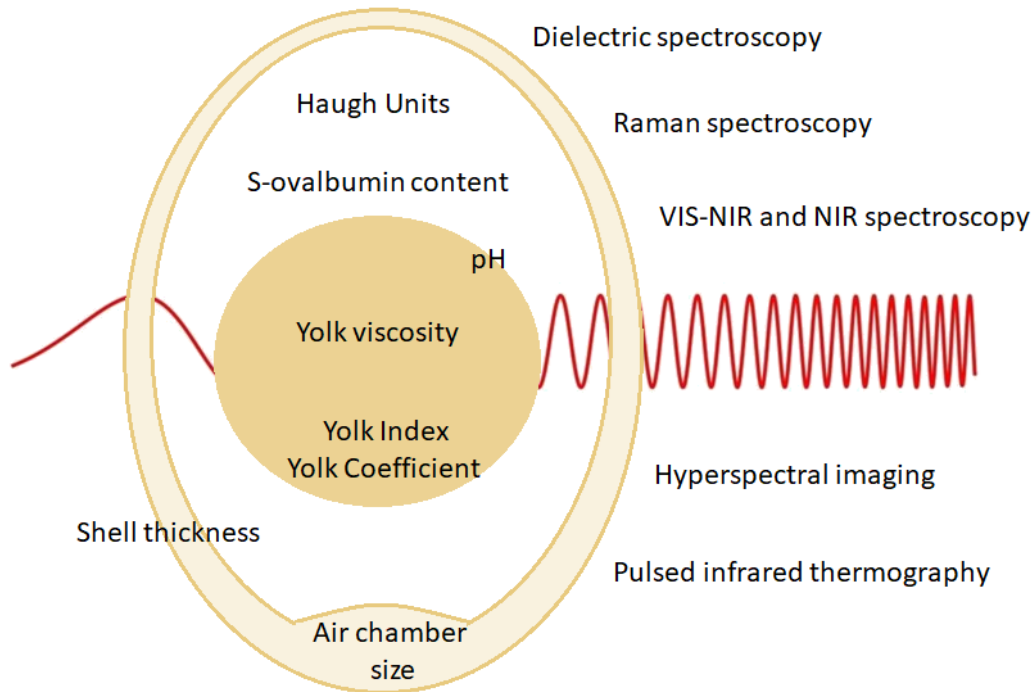
Figure 5 - Color version for online only



Highlights

- Food industries need non-destructive methods for shell egg quality evaluation.
- Recent applications of spectroscopy to egg quality assessment are reviewed.
- Spectroscopic techniques are useful tools for egg quality and freshness evaluation.
- The industrial implementation still presents some challenges to be faced.

Graphical abstract



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Declaration of interests

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.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: