Multispectral Imaging for Quality Determinations of White Meat

Subjects: Agricultural Engineering

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White meat is the nutritional term for lighter-colored meat that contains less myoglobin than red meat, which contains a great deal. White meat includes poultry (e.g., chicken, duck, goose and turkey), fish, reptiles (e.g., land snail), amphibians (e.g., frog), crustaceans (e.g., shrimp and crab) and bivalves (e.g., oyster and clam), but it excludes all mammal flesh such as beef, pork, and lamb. White meat has high nutritional value and plays an important role in human diet. The production and sale of white meat need to meet specific quality and safety standards. Fluorescence spectroscopy, color imaging and multispectral imaging (MSI) have emerged as effective analytical methods for the non-destructive detection of quality attributes of various white meat products such as fish, shrimp, chicken, duck and goose.

white meat multispectral imaging fluorescence spectroscopy convolutional neural network

quality detection

1. Introduction

As a global issue, food safety and quality are of increasing concern to companies and customers [1]. White meat is the nutritional term for lighter-colored meat that contains less myoglobin than red meat, which contains a great deal. Compared with white meat, the intake of red meat has a greater correlation with colorectal cancer (CRC), indicating that white meat intake is more beneficial to human health [2]. White meat includes poultry (e.g., chicken, duck, goose and turkey), fish, reptiles (e.g., land snail), amphibians (e.g., frog), crustaceans (e.g., shrimp and crab) and bivalves (e.g., oyster and clam), but it excludes all mammal flesh such as beef, pork, and lamb. White meat has high nutritional value and plays an important role in human diet. The production and sale of white meat need to meet specific quality and safety standards. The freshness of fish is one of the important indicators for evaluating its quality because of its high perishability [3]. Moreover, poultry products are particularly susceptible to oxidation as this meat contains relatively high levels of unsaturated fatty acids and low levels of natural antioxidants, such as vitamin E. In addition, chemical residues in white meat may have an adverse effect on human health. For example, fluoroquinolone antibiotics are effective against a wide range of Gram-negative and positive bacteria, thus they are widely used in the medical and veterinary fields. However, their use in animals has raised concerns, as this practice may lead to an increase in microbial resistance [4]. Moreover, nitrofuran drugs (NFs), including furazolidone (FZD), nitrofurazone (NFZ), and furantazone (FTD) are broad-spectrum antimicrobials. The potential risk of these compounds to human health is of great concern because of their carcinogenic and mutagenic properties. It is therefore crucial to ensure the quality and safety of white meat.

Traditional methods for meat quality and safety evaluation, such as manual inspection, mechanical and chemical methods, are time-consuming and destructive, and cannot meet the requirements of rapid inspection [5]. For example, methods for freshness evaluation are based on human sensory qualities, such as appearance, taste and texture. However, human senses exhibit a very high degree of subjectivity and can therefore be questioned in certain situations [3]. Even if manual inspection could meet accuracy requirements, it is still a labor-intensive and time-consuming process. Recently, the meat industry has adopted the most advanced high-speed processing technologies, and meat processors need fast, non-destructive, easy-to-use techniques to control the safety and quality of meat and meat products in order to achieve economic benefits. The requirement for real-time monitoring of food has encouraged the development of non-destructive measurement systems [6]. Optical technology is becoming increasingly important in research and industrial applications to measure the quality attributes of meat and meat products in real time, non-destructively and accurately [7]. Among these, the use of neural network-based RGB imaging technology has become very popular in recent years [8]. In addition, fluorescence spectroscopy and multispectral imaging (MSI) also show obvious advantages and capabilities in the non-destructive evaluation of white meat.

There have been several reviews of these new techniques of meat quality assessment. These papers show that these spectroscopic methods have been implemented as an alternative to traditional methods, but they mainly focus on one technique for quality detection of one specific category of meat, e.g., fish [3], shrimp [4], chicken [9], duck [10], or red meat [11]. As far as the researchers know, there is no literature review analyzing the application of various imaging techniques in the non-destructive quality inspection of various white meats. (The published reviews based on these three imaging techniques are tabulated in **Table 1**).

Table 1. Summary of reviews on fluorescence spectroscopy, RGB- and MSI techniques in food evaluation.

Technology	Product	Target Attributes	Reference
MSI	Meat	Adulteration	Ropodi et al. [12]
MSI, HSI	Meat	Defects	Feng et al. [13]
MSI	Food	Quality	Su and Sun [14]
MSI, IRS, SERS, LIBS and HSI	Food	Quality	Wang et al. [15]
MSI, HSI and VS	Food	Authenticity, quality and safety	Ropodi et al. [16]

Technology	Product	Target Attributes	Reference
Fluorescence spectroscopy	Food	Quality	Karoui and Blecker [17]
Fluorescence spectroscopy	Food	Quality	Strasburg and Ludescher [18]
Visible/Infrared, Raman and Fluorescence spectroscopy	Raw and processed food	Quality	He and Sun [19]
Fluorescence spectroscopy	Food	Quality	Ahmad et al. [20]
Fluorescence spectroscopy	Dairy products	Quality and safety	Shaikh and O'Donnell [21]
Fluorescence spectroscopy	Fresh and frozen-thawed muscle foods	Muscle classification	Hassoun [22]
RGB-Imaging	Meat	Quality and safety	Taheri-Garavand et al. [23]
RGB-Imaging	Fish	Quality	Dowlati et al. [24]
RGB-Imaging	Food	Quality	Gomes and Leta [25]
RGB-Imaging	Food	Quality	Amani et al. [26]

MSI—Multispectral Imaging; HSI—Hyperspectral Imaging; IRS—Infrared spectroscopy; SERS—Surface-Enhanced Raman Spectroscopy; LIBS—Laser induced breakdown spectroscopy; VS—Vibrational Spectroscopy.

3. Quality Evaluation of White Meat

The application of fluorescence spectroscopy, RGB imaging and MSI for white meat quality inspection has been thoroughly and extensively researched as shown in **Table 2**. For MSI techniques, correlation coefficient (*R*) or coefficient of determination (R^2) is an important statistical metric for assessing model fit, while root mean square error (RMSE) is considered an indicator of the sample standard deviation between measured and actual values, indicating that a well-performing model should obtain a high R or R^2 value and a low RMSE value. There are many different judgements due to the variability and multiplicity of the techniques.

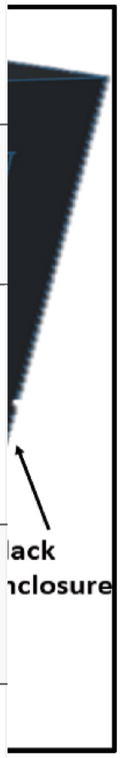
2. Fluorescence Spectroscopy, RGB- and Multispectral-Imaging

Fluorescence spectroscopy has proven to be an effective analytical technique over the last decade for monitoring the quality of various food products [27]. The number of published papers and citations on the use of fluorescence spectroscopy to study food quality and/or authenticity has increased exponentially over the last

Table 2. Applications of fluorescence spectroscopy, RGB imaging and MSI for quality evaluation of various white meat products.

White Meat	Module	Quality Parameters	Accuracy	Reference
Fish	MSI	TVB-N, PPC	R^2_p = 0.862 for TVB-N, R^2_p = 0.921 for PPC	Khoshnoudi-Nia and Moosavi-Nasab [39], Khoshnoudi-Nia and Moosavi-Nasab [40]
Fish	MSI	TVC	R^2 = 0.62	Govari, et al. [41]
Fish	MSI	TVC	R^2 = 0.683	Fengou, et al. [42]
Fish	MSI	Astaxanthin concentration	R^2 = 0.86	Dissing, et al. [43]
Fish	MSI	TVB-N, TBARS, K	R^2_p = 0.922 for TVB-N, R^2_p = 0.867 for TBARS, R^2_p = 0.936 for K	Cheng, et al. [44]
Fish	MSI	A ‘standard freshness index’ of K	R^2 = 0.94,	Omwange, et al. [45]
Fish	Fluorescence spectroscopy	A ‘standard freshness index’ of K	R^2 = 0.92	Omwange, et al. [46]

White Meat	Module	Quality Parameters	Accuracy	Reference
Fish	Fluorescence spectroscopy	A ‘standard freshness index’ of K	R^2 = 0.95	Liao, et al. [47]
Fish	Fluorescence spectroscopy	AEC; NADH	R^2 = 0.90 for AEC, R^2 = 0.85 for NADH	Rahman, et al. [48]
Fish	Fluorescence spectroscopy	NADH	90.5%	Hassoun and Karoui [49]
Fish	RGB imaging	Classification performance	99.5%	Park, et al. [50]
Fish	RGB imaging	Astaxanthin concentration	R^2 = 0.66	Dissing et al. [43]
Fish	RGB imaging	Freshness of tuna meat cuts	86.67%	Lugatiman, et al. [51]
Fish	RGB imaging	The main color of the sample	75%	Mateo, et al. [52]
Fish	RGB imaging	Texture features	86.3%	Gu, et al. [53]
Fish	RGB imaging	Color of Salmon Fillets	R = 0.95	Quevedo, et al. [54]
Fish	RGB imaging	Gill and eye color changes in the sparus aurata	R^2 = 0.994	Dowlati, et al. [55]
Fish	RGB imaging	Body color of carp	94.97%	Taheri-Garavand, et al. [56]



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White Meat	Module	Quality Parameters	Accuracy	Reference
Fish	RGB imaging	Freshness	98.2%	Rocculi, et al. [57]
Shrimp	Fluorescence spectroscopy	4-hexylresorcinol	81.6%	Jonker and Dekker [58]
Shrimp	Fluorescence spectroscopy	K, pH	R^2 = 0.80	Rahman, et al. [59]
Shrimp	RGB imaging	pH	100%	Witjaksono, et al. [60]
Shrimp	RGB imaging	Identification accuracy of the proposed ShrimpNet for shrimp	95.48%	Hu, et al. [61]
Shrimp	RGB imaging	Shrimp dehydration levels	R = 0.86	Mohebbi, et al. [62]
Shrimp	RGB imaging	Color changes in the head, legs and tail of pacific white shrimp (litopenaeus vannamei)	90%	Ghasemi-Varnamkhasti, et al. [63]
Chicken	Fluorescence spectroscopy	Hydroxyproline concentration	R^2 = 0.82	Monago-Maraña, et al. [64]
Chicken	MSI	Skin tumors	86%	Chao, et al. [65]
Chicken	MSI	TVC	90.4%	Spyrelli, et al. [66]
Chicken	MSI	pork-chicken adulteration	90.00% for fresh samples, 86.67%	Fengou, et al. [67]

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White Meat	Module	Quality Parameters	Accuracy	Reference
			for frozen-thawed samples	
Chicken	MSI	Sepsis in chickens	98.6% for septic chickens, 96.3% for healthy chickens	Yang, et al. [68]
Chicken	MSI	Contamination detection	96%	Park, et al. [69]
Chicken	MSI	Chicken heart disease characterization	100%	Chao, et al. [70]
Chicken	MSI; Fluorescence spectroscopy	Contamination detection	92.5%	Seo, et al. [71]
Chicken	Fluorescence spectroscopy	Lipid oxidation	$R = 0.73$	Gatellier, et al. [72]
Chicken	Fluorescence spectroscopy	*P. aeruginosa* concentration	96%	Abdel-Salam, et al. [73]
Chicken	Fluorescence spectroscopy	chicken meat tenderness	$R = 0.870$	Yu, et al. [74]
Chicken	Fluorescence spectroscopy	Contamination detection	96.6%	Cho, et al. [75]

White Meat	Module	Quality Parameters	Accuracy	Reference
Chicken	Fluorescence spectroscopy	Measurement of lipid oxidation	98%	Wold and Kvaal [76]
Chicken	RGB imaging	Avian flu infected chickens	97.43%	Cuan, et al. [77]
Chicken	RGB im-aging	Color	94%	Yumono, et al. [78]
Chicken	RGB im-aging	Freshness	R = 0.987	Taheri-Garavand, et al. [79]
Duck	Fluorescence spectroscopy	Gentamicin Residual in Duck Meat	R = 0.996	Wang, et al. [80]
Duck	Fluorescence spectroscopy	Doxycycline content in duck meat	R = 0.998	Wang, et al. [81]
Duck	Fluorescence spectroscopy	Carbaryl residue in duck meat	R = 0.976	Xiao et al. [10]
Duck	Fluorescence spectroscopy	Tetracycline content	R = 0.952	Zhao, et al. [82]
Duck	Fluorescence spectroscopy	Triazophos content	R^2_p = 0.974,	Zhao, et al. [83]
Duck	Fluorescence spectroscopy	Neomycin residue	R = 0.999	Jiang, et al. [84]
Duck	Fluorescence	Carbofuran residue	R^2_p = 0.999	XIAO, et al. [85]

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7. Peng, Y.; Dhakal, S. Optical Methods and Techniques for Meat Quality Inspection. Trans. ASABE 2015, 58, 1371–1386.

White Meat	Module	Quality Parameters	Accuracy	Reference
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69, 225–234.

10. Xiao, H.-B.; Liu, M.-H.; Yuan, H.-C.; Xu, J.; Zhao, J.-H. Study on determination of carbaryl content in duck meat based on synchronous fluorescence spectroscopy. Spectrosc. Spectr. Anal. 2012, 32, 3058–3062.
11. Wang, W.; Peng, Y.; Sun, H.; Zheng, X.; Wei, W. Spectral Detection Techniques for Non-Destructively Monitoring the Quality, Safety, and Classification of Fresh Red Meat. Food Anal. Methods 2018, 11, 2707–2730.
12. Ropodi, A.I.; Panagou, E.Z.; Nychas, G.-J.E. Multispectral imaging (MSI): A promising method for the detection of minced beef adulteration with horsemeat. Food Control 2017, 73, 57–63.
13. Feng, C.-H.; Makino, Y.; Oshita, S.; Martín, J.F.G. Hyperspectral imaging and multispectral imaging as the novel techniques for detecting defects in raw and processed meat products: Current state-of-the-art research advances. Food Control 2018, 84, 165–176.
14. Su, W.-H.; Sun, D.-W. Multispectral Imaging for Plant Food Quality Analysis and Visualization. Compr. Rev. Food Sci. Food Saf. 2018, 17, 220–239.
15. Wang, K.; Pu, H.; Sun, D.-W. Emerging Spectroscopic and Spectral Imaging Techniques for the Rapid Detection of Microorganisms: An Overview. Compr. Rev. Food Sci. Food Saf. 2018, 17, 256–273.
16. Ropodi, A.; Panagou, E.; Nychas, G.-J. Data mining derived from food analyses using non-invasive/non-destructive analytical techniques; determination of food authenticity, quality & safety in tandem with computer science disciplines. Trends Food Sci. Technol. 2016, 50, 11–25.
17. Karoui, R.; Blecker, C. Fluorescence Spectroscopy Measurement for Quality Assessment of Food Systems—A Review. Food Bioprocess Technol. 2011, 4, 364–386.
18. Strasburg, G.M.; Ludescher, R. Theory and applications of fluorescence spectroscopy in food research. Trends Food Sci. Technol. 1995, 6, 69–75.
19. He, H.-J.; Sun, D.-W. Microbial evaluation of raw and processed food products by Visible/Infrared, Raman and Fluorescence spectroscopy. Trends Food Sci. Technol. 2015, 46, 199–210.
20. Ahmad, M.H.; Sahar, A.; Hitzmann, B. Fluorescence Spectroscopy for the Monitoring of Food Processes. Meas. Modeling Autom. Adv. Food Processing 2017, 161, 121–151.

21. Shaikh, S.; O'Donnell, C. Applications of fluorescence spectroscopy in dairy processing: A review. Curr. Opin. Food Sci. 2017, 17, 16–24.
22. Hassoun, A. Exploring the Potential of Fluorescence Spectroscopy for the Discrimination between Fresh and Frozen-Thawed Muscle Foods. Photochem 2021, 1, 247–263.
23. Taheri-Garavand, A.; Fatahi, S.; Omid, M.; Makino, Y. Meat quality evaluation based on computer vision technique: A review. Meat Sci. 2019, 156, 183–195.
24. Dowlati, M.; de la Guardia, M.; Mohtasebi, S.S. Application of machine-vision techniques to fish-quality assessment. TrAC Trends Anal. Chem. 2012, 40, 168–179.
25. Gomes, J.F.S.; Leta, F.R. Applications of computer vision techniques in the agriculture and food industry: A review. Eur. Food Res. Technol. 2012, 235, 989–1000.
26. Amani, H.; Badak-Kerti, K.; Khaneghah, A.M. Current progress in the utilization of smartphone-based imaging for quality assessment of food products: A review. Crit. Rev. Food Sci. Nutr. 2020, 1–13.
27. Dufour, E.; Frencia, J.P.; Kane, E. Development of a rapid method based on front-face fluorescence spectroscopy for the monitoring of fish freshness. Food Res. Int. 2003, 36, 415–423.
28. Hassoun, A.; Sahar, A.; Lakhal, L.; Aït-Kaddour, A. Fluorescence spectroscopy as a rapid and non-destructive method for monitoring quality and authenticity of fish and meat products: Impact of different preservation conditions. LWT 2019, 103, 279–292.
29. Yokota, H.; Fukasawa, A.; Hirano, M.; Ide, T. Low-Light Photodetectors for Fluorescence Microscopy. Appl. Sci. 2021, 11, 2773.
30. Karbiwnyk, C.M.; Carr, L.E.; Turnipseed, S.B.; Andersen, W.C.; Miller, K.E. Determination of quinolone residues in shrimp using liquid chromatography with fluorescence detection and residue confirmation by mass spectrometry. Anal. Chim. Acta 2007, 596, 257–263.
31. Liu, Z.; Zhong, Y.; Hu, Y.; Yuan, L.; Luo, R.; Chen, D.; Wu, M.; Huang, H.; Li, Y. Fluorescence strategy for sensitive detection of adenosine triphosphate in terms of evaluating meat freshness. Food Chem. 2019, 270, 573–578.
32. Mohd Ali, M.; Hashim, N.; Khairunniza-Bejo, S.; Shamsudin, R.; Wan Sembak, W. RGB imaging system for monitoring quality changes of seedless watermelon during storage. In Proceedings of the III International Conference on Agricultural and Food Engineering 1152, Kuala Lumpur, Malaysia, 13 May 2016; pp. 361–366.
33. Rady, A.M.; Adedeji, A.; Watson, N.J.J.J.O.A.; Research, F. Feasibility of utilizing color imaging and machine learning for adulteration detection in minced meat. J. Agric. Food Res. 2021, 6, 100251.

34. Barbin, D.F.; Mastelini, S.M.; Barbon, S.; Campos, G.F.C.; Barbon, A.P.A.C.; Shimokomaki, M. Digital image analyses as an alternative tool for chicken quality assessment. Biosyst. Eng. 2016, 144, 85–93.
35. Taghizadeh, M.; Gowen, A.A.; O'Donnell, C.P. Comparison of hyperspectral imaging with conventional RGB imaging for quality evaluation of Agaricus bisporus mushrooms. Biosyst. Eng. 2011, 108, 191–194.
36. Bandara, W.; Prabhath, G.; Dissanayake, D.; Herath, H.; Godaliyadda, G.; Ekanayake, M.; Vithana, S.; Demini, S.; Madhujith, T. A multispectral imaging system to assess meat quality. In Proceedings of the 2018 IEEE Region 10 Humanitarian Technology Conference (R10-HTC), Malambe, Sri Lanka, 6–8 December 2018; pp. 1–6.
37. Jayasundara, D.; Ramanayake, L.; Senarath, N.; Herath, S.; Godaliyadda, R.; Ekanayake, P.; Herath, V.; Ariyawansha, S. Multispectral Imaging for Automated Fish Quality Grading. In Proceedings of the 2020 IEEE 15th International Conference on Industrial and Information Systems (ICIIS), Rupnagar, India, 26–28 November 2020; pp. 321–326.
38. Li, A.; Li, C.; Gao, M.; Yang, S.; Liu, R.; Chen, W.; Xu, K. Beef Cut Classification Using Multispectral Imaging and Machine Learning Method. Front. Nutr. 2021, 8.
39. Khoshnoudi-Nia, S.; Moosavi-Nasab, M. Prediction of various freshness indicators in fish fillets by one multispectral imaging system. Sci. Rep. 2019, 9, 14704.
40. Khoshnoudi-Nia, S.; Moosavi-Nasab, M. Nondestructive Determination of Microbial, Biochemical, and Chemical Changes in Rainbow Trout (Oncorhynchus mykiss) During Refrigerated Storage Using Hyperspectral Imaging Technique. Food Anal. Methods 2019, 12, 1635–1647.
41. Govari, M.; Tryfinopoulou, P.; Parlapani, F.; Boziaris, I.S.; Panagou, E.Z.; Nychas, G.-J. Quest of Intelligent Research Tools for Rapid Evaluation of Fish Quality: FTIR Spectroscopy and Multispectral Imaging Versus Microbiological Analysis. Foods 2021, 10, 264.
42. Fengou, L.-C.; Lianou, A.; Tsakanikas, P.; Gkana, E.N.; Panagou, E.Z.; Nychas, G.-J.E. Evaluation of Fourier transform infrared spectroscopy and multispectral imaging as means of estimating the microbiological spoilage of farmed sea bream. Food Microbiol. 2019, 79, 27–34.
43. Dissing, B.S.; Nielsen, M.C.E.; Ersbøll, B.K.; Frosch, S. Multispectral Imaging for Determination of Astaxanthin Concentration in Salmonids. PLoS ONE 2011, 6, e19032.
44. Cheng, J.-H.; Sun, D.-W.; Qu, J.-H.; Pu, H.-B.; Zhang, X.-C.; Song, Z.; Chen, X.; Zhang, H. Developing a multispectral imaging for simultaneous prediction of freshness indicators during chemical spoilage of grass carp fish fillet. J. Food Eng. 2016, 182, 9–17.
45. Omwange, K.A.; Saito, Y.; Zichen, H.; Khaliduzzaman, A.; Kuramoto, M.; Ogawa, Y.; Kondo, N.; Suzuki, T. Evaluating Japanese dace (Tribolodon hakonensis) fish freshness during storage using multispectral images from visible and UV excited fluorescence. LWT 2021, 151, 112207.

46. Omwange, K.A.; Al Riza, D.F.; Sen, N.; Shiigi, T.; Kuramoto, M.; Ogawa, Y.; Kondo, N.; Suzuki, T. Fish freshness monitoring using UV-fluorescence imaging on Japanese dace (Tribolodon hakonensis) fisheye. J. Food Eng. 2020, 287, 110111.
47. Liao, Q.H.; Suzuki, T.; Yasushi, K.; Al Riza, D.F.; Kuramoto, M.; Kondo, N. Monitoring Red Sea Bream Scale Fluorescence as a Freshness Indicator. Fishes 2017, 2, 10.
48. Rahman, M.M.; Shibata, M.; ElMasry, G.; Nakazawa, N.; Nakauchi, S.; Hagiwara, T.; Osako, K.; Okazaki, E. Expeditious prediction of post-mortem changes in frozen fish meat using three-dimensional fluorescence fingerprints. Biosci. Biotechnol. Biochem. 2019, 83, 901–913.
49. Hassoun, A.; Karoui, R. Front-face fluorescence spectroscopy coupled with chemometric tools for monitoring fish freshness stored under different refrigerated conditions. Food Control 2015, 54, 240–249.
50. Park, J.-H.; Hwang, K.-B.; Park, H.-M.; Choi, Y.-K.J.J.O.T.K.I.O.I.; Engineering, C. Application of CNN for fish species classification. J. Korea Inst. Inf. Commun. Eng. 2019, 23, 39–46.
51. Lugatiman, K.; Fabiana, C.; Echavia, J.; Adtoon, J.J. Tuna Meat Freshness Classification through Computer Vision. In Proceedings of the 2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), Laoag, Philippines, 29 November–1 December 2019; pp. 1–6.
52. Mateo-Aroca, A.; Soto, F.; Villarejo, J.A.; Roca-Dorda, J.; De La Gándara, F.; García, A. Quality analysis of tuna meat using an automated color inspection system. Aquac. Eng. 2006, 35, 1–13.
53. Gu, J.; He, N.; Wu, X. A new detection method for fish freshness. In Proceedings of the 2014 Seventh International Symposium on Computational Intelligence and Design, Hangzhou, China, 13–14 December 2014; pp. 555–558.
54. Quevedo, R.A.; Aguilera, J.M.; Pedreschi, F. Color of Salmon Fillets By Computer Vision and Sensory Panel. Food Bioprocess Technol. 2008, 3, 637–643.
55. Dowlati, M.; Mohtasebi, S.S.; Omid, M.; Razavi, S.H.; Jamzad, M.; de la Guardia, M. Freshness assessment of gilthead sea bream (Sparus aurata) by machine vision based on gill and eye color changes. J. Food Eng. 2013, 119, 277–287.
56. Taheri-Garavand, A.; Fatahi, S.; Banan, A.; Makino, Y. Real-time nondestructive monitoring of Common Carp Fish freshness using robust vision-based intelligent modeling approaches. Comput. Electron. Agric. 2019, 159, 16–27.
57. Rocculi, P.; Cevoli, C.; Tappi, S.; Genovese, J.; Urbinati, E.; Picone, G.; Fabbri, A.; Capozzi, F.; Dalla Rosa, M. Freshness assessment of European hake (Merluccius merluccius) through the evaluation of eye chromatic and morphological characteristics. Food Res. Int. 2019, 115, 234–240.

58. Jonker, K.M.; Dekker, C.P. Determination of 4-Hexylresorcinol in Shrimp by Liquid Chromatography with Fluorescence Detection. J. AOAC Int. 2000, 83, 241–244.

59. Rahman, M.; Bui, M.V.; Shibata, M.; Nakazawa, N.; Rithu, M.N.A.; Yamashita, H.; Sadayasu, K.; Tsuchiyama, K.; Nakauchi, S.; Hagiwara, T.; et al. Rapid noninvasive monitoring of freshness variation in frozen shrimp using multidimensional fluorescence imaging coupled with chemometrics. Talanta 2021, 224, 121871.

60. Witjaksono, G.; Hussin, N.H.F.B.M.; Rabih, A.A.S.; Alfa, S. Real time chromametry measurement for food quality detection using mobile device. In Proceedings of the IOP Conference Series: Materials Science and Engineering, Busan, Korea, 25–27 August 2017; p. 12024.

61. Hu, W.-C.; Wu, H.-T.; Zhang, Y.-F.; Zhang, S.-H.; Lo, C.-H. Shrimp recognition using ShrimpNet based on convolutional neural network. J. Ambient. Intell. Humaniz. Comput. 2020, 1–8.

62. Mohebbi, M.; Akbarzadeh-T, M.-R.; Shahidi, F.; Moussavi, M.; Ghoddusi, H.-B. Computer vision systems (CVS) for moisture content estimation in dehydrated shrimp. Comput. Electron. Agric. 2009, 69, 128–134.

63. Ghasemi-Varnamkhasti, M.; Goli, R.; Forina, M.; Mohtasebi, S.S.; Shafiee, S.; Naderi-Boldaji, M. Application of Image Analysis Combined with Computational Expert Approaches for Shrimp Freshness Evaluation. Int. J. Food Prop. 2016, 19, 2202–2222.

64. Monago-Maraña, O.; Wold, J.P.; Rødbotten, R.; Dankel, K.R.; Afseth, N.K. Raman, near-infrared and fluorescence spectroscopy for determination of collagen content in ground meat and poultry by-products. LWT 2021, 140, 110592.

65. Chao, K.; Mehl, P.M.; Kim, M.S.; Chen, Y.-R. Detection of chicken skin tumors by mutlispectral imaging. In Proceedings of the Photonic Detection and Intervention Technologies for Safe Food, Bellingham, WA, USA, 5–6 November 2000; pp. 214–223.

66. Spyrelli, E.D.; Ozcan, O.; Mohareb, F.; Panagou, E.Z.; Nychas, G.J.E. Spoilage assessment of chicken breast fillets by means of fourier transform infrared spectroscopy and multispectral image analysis. Curr. Res. Food Sci. 2021, 4, 121–131.

67. Fengou, L.-C.; Lianou, A.; Tsakanikas, P.; Mohareb, F.; Nychas, G.-J.E. Detection of Meat Adulteration Using Spectroscopy-Based Sensors. Foods 2021, 10, 861.

68. Yang, C.-C.; Chao, K.; Chen, Y.-R.; Kim, M.S. Application of Multispectral Imaging for Identification of Systemically Diseased Chicken. In Proceedings of the 2004 ASAE Annual Meeting, Ottawa, Canada, 1–4 August 2004; p. 1.

69. Park, B.; Kise, M.; Lawrence, K.C.; Windham, W.R.; Smith, D.P.; Thai, C.N. Real-time multispectral imaging system for online poultry fecal inspection using unified modeling language. Sens. Instrum. Food Qual. Saf. 2007, 1, 45–54.

70. Chao, K.; Chen, Y.R.; Hruschka, W.R.; Park, B. Chicken Heart Disease Characterization by Multi-spectral Imaging. Appl. Eng. Agric. 2001, 17, 99–106.
71. Seo, Y.; Lee, H.; Mo, C.; Kim, M.S.; Baek, I.; Lee, J.; Cho, B.-K. Multispectral Fluorescence Imaging Technique for On-Line Inspection of Fecal Residues on Poultry Carcasses. Sensors 2019, 19, 3483.
72. Gatellier, P.; Gomez, S.; Gigaud, V.; Berri, C.; Le Bihan-Duval, E.; Santé-Lhoutellier, V. Use of a fluorescence front face technique for measurement of lipid oxidation during refrigerated storage of chicken meat. Meat Sci. 2007, 76, 543–547.
73. Abdel-Salam, Z.; Abdel-Salam, S.A.M.; Harith, M.A. Application of Laser Spectrochemical Analytical Techniques to Follow Up Spoilage of White Meat in Chicken. Food Anal. Methods 2017, 10, 2365–2372.
74. Yu, F.; Xue, L.; Liu, M.-h.; Li, J. Preliminary study of laser-induced fluorescence spectroscopy detect chicken meat tenderness. In Proceedings of the 2nd International Conference on Information Science and Engineering, Hangzhou, China, 4–6 December 2010; pp. 6771–6774.
75. Cho, B.-K.; Kim, M.S.; Chao, K.; Lefcourt, A.M.; Lawrence, K.; Park, B. Detection of Fecal Residue on Poultry Carcasses by Laser Induced Fluorescence Imaging. J. Food Sci. 2009, 74, E154–E159.
76. Wold, J.P.; Kvaal, K. Mapping Lipid Oxidation in Chicken Meat by Multispectral Imaging of Autofluorescence. Appl. Spectrosc. 2000, 54, 900–909.
77. Cuan, K.X.; Zhang, T.M.; Huang, J.D.; Fang, C.; Guan, Y. Detection of avian influenza-infected chickens based on a chicken sound convolutional neural network. Comput. Electron. Agric. 2020, 178, 105688.
78. Yumono, F.; Subroto, I.M.I.; Prasetyowati, S.A.D. Artificial Neural Network for Healthy Chicken Meat Identification. IAES Int. J. Artif. Intell. (IJ-AI) 2018, 7, 63–70.
79. Taheri-Garavand, A.; Fatahi, S.; Shahbazi, F.; De La Guardia, M. A nondestructive intelligent approach to real-time evaluation of chicken meat freshness based on computer vision technique. J. Food Process. Eng. 2019, 42, e13039.
80. Wang, X.; Xu, J.; Liu, M.H.; Zhao, J.H.; Hong, Q. Determination of Gentamicin Residual in Duck Meat Using Fluorescence Analysis Method. Adv. Mater. Res. 2014, 1033–1034, 638–642.
81. Wang, P.; Hong, Q.; Liu, M.; Yuan, H.; Peng, Y.; Zhao, J.; Pengwei, W.; Qian, H.; Muhua, L.; Haichao, Y.; et al. Rapid detection of doxycycline content in duck meat by using silver nanoparticles and alkylphenols polyoxyethylene enhanced fluorescence of europium complex. Spectrosc. Lett. 2016, 49, 563–567.

82. Zhao, J.-H.; Yuan, H.-C.; Liu, M.-H.; Xiao, H.-B.; Hong, Q.; Xu, J. Rapid determination of tetracycline content in duck meat using particle swarm optimization algorithm and synchronous fluorescence spectrum. Spectrosc. Spect. Anal. 2013, 33, 3050–3054.

83. Zhao, J.H.; Bin Xiao, H.; Yuan, H.C.; Hong, Q.; Liu, M.H. Application of Three-Dimensional Fluorescence Spectroscopy Coupled with ATLD in Rapid Determination of Triazophos Content in Duck Meat. Appl. Mech. Mater. 2014, 651–653, 362–366.

84. Jiang, X.; Muhua, L.; Haichao, Y. A study on determination of neomycin residue in duck by fluorescence method. Acta Agric. Univ. Jiangxiensis 2013, 35, 635–640.

85. Xiao, H.-B.; Zhao, J.-H.; Yuan, H.-C.; Xu, J.; Li, Q.; Liu, M.-H. Prediction of Carbofuran Residue in Duck Meat by Synchronous Fluorescence Spectroscopy Based on Support Vector Regression (SVR). J. Instrum. Anal. 2013, 3, 357–361.