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COMPREHENSIVE REVIEW

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Non-destructive optical sensing technologies for advancing the egg industry toward Industry 4.0: A review

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Abstract

The egg is considered one of the best sources of dietary protein, and has an important role in human growth and development. With the increase in the world's population, per capita egg consumption is also increasing. Ground-breaking technological developments have led to numerous inventions like the Internet of Things (IoT), various optical sensors, robotics, artificial intelligence (AI), big data, and cloud computing, transforming the conventional industry into a smart and sustainable egg industry, also known as Egg Industry 4.0 (EI 4.0). The EI 4.0 concept has the potential to improve automation, enhance biosecurity, promote the safeguarding of animal welfare, increase intelligent grading and quality inspection, and increase efficiency. For a sustainable Industry 4.0 transformation, it is important to analyze available technologies, the latest research, existing limitations, and prospects. This review examines the existing non-destructive optical sensing technologies for the egg industry. It provides information and insights on the different components of EI 4.0, including emerging EI 4.0 technologies for egg production, quality inspection, and grading. Furthermore, drawbacks of current EI 4.0 technologies, potential workarounds, and future trends were critically analyzed. This review can help policymakers, industrialists, and academicians to better understand the integration of non-destructive technologies and automation. This integration has the potential to increase productivity, improve quality control, and optimize resource management toward sustainable development of the egg industry.

KEYWORDS

AI and IoT, computer vision, egg grading, Egg Industry 4.0, machine learning, optical sensing

1 | INTRODUCTION

Food security is a broad idea supported by four pillars: food availability, accessibility, stability, and use that aims to alleviate hunger by assuring a steady supply of nutritious foods (Alonso et al., 2020). Food security is an increasingly important issue worldwide due to several anthropogenic factors (such as climate change and air, water, and soil pollution) that are influenced by the fast growth of the world population. These factors also directly impact

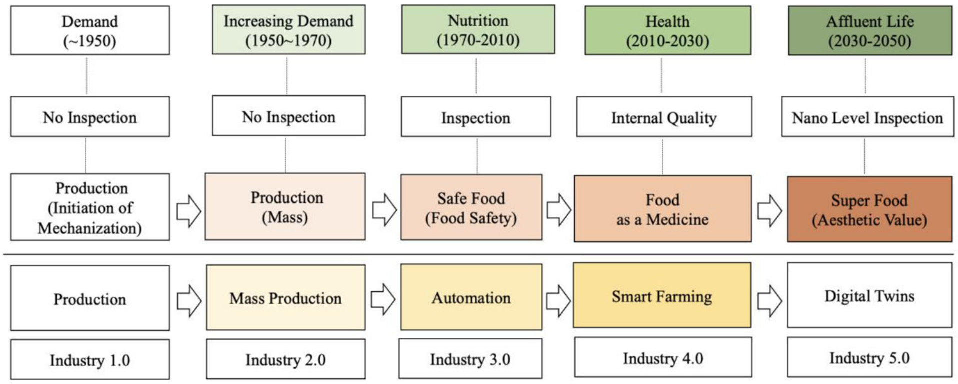

FIGURE 1 Evolution of food production and transformation concepts.

primary food production and contribute to the rising global demand. By 2050, when the world's population is projected to increase from 7.7 to 9.2 billion, there will be a significant scarcity of quality food. The urban population is also predicted to increase by 66%, increasing food demand by 59% to 98% (Abbasi et al., 2022). Therefore, the safe and steady production of commonly consumed foods like eggs and poultry meat must be increased globally to meet rising food demand. The appropriate utilization of safe and available food is the primary concern of food security. The modern industry aims to ensure food security and safety by creating a safer, more efficient, and more sustainable food supply chain from farm to plate. Much of the world's population is facing a global epidemic of diet-related chronic diseases, leading to increasing experimentation with the use of food as medicine to prevent, manage, and treat illness. With the progress of the industrial revolution, food scientists look forward to promoting targeted properties (such as high nutrient density, reducing the risk of certain diseases, and promoting digestive health) of foods so they are able to support a productive and meaningful life (Hassoun et al., 2022a).

An industry is a component of the economy that processes raw materials and converts them into finished products. The advent of steam power initiated the industrial revolution in the 19th century, and in the 21st century technological improvements have enabled the emergence of new scientific paradigms which are known as the Fourth Industrial Revolution (i.e., Industry 4.0; I4.0). Generally, I4.0 refers to automation of industrial activities using high interconnections to overcome the boundary between the physical, digital, and biological worlds (Lasi et al., 2014). The First Industrial Revolution began with the introduction of the steam engine and mechanization, which resulted in industrial mass production and advancements in manufacturing methods due to electrification during the Second Industrial Revolution. Electrification was the most outstanding engineering achievement of the 20th century. In the 1970s, the advent of memory-programmable systems and computers led to partial automation during the Third Industrial Revolution (David et al., 2022; Figure 1). Substituting human labor with intelligent machines, programs, and algorithms that perform a portion of the labor made labor more productive and effective. With the aid of hyper-technological solutions and super-intelligent equipment, I4.0, currently in the implementation phase, seeks to achieve higher levels of multi-industrial automation and information integration (Hassoun et al., 2022b, 2023b; Nuvolari et al., 2021; Zambon et al., 2019). The I4.0 approach comprises non-invasive and real-time sensing technologies, Internet of Things (IoT) and cloud computing, big data analysis, and cyber security, and is still a futuristic notion in many areas. I4.0 seeks to integrate devices that can quickly adapt to changing environmental circumstances. To help ensure sustainable global food security, I4.0 can have an important role from primary production to finished product manufacturing, providing enhanced food quality and safety (Chiles et al., 2021; David et al., 2022; Hassoun et al., 2023a). To achieve this, smart farming integrates technologies and systems that enable various devices to make complex human-like decisions on a computer. The current period is considered as the third AI boom, where built-in AI functions have been developed and marketed in various fields, from autonomous vehicles, surveillance cameras, and robots to home appliances (Gupta et al., 2023). To maximize the egg and poultry production in a sustainable manner, farming technology and the concept of mechanization are rapidly changing toward smart systems. Smart farming is the current and upgraded version of farm mechanization and some countries have already begun to implement it in cropping and poultry production systems (Ichiura, 2022). Application of cloud computing, IoT and IoT-based sensing system, augmented reality, robotics, simultaneous localization and mapping (SLAM)-based point cloud, and depth imaging move it further along toward advances like Digital Twins (DT). DT is a virtual twin of a physical system. It is a digital representation and control system that can control a poultry farm and egg processing facilities remotely. DT can be considered as a next phase or

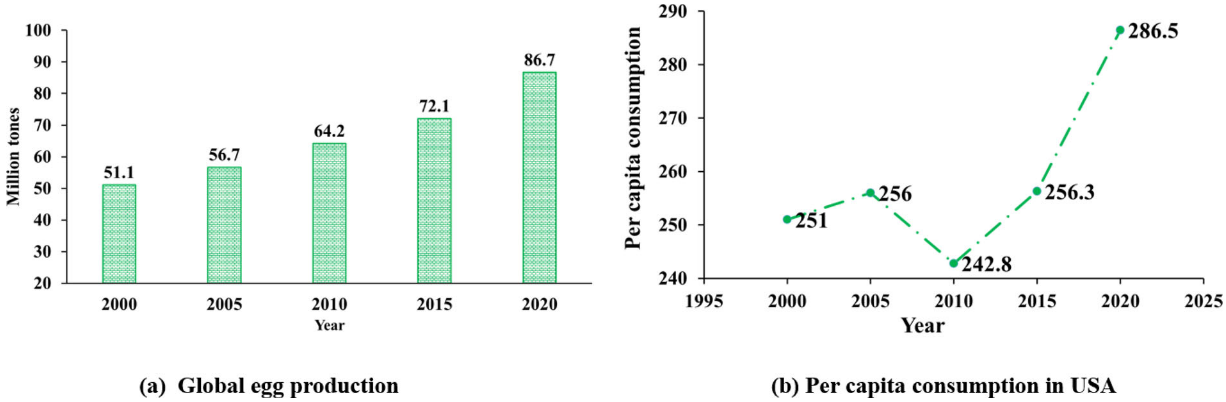

FIGURE 2 Global egg production trend (FAO, 2020) and per capita egg consumption trend in the United States (USDA, 2020).

next generation of smart egg and poultry production systems. This DT implementation will not only work for efficient management but also can work to build trust and the transparency of the system (i.e., traceability systems) in the food value chain (Istiak & Khaliduzzaman, 2022). It is a cyber–physical interface that seamlessly integrates sensing, monitoring, analyzing, planning, and smartly controlling all farm operations (Ichiura, 2022; Phuyal et al., 2020; Saha et al., 2022). Such visionary revolutions in the food and agriculture industries may aim to lead humans to a better life by promoting the consumption of food as a medicine or super-food (Haque et al., 2023; Hassoun et al., 2022a). Hopefully, people may enjoy greater satisfaction with a healthy lifestyle, including the highest quality of foods, which may promote overall well-being and potentially reduce healthcare costs.

Eggs have long been an important component of the human diet since they are regarded as one of the best dietary protein sources (Ochs et al., 2019; Zhao et al., 2018). Therefore, eggs have become important to the world economy as they are consumed and traded worldwide. As of 2020 statistics, global egg and poultry meat production has significantly increased in the past two decades since World War II (Gautron et al., 2021; Istiak & Khaliduzzaman, 2022). The rise in egg production since 2000 is shown in Figure 2. According to the Food and Agricultural Organization of the United Nations (FAO), the volume of global egg production exceeded 86 million metric tons in 2020 (FAO, 2020).

With more than 35% of global egg production, China is the biggest producer, followed by the European Union (EU), the United States, and India (Gautron et al., 2021). Nearly 60% of the world's eggs are produced in these four regions. World per capita egg consumption has risen in line with growing production. For example, the per capita egg consumption trend in the United States is given in Figure 2.

Digitalization and automation at every stage of the egg industry, from collecting to delivery, must be expanded for sustainable development. The I4.0 concept can be instrumental at every stage of the egg industry (including table eggs and hatching eggs), including early sex determination of layer egg embryos to prevent the hatching and killing of male chicks, grading (based on freshness, size, composition, and origin), quality evaluation, packaging, and storage.

The four basic stages of current table egg industry processing operations are collection, washing, grading, and packing. Although most table egg facilities have automated egg collection and washing, human labor is often still required for egg grading based on many internal and external qualities (Mehdizadeh et al., 2014; Rahman et al., 2021b). Non-destructive grading based on numerous parameters is a challenge, and although existing practices in the conventional egg industry grade eggs based on a few parameters, such as size and weight, the methods are still tedious. I4.0 technologies would promote further sustainable development in the egg industry by supporting more precise grading based on internal and external defects. I4.0 also has numerous potential applications in product and process monitoring, categorization, traceability, and quality control (Demir & Dincer, 2020; Konur et al., 2021).

In the 21st century, sensing technologies like acoustic, electronic, and optical sensing technologies have been focusing on the non-destructive studies of poultry eggs. But those technologies are not yet widely applied in the table egg industry for internal and external quality assessment of table and hatching eggs in real time. Many studies reported the benefits of optical sensing and computer vision technologies, such as hyperspectral imaging (HSI) and spectroscopic techniques and, accurate and non-destructive optical sensing technologies that have been used for the assessment of egg freshness (Giunchi et al., 2008; Karoui et al., 2006a; Liu et al., 2020), gender (Corion et al., 2022; Khaliduzzaman et al., 2019; Rahman et al., 2021a), fertility detection (Adegbenjo et al., 2020; Liu & Ngadi, 2013; Smith et al., 2008), size

(Narushin et al., 2004; Suktanarak & Teerachaichayut, 2017), gas composition (Zhang et al., 2022a), proximate composition (Zhao et al., 2018), and fabrication (Chen et al., 2019; Joshi et al., 2022). Although several studies have been published on the use of I4.0 technologies in agriculture (Araújo et al., 2021; Bernhardt et al., 2021; Liu et al., 2021; Patil & Shekhawati, 2019), the food and beverage industry (Akyazi et al., 2020; Demir & Dincer, 2020; Konur et al., 2021; Luque et al., 2017), the meat industry (Barbut, 2020; Echegaray et al., 2022; Kamruzzaman, 2023), supply chains (Ghadge et al., 2020; Mukherjee et al., 2021), resources nexus (David et al., 2022), and traceability (Hassoun et al., 2022c, 2023c), no review has been published on I4.0 applications for the egg industry. Therefore, this review article has focused on those I4.0 technologies for which contemporary research exists related to the egg industry. Specifically, this review focuses on I4.0 components and I4.0 technologies for egg production, inspection, and grading. Existing limitations and future trends are also discussed.

2 | AN OVERVIEW OF I4.0 TECHNOLOGIES

2.1 | I4.0 concept

I4.0, the Fourth Industrial Revolution, is a technology-based system that boosts process and production with intelligent automation and high interconnectivity. The term “revolution” refers to any radical societal change. The radical change in production, economy, and societal structure began with the Third Industrial Revolution (I3.0) in the 1950s with rapid computing and digitalization advances (Ghobakhloo, 2020; Mahmoodi et al., 2022). Even though automation largely started with the I3.0, there is still a dependency on human operators and a lack of interconnectivity. The I4.0 approach depends on building a system that integrates everything effortlessly and conveniently. Every service and instrument is in constant contact, leading to a high level of synchronization (Hassoun et al., 2022d). In this system, high interconnection and intercommunication between physical resources and innovative technologies facilitate making the correct decision (Gajek et al., 2022; Hughes et al., 2022). Non-destructive and real-time sensing technologies, AI, IoT, robots and actuators, and cloud computing are the pillars of the I4.0 approach (Hassoun et al., 2022e). Therefore, any industry adopting the “I4.0” model would be intelligent, responsive, and more flexible, resulting in more sustainable production. An illustration of the I4.0 concept is shown in Figure 3. This innovative manufacturing concept works based on four fundamental principles:

- Interconnectivity or interoperability: the capacity to interconnect everyone and everything within an organization (e.g., people, machines, devices, and sensors) globally to utilize data insights to boost productivity and enhance procedures. This interconnection can be made possible through IoT or IoP (Internet of People).
- Information transparency: providing comprehensive information to operators to make decisions. This may involve simulating the physical environment virtually by integrating cyber–physical space.
- Technical assistance: the ability of cyber–physical systems (CPS) to assist humans by gathering and comprehensibly interpreting information to make intelligent choices and quickly solve problems.
- Decentralized decisions: the capacity of CPS to take independent actions and complete their tasks as autonomously as conceivable. Higher-level operators would focus on work that is exceptional, conflicted, or interfered with work.

The goal of I4.0 is to transform traditional industry by integrating advanced digital technologies and automation to create intelligent, interconnected, and highly efficient systems. However, I4.0 is not intended to replace humans at all manufacturing phases but to boost their productivity. The system requires efficient human resources due to their decision-making abilities, problem-solving skills, technical expertise, adaptability, and ethical considerations. An efficient I4.0 can deliver sustainable development by integrating human capabilities with cutting-edge technologies.

2.2 | I4.0 technologies

2.2.1 | Non-destructive optical sensing technologies

Optical sensing technologies for egg quality inspection and grading include ultraviolet–visible–near infrared (UV–Vis–NIR), terahertz (THz), fluorescence spectroscopy, customized single wavelength optical sensors, and imaging technologies such as computer vision system (CVS), multispectral and HSI, fluorescence imaging, red–green–blue (RGB) and NIR imaging, and other techniques (Kamruzzaman, 2023; Rahman et al., 2021a; Yao et al., 2022b; Zhang et al., 2015). Their non-destructive and real-time application makes optical sensing technologies potentially suitable for the egg industry. One of the most important aspects of the egg industry is the use of comprehensive quality analysis methods to guarantee sustainable marketing and consumption of eggs and egg products. Unfortunately, egg quality analysis methods require expert professionals to do a substantial number of tasks manually,

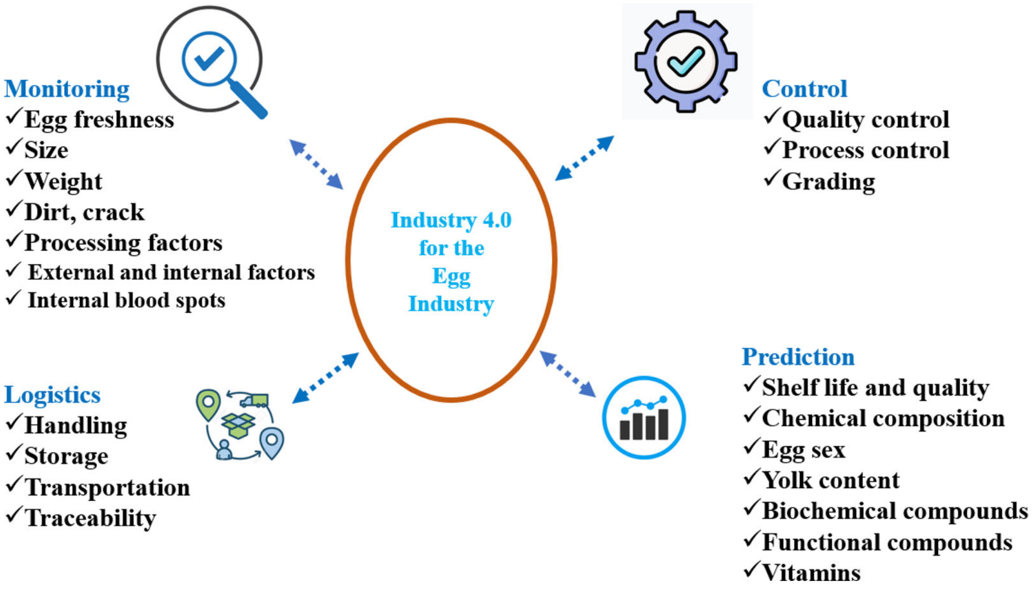

FIGURE 3 Industry 4.0 for the egg industry.

which is time-consuming, tedious, expensive, susceptible to human error, and, most importantly, often destructive (Wieme et al., 2022). Therefore, extremely accurate, fast, and non-contact technologies are needed to autonomously inspect and separate undesirable eggs.

Spectroscopy is considered one of the most promising technological solutions because it uses optical sensing to determine the physical or chemical characteristics of the sample (Hassoun et al., 2020; Pornchaloempong et al., 2022). For analyzing physico-chemical properties, there are several spectroscopic techniques available. The spectroscopic methods consist of spectra collection with a spectrometer and chemometric analysis. After collecting spectral data, reference data from the chemical analysis is coupled with corresponding spectral data and further processed for model development (Pu et al., 2020; Puertas & Vázquez, 2020; Skvaril et al., 2017). Models using the whole range of spectral data have some drawbacks for rapid and cost-effective use. Therefore, selectively using only informative bands, it is possible to build a more efficient model and effectively predict the target component. Since spectroscopic methods do not involve the use or production of dangerous compounds, they are regarded as green or sustainable analytical methods. Given their ease of use, speed, accuracy, and non-invasive sampling approaches, these methods have been reported as one of the most efficient technologies for egg characterization (Han et al., 2022; Khaliduzzaman et al., 2021a; Zhao et al., 2018).

Computer vision (CV) is a branch of AI that uses various deep-learning algorithms to train computers to analyze and interpret data from conventional images and videos (Kamruzzaman & Sun, 2016; Siswantoro et al., 2017; Valencia et al., 2021; Wang, 2014). With the help of CV, constant

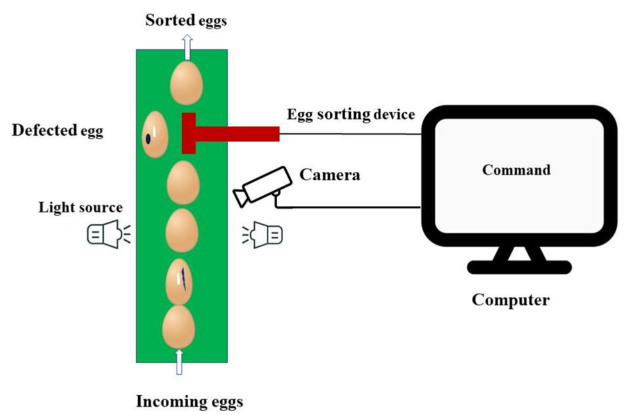

FIGURE 4 Schematic diagram of a computer vision system for the egg industry.

monitoring of any object can be done, which is impossible for a human. Technological development has increased the importance of machine vision (MV) technology many fold in the food and agriculture industries. Generally, any CV system consists of an image capture device (camera or sensor), illumination source, image processing board, and computer (Ma et al., 2017) (Figure 4). The imaging techniques provide more specific information on special variations than spectroscopic techniques.

Appropriate illumination substantially enhances image processing and analysis by improving picture contrast and minimizing shadows, noise, and reflections; thus, uniform lighting should be used to illuminate the whole scene to evaluate exterior quality (Kamruzzaman & Sun, 2016). An image processing board converts pictorial images into numeric forms for further analysis. The computer processes numerical data and makes decisions based on pre-set conditions and triggers a sorting device that removes any undesired product from the product stream. Different modeling methods, such as artificial neural networks (ANN), regression, support vector regression (SVR), support vector machine (SVM), and convolutional neural network (CNN)/deep learning, are used to classify products based on image information (Wang, 2014).

Besides conventional spectroscopic and imaging techniques, fluorescence spectroscopy and imaging techniques may have a greater potential to study biological objects. These methods could be potentially used for quantitative and qualitative analysis of functional compounds in food. Fluorescence imaging provides spatial information on how the fluorescence compounds are distributed and localized in the biological sample (Khaliduzzaman et al., 2021b).

2.2.2 | AI and IoT

The IoT describes the vast interconnection between physical technologies such as sensors, machines, computers, and software through collaborative data exchanges (McLamore et al., 2021; Saha et al., 2022; Yu et al., 2022). The ability of the IoT to apply to such a wide range of applications provides the interconnected system significant potential when discussing autonomous big data analytics. IoT technologies are already being implemented in many sectors, including food and agriculture, transport, and health (Chigwada et al., 2022; Wang et al., 2021). Intelligent IoT sensing technologies have been increasing for monitoring agriculture farms, plant diseases, food quality assessment, and many other operations (Alonso et al., 2020; Saha et al., 2022). AI is one of the primary forces propelling the deployment of I4.0, together with cloud computing and IoT. AI is a field of computer science that simulates human cognition, learning, and knowledge storage to carry out activities that ordinarily require human intelligence (Ramesh et al., 2022). As part of AI, machine learning (ML) focuses on developing computational methods or models to facilitate tasks such as accurately predicting target parameters (Patange & Pandya, 2022). Linear regression, logistic regression, the Naïve Bayes algorithm, the k-nearest neighbor (KNN) algorithm, SVM, and ANN are the most common ML currently being used in the context of poultry and Egg Industry 4.0 (EI 4.0) (Ojo et al., 2022a; Soltani & Omid, 2015). Because ML can recognize intricate patterns, trends, and relationships in multidimensional, heterogeneous data, and make precise predictions, it can serve as a solid foundation for improved decision-making and operations management, AI has been used to develop systems for grading and classifying eggs, poultry, meat and many agricultural items (Gupta et al., 2023). With the help of IoT, ML, and AI, it is possible to develop a system that can be controlled virtually or used by end users, even using smartphones.

2.2.3 | Big data analytics and cloud computing

Big data is defined as massive and complex data that is challenging or impossible to process using conventional methods. Volume, variety, velocity, variability, and value are the five key dimensions of big data analysis (Wang et al., 2021). For example, the rise in the use of social platforms led to a rapid increase in the volume, variety, and velocity (i.e., how fast information is generated) of data. It has become important in the modern industry as it serves as a reservoir of information. Big data analysis could be an important factor in the modern transformation to I4.0. For example, by analyzing social media data, it is possible to judge consumer demand trends and thus develop products desired by consumers. As consumers become more concerned about food quality and safety, the industry needs to thoroughly analyze the intrinsic and extrinsic factors that influence consumer acceptability to provide customized products (Bouchard et al., 2021; Prinyawiwatkul, 2023; Prinyawiwatkul & Chompreeda, 2017). It is anticipated that quality control and industrial operations will change significantly due to high-volume, multi-source real-time data with processing, forecasting, and tracking capabilities, encouraging the egg industry's continuous improvement (Hassoun et al., 2022b, 2022d). For example, using multiple quality parameters for eggs from different housing systems, big data analysis could help identify any undesirable batch, and sort eggs based on freshness, fertility, gender, fabrication, and origin (Astill et al., 2020; Chen et al., 2019; Joshi et al., 2022). Therefore, big data analysis could help monitor or control quality and safety parameters in the egg industry through faster decision-making and process automation.

Cloud computing is the delivery of computing resources over the internet space, known as the cloud, to enhance speed, availability, storage, and economic scale. Cloud computing enables users to access and store information virtually. For example, Zheng et al. (2021) proposed a cloud-based poultry farm where information is managed safely, efficiently, and effectively. The proposed system includes a bottom layer that gathers data using Wi-Fi-enabled transmitters and receivers, environmental sensors, and single-chip microcomputers. Parameters such as poultry weight, water, food intake, and egg quality can all be gathered. The upper layer will include the bulk of the software management system to provide the visual interface. The in-between layer would be the primary hub for cloud computing capabilities, allowing the top and bottom layers to communicate while centralizing the data and information collected from the other layers. This cloud computing system's overall feasibility was shown to have a high potential for future implementation (Zheng et al., 2021). The system effectively incorporates physical modules, software, a cloud database for data storage, and hardware to bring together farm and poultry networks more uniformly and efficiently, allowing for higher future yields.

The use of different sensors and robotics is one of the emerging trends in industrial-to-home applications because they significantly impact productivity, monitoring, and process control (Hjort et al., 2023). Wireless sensors can be added to physical devices that continuously provide environmental or product data. Different wireless sensor networks can effectively do nearly any function, including sensing data, data transfer, and communication with the host device (Kucherenko et al., 2021). Coupling with the sensors, the use of robotics has significantly increased in monitoring, implementing, and controlling systems in many industries, including poultry and eggs (Lasarte-Aragonés et al., 2023; Ren et al., 2020). For example, in the egg industry, sensors can detect when hens have laid eggs, and robots can then collect the eggs and transport them to a collection point. Moreover, sensors can be used for quality control (weight, size, and shape measurement), health monitoring (bird activity levels, feeding patterns, and interactions), environmental control (monitoring temperature, humidity, and ventilation), and feed management. Moreover, virtual or augmented reality (AR) systems would allow for remote management of these systems. The AR display is realistic and appears to the users to be a part of the actual environment. Even though AR has been used in the gaming and amusement industries, it may soon bring a radical change in many other industrial operations (Devagiri et al., 2022). With the help of AI, cloud computing, and big data analysis, AR may become the smartest dimension of I4.0 to boost productivity and profitability.

3 | APPLICATION OF I4.0 TECHNOLOGIES IN THE EGG INDUSTRY

As consumer demands for quality and safety have been increasing globally, the contemporary egg industry needs quick and automated egg quality assessment techniques. To assure high levels of accuracy and integrity, the technologies of I4.0 are transitioning toward improved performance, automation, and predictability. In the current egg industry, several I4.0 technologies, including electronic sensors, acoustic sensors, and optical sensing technologies (sensors, spectroscopy, and imaging technology) are replacing older methods (Astill et al., 2020; Eyvazi et al., 2021). IR spectrophotometer methods, for example, are rapid, inexpensive, non-destructive I4.0 technology used to detect the color, freshness, composition, manufacturing, and gender of hatching eggs (Dong et al., 2019a; Narushin et al., 2004). Using the MV, the outer physical information of eggs, including their shape and color, can be determined. IoT and robotics technologies automatically enable the collecting, washing, grading, sorting, and packaging of eggs (Ammar et al., 2022; Luperto et al., 2023). With the help of cloud computing and ML, sensor technology helps detect storage parameters, predict quality, and even observe product history by end users using smart gadgets (Khan et al., 2022; Kumar et al., 2022; Soni & Kumar, 2022). To satisfy the growing need for safe egg production, industry must adopt appropriate modern technologies. This section will focus on primary optical sensing and CV technologies of EI 4.0 for egg quality inspection and grading.

3.1 | Spectroscopy

For determining the quality parameters of eggs, NIR spectroscopy (780 to 2500 nm) has been used more often than other forms of spectroscopy, such as UV (100 to 400 nm), visible light (400 to 780 nm), and mid (M)-IR (2500 to 4000 nm) (da Costa Filho et al., 2022; Harpaz et al., 2022). The dataset produced from a collection of spectroscopic signatures is processed using an advanced computer language to extract meaningful information. This is a "calibrate–collect–predict" method for quantifying target composition, where the spectroscopic signatures of a set of samples serve as a fingerprint. Then multivariate statistical or ML approaches are used to determine whether the fingerprint of an unknown sample is typical or atypical (Kamruzzaman et al., 2022). Spectroscopy could be a reliable, and non-destructive egg quality evaluation technique that may replace the existing traditional industrial practices. The application of spectroscopy in egg research is summarized in Table 1.

Numerous studies have reported quick and non-destructive spectroscopic detection methods for table egg freshness and for the hatching egg applications (Table 1). By scanning the exterior surface of the egg with a Raman spectroscope, the chemometrics approach was used to evaluate the freshness of the eggs. Spectra were collected from the top, middle, and bottom of 125 eggs over 60 days. A partial least squares regression (PLSR) model was developed using physical and chemical freshness parameters. The Haugh Units (HU), albumen pH, air chamber diameter, and air chamber height had correlation coefficients >0.9, indicating a strong correlation between the Raman spectrum (100–3000 cm^{-1}) of the egg surface

TABLE 1 Use of spectroscopic techniques for egg quality determination.

Egg parameter	Spectroscopic method	Spectral range/frequency	Model algorithm	Accuracy indicators	Reference
Freshness	Raman	100–3000 cm^{-1}	PLSR	R_p = up to 93.5	(Liu et al., 2020)
	Vis–IR	340–1030 nm	PLSR	$R_p = 0.91$	(Dong et al., 2019b)
	Microwave	0.9–1.7 GHz	PLSR and ANN	100%	(Akbarzadeh et al., 2019)
	NIR	10,000–4000 cm^{-1}	GA-ANN	$R_p = 0.87$	(Lin et al., 2011)
	Vis–IR	400–1100 nm	GA-ANN	Up to 100%	(Mehdizadeh et al., 2014)
	Radio	0.1 Hz–20 MHz	ANN	100%	(Soltani & Omid, 2015)
	Vis–IR	570–750 nm	PLSR	$R = 0.86$	(Kemps et al., 2006)
	FT–NIR	833–2500 nm	PLSR	R^2_p = up to 0.76	(Giunchi et al., 2008)
	Vis–IR	340–1030 nm	PLSR	$R^2_p = 0.89$	(Dong et al., 2020)
Fertility	Vis–IR	330–1030 nm	NB classifier	95.1%	(Dong et al., 2019a)
	Vis–NIR	575–578 nm	LDA	100%	(Islam et al., 2017)
Shell color, integrity	NIR	400–2400 nm	BP-NN	Up to 100%	(Han et al., 2022)
Shell thickness	THz	0.5–1.2 THz	LR	$R^2 = 93.4\%$	(Khaliduzzaman et al., 2020a)
Shell refractive index	THz	0.5–1.2 THz	LR	$R^2 = 49\%$	(Khaliduzzaman et al., 2020b)
Proximate composition	NIR	950–1650 nm	PLSR	$R^2_p = 0.80$	(Zhao et al., 2018)
Fabrication	FT-IR	1800–600 cm^{-1}	PLS-DA	R_p of 0.99	(Joshi et al., 2022)
	NIR	10,000–4000 cm^{-1}	DDCM	98.8%	(Chen et al., 2019)
Cholesterol	UV–Vis–NIR	190–2500 nm	PLSR	$R^2 = 0.93$	(Puertas & Vázquez, 2019a)
Omega-3 FA	FT–Raman	3100–990 cm^{-1}	PLS-DA	100%	(de Oliveira Mendes et al., 2019)
Housing system	UV–Vis–NIR	190–2500 nm	QDA	100%	(Puertas & Vázquez, 2019b)
Gender	Vis–NIR	300–1145 nm	PLS-DA	99.5%	(Corion et al., 2022)
	NIR sensor	870 nm	LDA	84%	(Alin et al., 2019)
	NIR sensor	870 nm	KNN	84.6%	(Khaliduzzaman et al., 2021a)
	Vis–NIR	500–654 nm	LR	76%	(Rahman et al., 2021a)

Abbreviations: ANN, artificial neural network; BPNN, back propagation neural network; DDCM, data driven-based class-modeling; GA, genetic algorithm; KNN, k-nearest neighbor; LDA, linear discriminant analysis; NB, Naïve Bayes; PLS-DA, partial least square discriminate analysis; PLSR, partial least square regression; QDA, quadratic discriminant analysis; SVM, support vector machine.

and freshness, which would aid in on-site testing of egg freshness (Liu et al., 2020).

For a fast evaluation of egg freshness, Vis–NIR spectroscopy has also shown good results. The Vis–NIR approach predicted albumen pH as the freshness evaluation parameter of two egg varieties (White Leghorns and Bantam) (Dong et al., 2019a). Various pre-processing techniques and PLSR were used to create prediction models. In addition, methods for transferring calibration models from one variety to another were investigated, including global updating, direct standardization (DS), and slope/bias correction (SBC). The best albumen pH prediction was achieved using the SBC approach, where the correlation coefficient for the predicted set was ~0.9.

In another study, a group of 60 eggs was kept in storage (18°C, 55% RH) for 0, 2, 4, 6, 8, 10, 12, 14, or 18 days to produce a difference in freshness (Kemps et al., 2006). Based on the transmission spectra, a PLS model was developed to anticipate the albumen's HU and pH. The HU and pH of the albumen had correlation coefficients of 0.842 and 0.867 between the predicted and the reference value, respectively. The comprehensive freshness indexes (shape, yolk, HU, albumen pH, air cell width, and eggshell thickness) were also reported in another study (Dong et al., 2020).

The results showed that when compared to individual freshness indexes, the freshness indicator had a greater capacity to predict outcomes, with a predictive correlation value of 0.891 and a root mean square error (RMSE) of 1.0.

Recently Vis–NIR spectroscopy technology has been shown to have promise as an egg-sorting model that could be automated based on eggshell color, integrity, and feeding mode (Han et al., 2022). The eggshell color, integrity, and laying hen feeding mode (caged or cage free) were identified by their characteristic bands using the backpropagation (BP) neural network combined with Soft Independent Modeling of Class Analogy (SIMCA) methods. Large-scale laying hen farms may use this I4.0 technology for smart and intelligent grading. The light scattering properties were successfully characterized between 0.9 and 1.7 GHz. Akbarzadeh et al. (2019) were able to predict air cell height, thick albumen height, HU, and albumen pH of eggs with up to 100% accuracy. Even though lower prediction accuracies for freshness determinations using spectroscopic techniques have been reported (Giunchi et al., 2008; Karoui et al., 2006b), using different chemometrics led to better prediction models (Granato et al., 2018; Lin et al., 2011; Soltani & Omid, 2015).

The traditional process of determining the fertility of chicken eggs, known as candling, is laborious, sluggish, and ultimately less effective, resulting in significant economic losses (Ramiro et al., 2018). Therefore, a non-destructive, quick, and online prediction method is required to help with the detection of early egg fertility. Spectroscopy is one of the popular methods for non-destructively detecting the fertilization of eggs. The Vis–NIR transmittance spectroscopic method was used to identify unfertilized duck eggs (Dong et al., 2019a). Transmittance spectral data were collected with eggs deposited by the same flock of ducks. Overall validation set prediction accuracy was 94.5%, while internal validation prediction accuracy was 95.1%. With the NB modeling and SNV pre-processing, the prediction accuracy for 667 duck eggs was 94.8%. These results showed that the Vis–NIR transmittance spectroscopy method successfully identified unfertilized eggs.

Culling of male day-old chicks is an animal welfare issue in the table egg industry that leads to significant ethical concerns (Krautwald-Junghanns et al., 2018; Reithmayer & Mußhoff, 2019; Reithmayer et al., 2021). Recent research indicates that Vis–NIR imaging is more accurate than HSI in determining the gender of eggs during incubation, which might reduce testing costs (Corion et al., 2022). In their work, 600 Isa brown chicken eggs were individually lit with halogen lights on days 8, 14, and 18 of incubation. The signal was obtained between 300 and 1145 nm in the Vis–NIR region. They obtained prediction accuracies of 97.8% and 99.5% on the 13th and 14th days of incubation, respectively. This study opens the door to the high-throughput and economical use of smaller, less expensive spectrophotometers in commercial layer industry hatcheries.

Eggshell color is the most apparent exterior characteristic of eggs and also serves as a benchmark for customers to assess the quality of eggs (Berkhoff et al., 2020; Samiullah et al., 2015). Studies have also shown that colored eggs have greater physiological and antioxidant activity than white eggs (Mertens et al., 2010). Recently, a NIR spectroscopy-based automated egg-sorting model based on eggshell color, integrity, and feeding mode was published (Han et al., 2022). The egg industry needs to determine the suitability of this fast-response, non-contact, and non-destructive detecting technique. To distinguish between eggshell colors, integrity, and feeding modes, researchers used BP neural networks, principal component analysis (PCA) combined with BP and SIMCA. According to the predicted outcomes, pink, green, and white were correctly categorized with up to 100% accuracy. As a result, with further study and validation, this technique might be used commercially in the egg industry.

According to EU regulations, there are four types of hen housing systems: organic, free range, barn, and cages (Puertas & Vázquez, 2019b). Unfortunately, many dishonest traders identify their products as organic even when they come from other housing systems to profit financially (Matthews & Sumner, 2015; Ochs et al., 2019). However, no analytical techniques can fully identify the housing systems listed on an egg label. Puertas and Vázquez (2019b) successfully categorized eggs based on housing systems, using UV–Vis–NIR spectroscopy, and extracted lipid information as the reference value. Six eggs were collected in duplicate from each of the four farming systems supplied by Granja Campomayor (Lugo, Spain). Results from the quadratic discriminant analysis of the spectrum of the yolk lipid extract showed 100% accuracy of egg categorization. Thus, UV–Vis–NIR technology may be a viable innovative tool for analytically verifying farming techniques, which will aid in ending unethical egg labeling practices.

Fluorescence techniques can be used to assess egg freshness as well as the chemical nature of the egg and eggshell. The eggshell emits a red fluorescence, whereas albumin emits blue and green fluorescence when UV light is used (Aboonajmi & Mostafaei, 2022). THz spectroscopy could potentially be used for shell quality estimation and grading for parameters such as shell strength, compactness, and thickness (Khaliduzzaman et al., 2020a, 2020b).

Determination of egg fat, protein, and moisture content is essential since they are closely related to nutritional value and quality. Soxhlet extraction, Kjeldahl, and oven drying are the standard methods to determine fats, proteins, and moisture, respectively, in biological products.

However, these techniques are costly, time-consuming, and destructive. On the other hand, NIR spectroscopy is rapid, affordable, safe, and non-destructive in determining the composition of meat (Kamruzzaman, 2021; Serva et al., 2023; Silva et al., 2020), grain (Ba et al., 2023; Fatemi et al., 2022), dairy (Balabin & Smirnov, 2011; Pu et al., 2020), and poultry (Parastar et al., 2020). To replace traditional approaches, a technique based on NIR reflectance spectroscopy can be used to determine the moisture, protein, and fat contents of homogenized egg albumen and egg yolk (Zhao et al., 2018). For all chemical compositions, the $R^2{}_p$ for external validation was >0.8. The spectroscopic approach may be a promising technique for quantifying the nutritional composition of eggs.

Cholesterol acts as a precursor to vitamin D, the synthesis of which is essential for bone health and several other physiological functions, including the production of certain hormones, while too much cholesterol intake can increase the risk of cardiovascular diseases (Palomar et al., 2023; Puertas & Vázquez, 2020). Therefore, knowing the cholesterol content of different egg varieties may be helpful for human health. The most effective methods for quantifying cholesterol include gas chromatography, liquid chromatography, and enzymatic approaches (Palomar et al., 2023). However, these methods need expensive instruments that require expensive upkeep and must be maintained by careful, trained employees. Recently, a simple and affordable approach for measuring the cholesterol in egg yolks using UV–Vis–NIR spectroscopy was developed (Puertas & Vázquez, 2020). Two types of yolk samples (from shell eggs and pasteurized yolk) were homogenized, and then the UV–Vis–NIR spectra were acquired. The reference cholesterol contents were determined using a commercial enzymatic photometric test kit. The results showed that UV–Vis–NIR spectroscopy could measure cholesterol from egg yolks or pasteurized egg yolks with a 93% prediction accuracy.

A class of essential (E) fatty acids (FA) known as omega-3 fats serve important functions in the human body and provide several important health benefits. All eggs have some omega-3 polyunsaturated EFA from dietary sources (Samman et al., 2009). Precursors of EFA have been added to chicken feed to produce eggs high in omega-3 FA (Irawan et al., 2022). Therefore, verifying and classifying eggs according to their omega-3 FA concentration is helpful for health reasons and to prevent misbranding. The most used technique for measuring FA is gas chromatography, which is laborious and involves several sample preparation steps (Zhou et al., 2019). All segments of the food industry pay attention to how long analytical processes take, especially when it comes to perishable foods like fish, milk, eggs, and meat. The food industry's quality control teams would like to develop unique, efficient, and simple approaches that require minimal sample preparation. To differentiate eggs that are omega-3 FA-enriched, Raman spectroscopy and multivariate supervised classification have been developed (de Oliveira Mendes et al., 2019). Using a PLS-DA model, almost all samples could be categorized correctly.

Egg fabrication with chemical compounds has drawn attention and increased food safety concerns worldwide due to publicized incidents of imitation eggs in Beijing in 2011 (Fearnley, 2022). As a result of the use of hazardous chemicals in fabricating, consumers may be at risk. Fake eggs will have different optical characteristics from actual eggs because of their differing elemental composition. Recently, FT-IR spectroscopy was used to obtain the optical properties for the non-destructive identification of fabricated and natural eggs (Joshi et al., 2022). One-way ANOVA and PCA were done to evaluate the FT-IR data corresponding to the chemical composition of fabricated eggs. Specific informative wavelengths for the exterior and interior components of real and fabricated eggs were identified. Then, the PLS-DA and SVM models were able to classify real and fabricated eggs with 100% accuracy.

3.2 | Computer vision

Due to their non-invasive and unintrusive nature, CV technology has been applied for size, mass, and volume determination and sorting and grading of eggs. Recent applications of CV in the egg industry are listed in Table 2.

Dong et al. (2021) used an MV system to classify fertile and infertile duck eggs. They used linear discriminant analysis (LDA), Naïve Bayes (NB), and SVM algorithms to develop discriminant models for various incubation durations. On day 5, the SVM classifier showed the best results with four features in the validation set. The prediction accuracy for the fresh unidentified duck eggs was 92.1% on day 5 using the existing SVM model. Recently Zhu et al. (2022) used the SVM and LS-SVM models to identify infertile eggs using CV. The LS-SVM model achieved greater accuracy using less time in identifying infertile and dead embryo eggs than the SVM model. The LS-SVM model achieved a 100% accuracy to detect infertile eggs at day 4.0.

CV technology with deep-learning approaches is used for defect detection in commercial eggs (Valencia et al., 2021). These authors used a set of algorithms for identifying and classifying dirty and cracked eggs based on three distinct methods: classical approaches, CNN, and semantic segmentation. The average accuracy for the three approaches was 94%, 91.3%, and 85.7%, respectively. The average processing time for each approach was 0.049, 0.11 and 0.47 ms, respectively. The grey level concurrence matrix (GLCM) was used to reconstruct a high-frequency

TABLE 2 Application of computer vision technology in egg classification.

Classification basis	Data analysis	Accuracy	Reference
Fertility	ANN	Up to 98.3%	(Hashemzadeh & Farajzadeh, 2016)
	SVM	92.1%	(Dong et al., 2021)
	SVM, LS-SVM	100%	(Zhu et al., 2022)
Crack, breakage, dirt, hole	CNN	94.8%	(Nasiri et al., 2020)
	GLCM	96.7%	(Wang, 2014)
	PC CNN	94% 91.3%	(Valencia et al., 2021)
Volume	ANN	97.4%	(Siswantoro et al., 2017)
Double yolk	CNN	98.8%	(Ma et al., 2017)

Abbreviations: ANN, artificial neural network; CNN, convolutional neural network; GLCM, grey level cooccurrence matrix; LS-SVM, least square SVM; PC, pixel counting; SVM, support vector machine.

sub-image from the captured image for egg damage detection (Wang, 2014). Experimental results showed a prediction accuracy of 96.7% after PCA dimensionality reduction. An automatic egg-sorting system using a deep CNN was proposed for detecting undesirable (broken, cracked, or with a hole in the shell) eggs (Nasiri et al., 2020). VGG16 architecture was modified with a global average pooling layer, dense layers, a batch normalization layer, and a dropout layer to categorize unwashed egg images. Using five-fold cross-validation, the CNN model attained an overall average accuracy of 94.8%.

Volume is another crucial aspect of the egg-sorting process. Egg volume has been predicted using a CVS and an ANN model (Siswantoro et al., 2017). A top-down picture of an egg was taken and then processed to extract one- and two-dimensional (2D) size properties, which were utilized as input for the ANN. The results had a classification accuracy of 97.4%, indicating that the predicted volume had a high linear correlation with the measured volume. Utilizing CV to detect double-yolked (DY) eggs may enhance the efficiency of the poultry business by reducing egg waste during incubation and/or boosting sales revenue. Ma et al. (2017) established two ways for determining DY eggs using the CVS. A charge-coupled device (CCD) camera recorded transmittance pictures of DY and single-yolked (SY) duck eggs to identify them based on their form characteristics. Fisher's linear discriminant (FLD) model and the CNN model were used to classify eggs. The classification accuracy of the FLD model for SY and DY eggs was 100% and 93.2%, respectively, whereas the classification accuracy of the CNN model for SY and DY eggs was 98% and 98.2%, respectively.

3.3 | Hyperspectral imaging

HSI is a prospective I4.0 technology that provides spectral and spatial information about each pixel in the image to model the expected quality parameters of eggs (ElMasry et al., 2012; Goetz et al., 1985). With HSI, it is possible to remotely obtain images of many bands. The HSI data can be analyzed to characterize the product's physico-chemical and geometrical properties due to the integrated nature of the imaging and spectroscopy (Jia et al., 2017). With HSI, any image is a three-dimensional (3D) data block that contains a stack (i.e., one behind another) of 2D images (x rows $\times$ y columns) at different wavelengths (λ), which provides precise information about the properties of the object (Basantia et al., 2019; Kamruzzaman & Sun, 2016). The behavior of electromagnetic energy being absorbed, reflected, scattered, and emitted when the light of a particular wavelength passes through an item is known as the spectral signature or fingerprint and is unique to each object. By analyzing the spectral data of any object, it is then possible to identify different components or properties of the object. A schematic diagram of HSI techniques is shown in Figure 5.

Recently, HSI has become industrially known for its use in process monitoring, product quality control, and raw material analysis (Kamruzzaman, 2023). It is one of the efficient optical methods used to assess the quality of various products, including meat (Kamruzzaman, 2023), poultry (Li et al., 2023; Yoon et al., 2011), fish (Cheng & Sun, 2014; Qin et al., 2020), and fruits and vegetables (Çetin et al., 2022; Tung et al., 2018; Wieme et al., 2022). Several research projects on egg characterization using HSI technology have been done. However, numerous processes in the egg industry are still done manually, which significantly increases the possibility of mistakes. Therefore, as a fast, accurate, and non-destructive method, HSI may be a state-of-the-art technology for the egg industry. The accuracy of HSI is notably higher in distinguishing origin, transparency, freshness, fertility, and hatching properties (Liu & Ngadi, 2013; Sun et al., 2017; Yao et al., 2022b; Zhang et al., 2014). The application of HSI in egg research is summarized in Table 3.

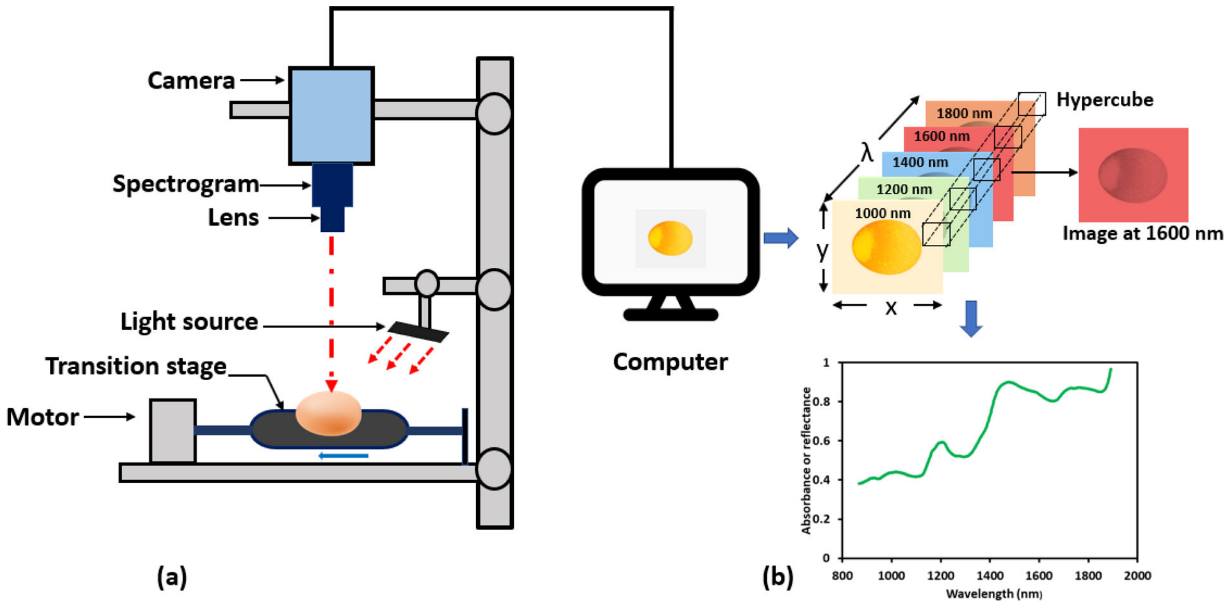

FIGURE 5 Schematic diagram of a typical hyperspectral imaging system: (a) Components of a typical line scan hyperspectral reflectance imaging system and (b) conceptual view of hypercube comprising spatial (x and y) and spectral (λ) dimensions.

TABLE 3 Summary of hyperspectral studies for egg parameters.

Application	Spectral range (nm)	Data analysis method	Accuracy (%)	Reference
Freshness	900–1700	PLSR	85–91	(Suktanarak & Teerachaichayut, 2017)
Egg hatching properties	400–1000	LVQNN	70–100	(Zhang et al., 2014)
Egg fertility	900–1700	K-M clustering	81.2–99.4	(Liu & Ngadi, 2013)
Internal quality (freshness, bubble formation)	380–1010	PLSR	90–96.3	(Zhang et al., 2015)
Freshness, scattered yolk, and eggshell cracks	401–1002	XGBoost	93.3–97.3	(Yao et al., 2022b)
Gas composition	380–1038	CNN	99.9	(Zhang et al., 2022a)
Origin of table egg	871.6–1766.3	SVM	96-99.3	(Sun et al., 2017)

Abbreviations: CNN, convolutional neural network; LVQNN, learning vector quantization neural network; PLSR, partial least square regression; SVM, support vector machine.

Egg freshness is an important parameter for consumers and egg processing plants. Due to gas exchange and moisture loss through the shell, the egg white or albumen becomes thinner, a primary measure of egg freshness reduction (Xu et al., 2022; Yao et al., 2022a). In traditional practice, HU are used as an indicator of egg freshness. This measurement requires the breaking of egg samples to measure the height of the albumen layer (Narushin et al., 2021; Sehirli & Arslan, 2022). The HSI has been used to non-destructively determine egg freshness to categorize eggs (Özdoğan et al., 2021; Suktanarak & Teerachaichayut, 2017; Xu et al., 2022; Zhang et al., 2022a, 2015). It has been shown to be feasible to instantaneously determine egg freshness. The conventional technique of determining freshness could thus be replaced with HSI technology, ensuring optimal data integration and used under the umbrella of the I4.0 approach. HSI was successfully used to assess the interior quality of eggs, including freshness, bubble formation, and scattered yolk (Zhang et al., 2015). They used successive projection algorithms, SVR, and support vector classification models to predict a particular egg parameter. They proposed that HSI might be helpful to evaluate the interior characteristics of eggs quickly with a prediction accuracy of >90%. Yao et al. (2022b) successfully determined eggshell cracks, scattered yolks, and freshness of the egg. The spectrum data were normalized using a standard normal variate, and wavelength selection was optimized using an iterative retains informative variable. The XGBoost egg freshness model has a coefficient of R^2_p of 0.9 and an RMSE of 4.6. Predictions of eggs with a scattered yolk had an accuracy of 97.3% based on the morphological feature ratio, whereas predictions for cracked eggs had an accuracy of 93.3%.

Gas composition, which may change during storage and transportation, is another important indication of egg freshness. The electronic nose (e-nose) and HSI method were merged with the multi-data-fusion-attention network (MDFA-Net) technology described by Zhang et al. (2022a) to determine the gas composition. The MDFA-Net showed strong prediction accuracy (99.9%) for egg categorization based on gas composition compared to other deep-learning techniques. Several researchers found that the assessment of freshness and quality criteria using HSI had a good prediction accuracy (Dai et al., 2020; Fu et al., 2020; Huang et al., 2020). Furthermore, advanced multivariable analysis and feature selection techniques might improve the model accuracy for egg freshness and interior quality prediction (Fu et al., 2020; Huang et al., 2020).

Commercial hatcheries may operate more efficiently and save money by saving space and maintaining hatching quality through the use of non-destructive technologies such as HSI. An egg requires considerable time and energy to hatch, taking 21 days on average, for example, for chickens (Jalili-Firoozinezhad et al., 2020; Nordquist et al., 2022). The percentage of egg embryos that develop ranged from 86% to 95%, meaning that a significant number of eggs fail to hatch every year (Ipek & Sozcu, 2017). These unhatched eggs require space and energy. This is an issue for the company and might contaminate a hatching unit by spreading diseases or other biological material on which bacteria can readily grow.

HSI has been used to identify an egg's early hatching characteristics (Adegbenjo et al., 2020; Liu & Ngadi, 2013; Smith et al., 2008; Zhang et al., 2014). By assessing the changes in light transmission and morphological traits of infertile eggs, this system evaluated the hatching potential. HSI can effectively predict egg fertility with an accuracy of up to 100%, depending on the incubation periods. Liu and Ngadi (2013) incubated 174 white eggs (of which 18 were infertile) for 4 days in a commercial incubator. Using an HSI technique, the area of interest of individual images was segmented, and then, using Gabor filters, the image information was retrieved. This approach showed a prediction accuracy of up to 100% for egg categorization. But several studies have also observed lower accuracy (63%–95%) of early egg fertility determinations (Lawrence et al., 2006; Smith et al., 2008). Therefore, PCA was done by Zhang et al. (2014) to extract spectral features from HSI, and an image segmentation technique was used to separate morphological data. The results showed that a model utilizing image morphological features could obtain better precision and applicability than one using characteristic spectral parameters, and the discrimination accuracy for eggs with embryo development was 97% and 100% on days 3 and 4, respectively.

Shell eggs production is divided into two primary categories: extensive eggs, where hens produce in a more natural environment, and intensive eggs, where hens produce on indoor farms (Pires et al., 2021). Many people believe that extensive eggs have higher protein and fat content (Ochs et al., 2019). Studies also showed that extensive eggs have a distinct chemical composition and some physical characteristic differences from intensive eggs (Kowalska et al., 2021; Lordelo et al., 2020; Vlčková et al., 2019; Zita et al., 2018). It is challenging to classify eggs based on origin visually or using a cholesterol content-based identification technique. Using HSI, Sun et al. (2017) successfully categorized eggs based on the housing systems. The grid search (GS) algorithm, genetic algorithm (GA), particle swarm optimization (PSO), and cuckoo search (CS) algorithms were combined using SVM methodologies to give an SVM identification model with an accuracy ranging from 96% to 99.3%.

3.4 | AI, IoT, and cloud computing

AI is a fundamental component of computer science that enables the development of intelligent systems capable of doing tasks that generally require human cognition. It is a versatile tool that allows information to be integrated, analyzed, and applied to give enhanced decision-making, thereby increasing productivity and profitability. The Google search engine, for example, uses AI to decrease the amount of human effort required to locate desired information accessible on the internet. AI, IoT, and cloud computing can effectively address various production-related difficulties encountered by the egg industry, including grading and classification costs, various animal welfare considerations, a lack of trained and skilled workers, and environmental consequences (Ojo et al., 2022b; Wongchai et al., 2022). It is anticipated that by 2050, an average size (~50,000 birds) chicken farm will be able to create 4.1 million data points using different sensors and other IoT-connected appliances (Astill et al., 2020; Wongchai et al., 2022). On today's high-tech farms, a vast array of sensors are used to measure bird weight, temperature, feed and water intake, humidity, ammonia levels, CO_2 levels, and several other characteristics (Astill et al., 2020; Lin et al., 2016; Zhang et al., 2023). Data analytics also help to project outcomes by collecting and analyzing this data. For example, monitoring and analyzing data can predict birds' weight after 30 days. Computer-controlled technology and robots might significantly minimize human engagement with the birds, minimizing sources of contamination and stress, and maximizing production output compared to

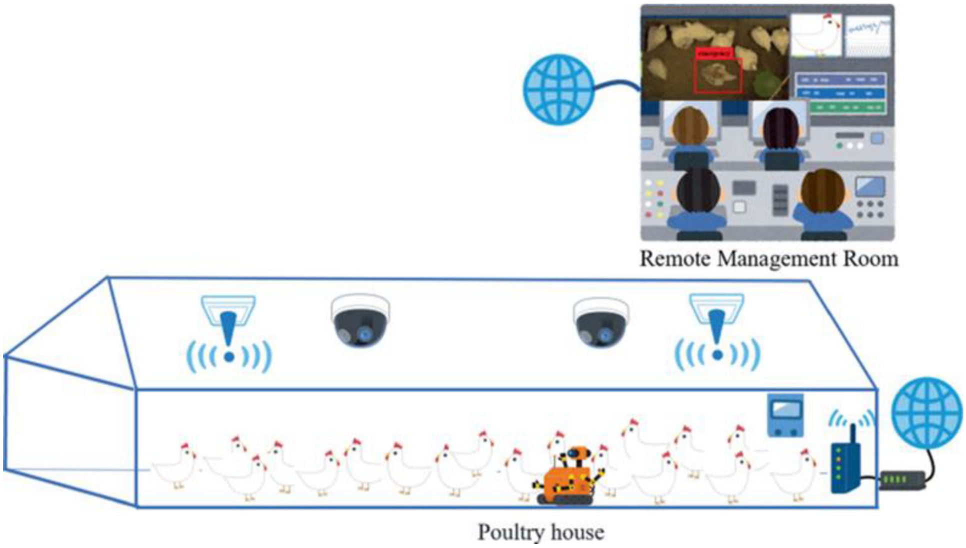

FIGURE 6 Schematic diagram giving an overview of an Internet of Things and artificial intelligence-based smart poultry farming system (Ichiura, 2022).

complete reliance on humans. AI can reduce mistakes in industrial tasks by automating certain processes, providing real-time monitoring and analysis, and identifying potential errors before they occur. An AI-based innovative poultry farm is shown in Figure 6.

The introduction of AI is a four-step process that has become less complicated due to the invention of accurate sensing, internet access, and cloud-based services (Debauche et al., 2020; Devagiri et al., 2022; Singh et al., 2020). The first stage is automated data collecting using accurate sensors throughout the industry. All data is transferred to an online storage system in the second stage. Better connectivity, including fiber optics and 5G connectivity, improve the precision and speed of this transmission. The third stage delivers current information to the manager or controller for them to make choices about processing or packing. Similarly, product history can be accessible by end users through smart gadgets over the internet and cloud-based computing. AI's most useful and last step is predicting the future based on existing data. Due to the limited analytical capacity of the human brain, a virtual storage system with ML can forecast numerous product characteristics that are beneficial to primary producers and end users. A cloud-based AI system is shown in Figure 7.

Likewise, in poultry production, AI could significantly reduce the usage of energy, space, workforce, and time in egg inspection and in processing plants. AI offers real-time assessment, grading, and other need-based actions. Currently, AI-assisted equipment identifies surface and interior flaws in shelled eggs, increasing the production line speed to 70 eggs/s (Puertas & Vázquez, 2020; Soltani et al., 2015). AI-assisted egg breakers quickly separate the egg white from the yolk without leaving any trace behind. These AI-assisted egg breakers process 200,000 eggs/h, or ~60 eggs/s, making it impossible for a worker to recognize a problem if it exists. AI can gather and analyze data utilizing cloud storage. After processing the results, AI may be used for instantaneous decision-making, thereby enhancing production line efficiency (Astill et al., 2020; Ichiura, 2022). For example, robots and sensors may be programmed to gather data on freshness, humidity, contamination, and cracks. These results would enable machines to make separation, classification, and packing decisions independently. Numerous characteristics, such as cracks, breakage, weight, yolk quantity, and composition, would be readily recognized on the monitoring farm or on a processing line, and then sent to controllers so that decisions can be taken more quickly (Ma et al., 2017; Siswantoro et al., 2017; Valencia et al., 2021; Wang, 2014).

Cloud-based storing and ML may help end users or consumers know an egg's history from farm to purchasing stages, using smartphones. The meat processing industry has explored MV technology for categorizing meats and detecting defective carcasses (Chowdhury & Morey, 2020). Since machines can readily distinguish between the density of albumen and yolk, processes such as albumen separation are ideal for an AI operation (Ma et al., 2017). AI has been used on layer farms to rapidly analyze and identify high-quality eggs (Ichiura, 2022). The MV and intelligent automation have enabled the meat and egg processing sector to increase the rate of processing and packing (Chowdhury & Morey, 2020; Innocente et al., 2009; Kamruzzaman, 2023). Spectral imaging devices driven by AI have been successfully shown to increase in multiple studies in terms of increased efficiency, improved

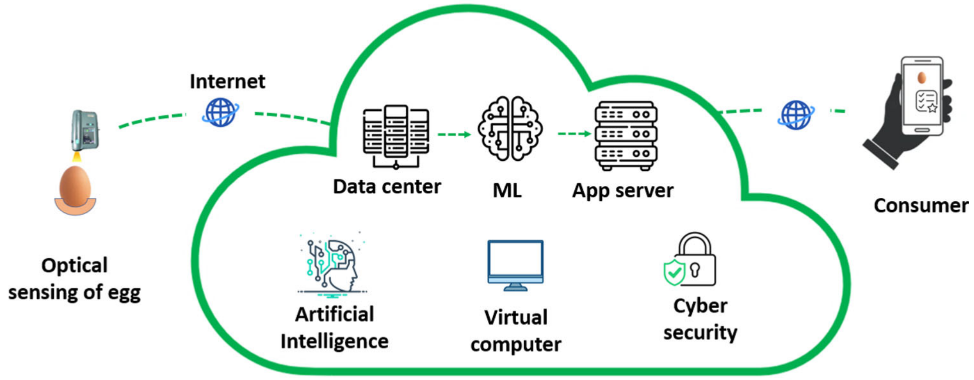

FIGURE 7 An artificial intelligence-based cloud computing system for the smart egg industry: transfer of sensing data into a data center—machine learning of data and transfer to the consumer using an app server—end-user quality check to help with purchasing decision.

quality control, reduced costs, and enhanced safety (Debauche et al., 2020; Puertas & Vázquez, 2020; Singh et al., 2020; Soltani et al., 2015; Wieme et al., 2022).

4 | CHALLENGES AND FUTURE TRENDS

The egg industry will face new challenges to meet the ever-increasing demand with more stringent safety and quality standards. To overcome challenges, the egg industry needs to carefully adopt I4.0 technologies. While I4.0 offers numerous advantages and opportunities, several constraints must be considered specifically for small businesses for sustainable development. Any technological development can be called sustainable only if it meets three basic dimensions (also known as pillars), such as social sustainability (i.e., improving the quality of life), economic sustainability (i.e., economic stability), and environmental sustainability (i.e., protecting and preserving the environment) (Yavuz et al., 2023). The three sustainability pillars are interdependent and complementary. Any of these aspects, if neglected, can jeopardize the sustainability objective (Ghobakhloo, 2020). Industry requires a holistic approach to ensure a resilient and equitable EI 4.0 that meets the needs of present and future generations. Considering the existing limitations of the conventional egg industry, different optical sensing technologies can improve efficiency, quality, biosecurity and biosafety, and sustainability, facilitating the transition toward a robust sector I4.0 system.

CV has been increasingly used for egg sorting due to its fast, consistent, and precise results. The studies reported the effectiveness of a CVS for egg classification based on fertility, cracks, holes, dirt, volume, and yolk content (Dong et al., 2021; Ma et al., 2017; Siswantoro et al., 2017; Wang, 2014; Zhu et al., 2022). Therefore, CV has the potential for auto-grading eggs based on specific parameters. Nevertheless, there are challenges in the egg industry associated with adopting CV despite the growing usage of this technology in the food and agriculture industries. The CVS mainly used 2D images, which is insufficient to capture all variability required for sorting, classifying, and grading. Depth imaging for 3D construction using two cameras or depth cameras (e.g., an intel RealSense Depth Camera) could be used to overcome this limitation. Linear modeling techniques may not be effective enough, requiring more advanced algorithms for egg sorting. Nonlinear techniques, especially deep learning, have been reported to be effective for egg sorting with CV using color and textural features (Valencia et al., 2021). In product lines, eggs often travel at a relatively rapid speed. Therefore, with CV, image blurring is another issue. However, this problem can be solved by high quality illumination, a high speed camera, and other image acquisition techniques. Device and time dependencies exist in egg classification algorithms developed using CV techniques. Therefore, more work is necessary to create device-independent algorithms so the system can be controlled remotely, even using a smartphone. In addition, due to I4.0 technologies such as big data and cloud computing, it is expected that CV would have new dimensions like smartphone-based end-user egg testing.

Spectroscopy is a good tool for identifying the intrinsic and extrinsic characteristics of eggs. Real-time applications for determining various quality characteristics from a small number of essential spectra or even from a single spectrum have a significant advantage over existing techniques, especially the development of affordable handheld devices. Recent technological improvements have reduced the size of spectroscopic instruments, enabling the development of handheld gadgets and portable sensing systems that enable in situ, real-time monitoring of crops, food, and egg quality (Brasil et al., 2022;

Cruz-Tirado et al., 2021; Folli et al., 2022; Freitag et al., 2022; Xu et al., 2022). Therefore, the use of intelligent optical sensors has become more popular. Among different spectroscopic methods, Vis–NIR and THz have shown significant effectiveness in egg and eggshell quality determinations. However, despite much progress in ML, some drawbacks must be overcome to ensure sustainability. For example, spectroscopy is a secondary technique that predicts parameters based on reference data obtained using chemical analyses. Therefore, the inaccuracies of reference information might lead to improper classification. Moreover, developing a predictive model requires complex chemometric analysis to extract the essential information from a number of multiple variables. Several approaches for outlier detection, pretreatments, regression analysis, and informative band selection, require better models. But there are no current rules or standards for designing and evaluating multivariate data mining techniques. Since there is no single formula for selecting a data mining procedure for a specific application, it needs the right skills to identify the right chemometrics to create effective models.

In addition, calibration transfer between spectroscopic devices is another challenge that must be met to ensure a robust system for I4.0. For example, a model for one device may not accurately fit with other devices due to structure and detection mechanism variations. Changes in type, and intrinsic and extrinsic compositions due to variations in factors such as breed, feed, and rearing environment, could lead to inaccuracies in the calibration model. It is a challenge with present spectroscopic techniques. However, researchers need to focus on developing a well-fitting calibration model with self-propelled adjustment of device-to-device variations with constant prediction accuracy. This could be possible if one device can combine all spectroscopic approaches simultaneously. Besides, online spectral data benchmarking could be considered to evaluate the methods. Even though researchers are striving to transfer calibration from one device to another with the same prediction accuracy, they have not yet succeeded. Because deep-learning systems do not need typical samples for transferring algorithms, it is anticipated that they would offer new opportunities for calibration transfer (Khademi et al., 2023; Mishra & Passos, 2021; Xu et al., 2023; Yang et al., 2022). In addition to standard calibration transfer, automated updating and reliable maintenance must ensure any spectroscopic approaches under the umbrella of I4.0.

HSI is being considered for egg analysis because of features like being rapid, accurate, chemical free, and nondestructive. However, because of the relatively high cost and poor industrial environment adaptation, HSI has not been used extensively in the egg industry. Despite its benefits over conventional techniques, the technology has some intrinsic limitations like cost, computational speed, hardware, and inconvenience. Computational speed is one of the most critical bottlenecks with HSI. Furthermore, this technology requires considerable time for data acquisition, processing, and visualization of output which hinders its real-time application. More research on developing high-speed and real-time HSI is in progress. Another significant limitation of this technology is the mode of implementation. Most HSI technologies (see Table 3) were done offline, while the industry prefers an in-line or online approach for better inspection and monitoring. It is expected that small and portable HSI devices with robust algorithms will open a new door for the optical analysis of biological samples, including eggs.

AI, IoT, and cloud-computing technologies are forecasted to assist in fine-tuning cognitive processes utilizing networked machines and tools to enhance performance and optimize time, energy, and the workforce. AI is now a global paradigm capable of radically transforming any industry with sensing, identification, remotely control, and industrial automation capabilities. Existing practices confront various obstacles and complications that the future AI-based high-tech egg industry can overcome. However, several obstacles remain in the application of these concepts. Existing equipment and systems are incompatible with ensuring a sustainable cloud-based AI system. For example, massive amounts of heterogeneous data created by many IoT-connected devices will need a great deal of memory and processing power (Cioffi et al., 2020; Mao et al., 2019). Consequently, a robust centralized storage and processing is needed. Currently, IoT devices with little or no storage space need centralized ML for synchronized data processing; hence, a lack of synchronization may result in inaccurate or no results. Additionally, due to the limited capacity of IoT devices, processing takes longer, and in certain instances, even a tiny delay might have disastrous effects on the system (Phuyal et al., 2020). To address these issues, the use of a dynamic network is being proposed (Ismayilov & Topcuoglu, 2020; Ruuskanen et al., 2021; Yue et al., 2022; Zhang et al., 2022b). The egg industry needs to emphasize the generation of quality data, further usage for processing, and the invention of energy-efficient devices and IoT sensors. Low-cost and energy-efficient dedicated hardware and platforms for AI are available on a certain scale, such as the NVIDIA Jetson developer kits. Data filtering, real-time analysis to minimize cloud or central storage, application of a pre-defined approach for data sorting, and freeing up storage space by periodic deletion of older data can optimize data storage, reduce cost, and improve overall performance. However, this area needs to be explored more to implement a sustainable AI- and IoT-based CPS.

The impacts of using AI for one service ahead of another and one network segment for a particular purpose versus another must be allocated correctly. For example, collecting and processing raw data and spreading the resultant information or judgments of AI may raise communication overhead, resulting in data traffic that causes delays in various network operations, such as navigation or authentication protocols. Therefore, it is important to explore the resultant issues in the underlying network architecture as a consequence of the incorporation of AI techniques into the communication network infrastructures that the IoT will use. AI-, IoT-, and cloud-based systems need device-to-device and end-user communication. Sharing digital information requires network security at several points across the system, including universal identity and end-to-end file encryption (AlAhmad et al., 2021; Sun, 2020). Every network node must be protected against abuse or cyber threats. Furthermore, malware, invasion, and data outlier detection should receive greater attention with all connected devices. Existing limitations on transmission bandwidth, operating frequency, communication mode, and hardware capabilities, among others, provide a formidable obstacle to the interoperability of the intelligent cloud-based system (Ahmad et al., 2021). An AI-, IoT-, and cloud-based system may become unresponsive, lose the ability to control it remotely, face cyber security issues, or completely lose functionality. Therefore, a sustainable system should consider redundancy measures, backup systems, failover mechanisms, and disaster recovery plans to ensure system resilience and minimize downtime. Extensive research is required to ensure a functional system. Standards, norms, and models must be established for successful cloud-based interoperable systems.

The utilization of automated and intelligent technologies has opened the door to the next level of integration, generally referred to as the intelligent industry, which leverages data and information from industry to end-users through cloud computing. To efficiently apply AI–IoT systems in EI 4.0, allied technologies like CPS, data mining, augmented reality, the IoT, and robotics technology must be used effectively. However, there is a big gap between such intelligent EI 4.0 and the existing egg production industry, which provides significant opportunities. AI and IoT have become significant. The IoT market is seeing exponential growth, and the IoT sector is anticipated to increase 10-fold by 2025 (Saha et al., 2022). In the future, all IoT will be adopted to perform almost all tasks by automation. Crewless aerial vehicles, swarm robotics, or automatic guided vehicles (AGV) with self-loading and unloading capacity are other important prospects. With the help of ML and cloud computing, remotely controlled AVG could be used for purposes such as cleaning and transportation. Vision cameras, radio waves, or lasers for navigation with IoT technology are other prospects, leading to a smart egg industry. However, using AI processes needs a thorough examination of the repercussions with respect to different benchmarks.

I4.0 is a realistic approach since it increases productivity, reduces operating and labor costs, and provides accurate and reliable data for management and planning. However, a successful transition from the present egg industry to I4.0 must overcome several challenges, such as initial costs, a lack of flexibility to adapt to the current industrial environment, and a lack of technical expertise. Despite significant technological improvements, there are still obstacles to operating a robust EI 4.0. Challenges include growing digital inequality, access to energy and other resources, system standardization, data interoperability, control and security, and adaptability for small-size egg processing facilities. Given the focus on creating technological advancements and digital solutions, and the continuous close cooperation needed between many stakeholders and academics, the present difficulties are expected to be resolved. Cyber security is seen as the biggest concern in the I4.0 idea based on the need for intelligent factories. Smart factories may be susceptible to vulnerability exploitation, malware, denial of service, system hacking, and other frequent attacks that affect other digital systems since every linked component has a potential risk. Sufficient research innovation and regular system validation of all interconnected systems are required to prevent cyberattacks or industrial espionage.

Another important aspect of sustainability for the intelligent industry is skilled operators. Employees must be qualified to handle the new technology concepts and have good work and technical competencies. However, sourcing people with competent skills is a challenge and a potential obstacle to implementing EI 4.0. As discussed, calibration transfer and model adaptation in new devices are still challenges; the industry needs new deep-learning techniques to overcome these problems. Processing data from AI devices or sensors requires the development of new algorithms for effective decisions. Finally, deploying a high-speed industrial network is necessary for the interconnectivity and interoperability of the I4.0 systems. Hopefully, the poultry and egg industries are trying to replace conventional techniques with different I4.0 or AI technologies to save time, energy, and cost. However, transformation to I4.0 may not always be sustainable. While I4.0 offers numerous advantages and opportunities, small industrial establishments may encounter several obstacles when employing these technologies. Implementing I4.0 technologies could require a substantial initial investment. Investing in new equipment, sensors, data analytics systems, and training may be difficult for small enterprises. Costs for ensuring scalable and flexible EI 4.0 systems, including data security and system management, can be a barrier for small enterprises. However, starting with smaller-scale implementations, collaborating with business partners, leveraging cloud-based solutions, and focusing on specific areas that provide the most immediate benefits, small-size egg processing facilities can gradually integrate I4.0 technologies and leverage their advantages. Currently, small and portable I4.0 devices have shown potential in various applications (Eyvazi et al., 2021; Harpaz et al., 2022; Lu et al., 2019; McVey et al., 2021). For example, such portable technologies will increase on-site or in-line assessment of egg quality parameters. Additionally, it is anticipated that the current AI and deep-learning boom will contribute to creating more robust algorithms for accurate and real-time applications of such handheld devices. Developing smartphone-based apps will provide significant prospects for remotely controlling automated systems.

5 | CONCLUSIONS

The egg industry has to deal with increased consumer demand, higher consciousness, introduction of fabricated eggs, animal welfare, biosecurity, and other contemporary issues. The ongoing COVID-19 pandemic has further fueled the demand for shell eggs, focusing on different quality parameters such as nutritional composition, including, omega-3 FA content. To meet these demands, the egg industry needs to adopt I4.0 technologies for the smart categorization of eggs with higher efficiencies. I4.0 consists of the IoT, industrial IoT (IIoT), cloud computing, big data analysis, simulation, and cyber security, which ensures the automation of industrial activities with high interconnections and blurs the boundary of the physical world. This review covered the components of I4.0 for eggs with a special focus on non-invasive optical sensing technologies for fast and accurate egg characterization. Traditional egg quality determinations and categorizations practices are tedious, require chemical analysis, and are destructive. But, different I4.0 technologies, such as optical sensing devices, are gaining popularity due to being fast, accurate, chemical free, and most notably because of their non-destructive or non-invasive nature. The various studies discussed in this review confirm that HSI or spectroscopic technique coupled with appropriate multivariate analysis provides better and faster results than conventional practices. Despite significant technological improvement, I4.0 technologies have limitations like cyber security, network stability, data interpretability, algorithm transfer, and system control. The existing drawbacks could be resolved given the focus on smart solutions and the continuous cooperation between academia and industry.

AUTHOR CONTRIBUTIONS

Md Wadud Ahmed: Conceptualization; methodology; investigation; writing—original draft; writing—review and editing. **Sahir Junaid Hossainy**: Writing—original draft. **Alin Khaliduzzaman**: Conceptualization; writing—review and editing. **Jason Lee Emmert**: Writing—review and editing; funding acquisition; project administration. **Mohammed Kamruzzaman**: Conceptualization; funding acquisition; writing—review and editing; project administration.

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CONFLICT OF INTEREST STATEMENT

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