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Review

Internet of Things and Machine Learning techniques in poultry health and welfare management: A systematic literature review

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ABSTRACT

The advent of digital technologies has brought substantial improvements in various domains. This article provides a comprehensive review of research emphasizing AI-enabled IoT applications in poultry health and welfare management. This study focused on poultry welfare since modern poultry management is confronted with issues relating to standardized parameters for welfare assessment and robust monitoring systems, particularly for broilers' health and disease outbreak prevention. Evidence has shown that modern digital technologies have high possibilities for intelligent automation of current and future poultry management operations to facilitate high-quality and low-cost poultry production. Therefore, this study presents a systematic review of the current state-of-the-art AI-enabled IoT systems and their recent advances in developing intelligent systems in this domain. Also, the study provides an overview of the critical applications of identified digital technologies in poultry welfare management. Lastly, the study discusses the challenges and opportunities of AI and IoT in poultry farming.

1. Introduction

The demand for poultry meat is progressively increasing because of its high protein, low energy, and low cholesterol (Lashari et al., 2018). However, poultry high production depends on the environmental condition, disease outbreaks, breeding process, and active management operations (Lashari et al., 2018). Therefore, efficient poultry health and welfare management is essential to prevent infectious diseases, boost production, and ensure healthy broilers. Nevertheless, traditional chicken poultry welfare management approaches are fraught with high labour costs and inefficient resources management, i.e., feed, water, and power consumption. In this context, the integration of Internet of Things (IoT) and Machine Learning (ML) has been considered promising technologies for delivering smart poultry farming, continuous data monitoring and prescriptive analytics in order to address the above identified challenges for efficient resource control and optimal decision-making (Fang et al., 2021; Ribeiro et al., 2019). Accordingly, Raj and Jayanthi (2018) posited that AI-enabled IoT systems could help poultry farm owners enhance production while substantially lowering costs.

IoT comprises many physical sensing devices connected to a Wide Area Network (WAN) to collect, share, and convey information for analysis purposes, while ML is a computational process of unearthing new insights and facts through analytics and a learning process (Michalski et al., 2013). Evidence abounds in the literature on how IoT technologies have been used to assess and control variables such as temperature, humidity, vibration, and air pollutants in poultry houses (Lashari et al., 2018; Lin et al., 2016; W. Pereira et al., 2020). Moreso, poultry feeding and watering systems can incorporate IoT for optimal disease control and management to increase production, enhance safety, and improve profit (Lashari et al., 2018; Ribeiro et al., 2019). When fed into ML, IoT data have been used to detect and classify diseases that are known to have devastating impacts on poultry production and human health, especially the zoonotic poultry pathogens (Cuan et al., 2020).

Due to the recent advances in AI-enabled IoT systems for poultry welfare management, this study presents a systematic survey of the current state-of-the-art technologies regarding poultry health and welfare management. A growing body of literature on digital technology applications in the agro-industry has been published in recent years, however, available peer-reviewed articles on AI-enabled IoT systems in poultry health and welfare management are very scarce. Besides, most of the earlier studies are focused on specific aspects of poultry welfare

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Nomenclature

ABN	Additive Bayesian Network
NH3	Ammonia
AUC	Area Under the Curve
ANN	Artificial Neural Networks
BANN	Bayesian Artificial Neural Network
BMLR	Bayesian Multivariate Linear Regression
BN	Bayesian Network
BiLSTM	Bidirectional Long Short-Term Memory
CO_2	Carbon Dioxide
CO	Carbon Monoxide
CNN	Convolutional Neural Networks
DT	Decision Trees
DNN	Deep Neural Network
DST	Dempster-Shafer Theory
DCT	Discrete Cosine Transform
ELM	Extreme Learning Machines
FFT	Fast Fourier Transform
FL	Fuzzy Logic
GRU	Gated Recurrent Unit
GSP	Generalised Sequential Pattern
GLM	Generalized Linear Model
GA	Genetic Algorithm
GBM	Gradient Boosting Machines
kNN	K-Nearest Neighbours
LD	Linear Discriminant
LR	Linear Regression
LSTM	Long Short-Term Memory
ME	Maximum Entropy
MTPE	Mixed Tracking Performance Evaluation
MS	Mean Shift
NB	Naïve Bayes
NF	Neuro-Fuzzy
PSO	Particle Swarm Optimization
PCC	Pearson Correlation Coefficient
QD	Quadratic Discriminant
RF	Random Forests
RCE	Rapid Centroid Estimation
RNN	Recurrent Neural Network
RE	Relative Error
RH	Relative Humidity
SPM	Sequential Pattern Mining
SD	Standard Deviation
SVM	Support Vector Machines
WS	Weighing Systems
OpenCV	Open-Source Computer Vision Library

management, including smart poultry management in the contexts of sensors, big data, and IoT (Astill et al., 2020), application of IoT in the agro-industry and environment (Talavera et al., 2017), poultry weight and volume estimation with computer vision (Nyalala et al., 2021), and computer vision in welfare management (Okinda et al., 2020). Others have also looked into sound analysis developments in animal health and welfare monitoring (Mcloughlin et al., 2019) and analysis of ML application in broilers growth and health prediction (Milosevic et al., 2019). Regardless of the above, a systematic review of earlier literature on AI-enabled IoT with ML remains a desirable but unresearched area with the body of literature.

Based on the above, this study aimed to provide a proper synthesis for clear guidance on the state-of-the-art techniques and the potential future direction of digital technology-enabled welfare management in chicken production. Therefore, this work focussed on up-to-date research advances to provide valuable technical information to develop more relevant and reliable digital technologies for health and welfare management in chicken production. The authors provided information, specifically in the context of data aspects (i.e., data measured and types, critical features for models), data processing and analysis methods, hardware, and software for poultry health and welfare management. Thus, this study meets the expectations of poultry managers and other stakeholders concerning efficient welfare management through AI-enabled IoT systems by providing an extensive appraisal of up-to-date digital technology solutions for poultry health and welfare management in breeding farms from 2010 to 2022. Additionally, the study discussed trends, opportunities, and challenges in this sector.

The rest of the paper is organized as follows: Section 2 presents the methodology for selecting articles used in the review. Section 3 discusses the various applications of AI/ML and techniques in poultry health and welfare management, processing techniques, and sensor technologies in poultry welfare. In section 4, key challenges in poultry welfare management are discussed. Section 5 illustrates the proposed framework and implication. Finally, the conclusions achieved from the study are discussed in section 6.

2. Research methodology

This study adopted a Systematic Literature Review (SLR) methodology, as recommended in (Torres-Carrion et al., 2018). SLR methodology uses a thorough and distinct approach for research synthesis, with the main objective of assessing and possibly minimising bias in the findings (Bearman & Dawson, 2013). In obtaining a comprehensive analysis of relevant literature, articles from four popular academic databases IEEE Xplore, Science Direct, Google Scholar, and Taylor & Francis Online were examined. The authors selected these databases for the literature search based on the comprehensive coverage of their quality peer-reviewed articles and conference proceedings.

Coming from the above, the research questions for this study are: (i) How have IoT and ML been used for chicken poultry health management? and (ii) How have chicken poultry health and welfare systems been previously developed based on IoT and ML? To adequately answer these research questions, a literature search was conducted using the following keywords: ("data mining" or "machine learning" or "deep learning" or "sensor networks" or "IoT technology") and ("poultry welfare" or "poultry health" or "smart poultry"). Thereafter, a pair of keywords from the two classes were combined to search the selected databases. Specifically, 18 rounds of searches were conducted in each database, which resulted in initial 2328 documents. Subsequently, duplicate articles (1567) due to four of the literature databases' overlapping were removed, leaving 761 articles and conference proceedings for further processing. Finally, inclusion and exclusion criteria (depicted in Table 1), were applied to further reduce the collected articles to 147

Table 1
Inclusion and exclusion criteria for selecting articles.

Inclusion	Scientific articles or conference proceedings
	Belong to Computer Science or Engineering
	Belong to Agricultural and Biological Sciences
	Belong to Veterinary Science and Veterinary Medicine
	Publications in English
	Publication year: 2010 – June 2022
Exclusion	Patents
	Publications not available for full review

after this procedure.

Hereafter, the quality of documents was evaluated through an exhaustive review to ensure they were relevant to the study's research questions. For example, concerning poultry health management, each article was checked to determine whether it satisfies the following:

Explains the use of ML or deep learning in poultry health and welfare,
Describes the use of IoT or sensors to enrich data collection in poultry health and welfare, and,
Describes smart poultry management systems in the context of Precision Livestock Farming (PLF).

A Precision Livestock Farming (PLF) system employs data collection and monitoring, analysis, ML, control systems, and ICT. Consequently, a total of 93 articles for the period between 2010 and 2022 were left for further analysis after the selection and filtering procedures. These 93 articles provided a representative sampling of IoT and ML applications in poultry health and welfare management. Table 2 shows the number of selected articles by journals and conference proceedings. The current study found the top four journals outlets related to IoT and AI in poultry health and welfare management as Computers and Electronics in Agriculture (26 papers), Biosystems Engineering (14 papers), Information Processing in Agriculture (3 Papers), Poultry Science (3), and Sensors (3 papers). Also, IEEE organized conferences have the largest number of papers (9) related to IoT and ML when compared to other conferences.

Table 2
Selected articles and conference proceedings.

	Publishers	Journal Title	Count
Journals	Elsevier (61)	**Computers and Electronics in Agriculture**	**26**
		Biosystems Engineering	**14**
		Information Processing in Agriculture	**3**
		Poultry Science	**3**
		Applied Animal Behavior Science	2
		Expert Systems with Applications	2
		Applied Acoustics	1
		Engineering in Agriculture, Environment and Food	1
		Food Research International	1
		Journal of Environmental Management	1
		Computational Biology and Chemistry	1
		Journal of Environmental Chemical Engineering	1
		Animal	1
		Procedia Computer Science	1
		Heliyon	1
		Preventive Veterinary Medicine	1
		Science of the Total Environment	1
	MDPI (6)	**Sensors**	**3**
		Agriculture	1
		Animals	1
		Entropy	1
	Taylor & Francis (2)	British Poultry Science	1
		International Journal of Production Research	1
	Royal Society (2)	Journal of the Royal Society Interface.	2
	Cambridge (2)	Animal	1
		World's Poultry Science Journal	1
	Springer (1)	Neural Computing and Applications	1
	BMC (1)	Journal of Animal Science and Biotechnology	1
	IJABE (1)	International Journal of Agriculture and Biological Engineering	1
	World Scientific (1)	International Journal of Pattern Recognition and Artificial Intelligence	1
	Universiti Malaysia (1)	Pertanika Journal of Science and Technology	1
	PLoS One (1)	PLoS One	1
Conferences	**IEEE (9)**	**IEEE conference proceedings**	**9**
	Others (5)	Springer conferences	2
		Other conferences	3
		Total	93

3. Results and discussion

3.1. Quantitative content analysis

(1) Publication's timeline- The 89 articles published from January 2010 to June 2022 revealed the rapid interest in AI-enabled IoT technologies for poultry welfare management. As shown in Fig. 1, IoT or ML applications for chicken poultry health and welfare management could be divided into three phases according to their publication year. The first phase, 2010 to 2013, had a relatively small number of articles due to the complexity and limited coverage of applying the latest digital technologies in poultry health management. Thus, they have not received much academic attention. The second phase, 2014 to 2018, showed the number of related articles increasing slightly, indicating a growth in the research interest in digital technologies for chicken poultry health and safety management. Finally, the third phase from, 2019 to 2022, revealed a sharp increase in IoT and AI, especially the deep learning research for poultry health and welfare management. A slight drop in publications is noticeable in 2021 and 2022, probably due to Covid-19 impacts on quality research outputs. However, it is anticipated that this number will continue to surge, considering the success of deep learning-based models over classical ML-based approaches in other application domains.

(2) Geographical distribution- Fig. 2 summarizes the country of origin of the selected papers. Every continent is represented by at least one research work as follows: Africa (4, 3.22 %), America (24, 26.88 %), Asia (33, 35.48 %), Europe (31, 33.33 %), and Oceania (1, 1.07 %). China has the largest number of peer-reviewed papers, followed by the USA, Brazil, and Belgium. It is interesting to note that Chinese researchers have been actively involved in this research area because China is home to several artificial intelligence and sensor superpowers and are heavily investing in agriculture, including animal production.

(3) Word distribution- In this study, 86 articles were text mined for common words relating to IoT and ML in poultry management and constructed a word cloud (a holistic picture) of IoT and ML's main applications in this domain. Fig. 3 revealed common IoT and ML applications as environment monitoring (i.e., temperature and humidity), behavior monitoring (i.e., eating, walking, pecking), disease detection and classification, and control. Most frequently used ML techniques include Support Vector Machines (SVM), deep learning, Bayesian networks, linear regression, neural networks, and decision trees. Everyday IoT technology for data acquisition includes cameras, microphones, and sensors. The visualization in Fig. 3 will enable stakeholders (designers and farm managers) to be well informed of relevant IoT and ML knowledge in poultry welfare management.

3.2. Applications of IoT and Machine learning in poultry welfare monitoring

This subsection presents the Systemic Literature Review (SLR) results (Tables 3, 4, and 5) concerning answers to research questions. Consequently, the leading IoT and ML applications in poultry health and welfare management were identified in the literature as (1) Behavior/Environment monitoring, (2) Disease Analytics, and (3) Control/Intervention. Also, Fig. 4 summarizes a holistic view of digital technology for poultry health and welfare applications, AI/ML techniques, tools, data monitored, data types, processing types, diseases, and health status.

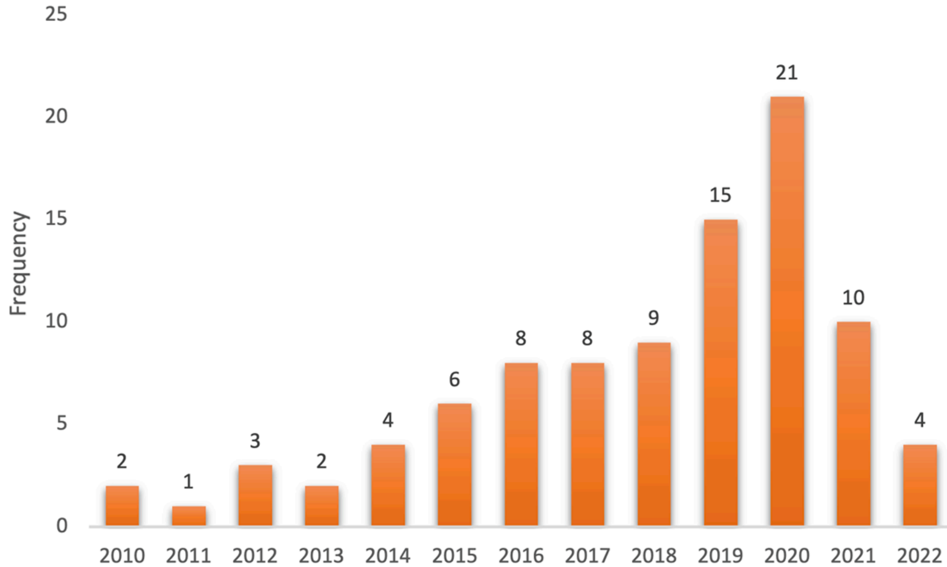

Fig. 1. Selected papers distribution by publication year.

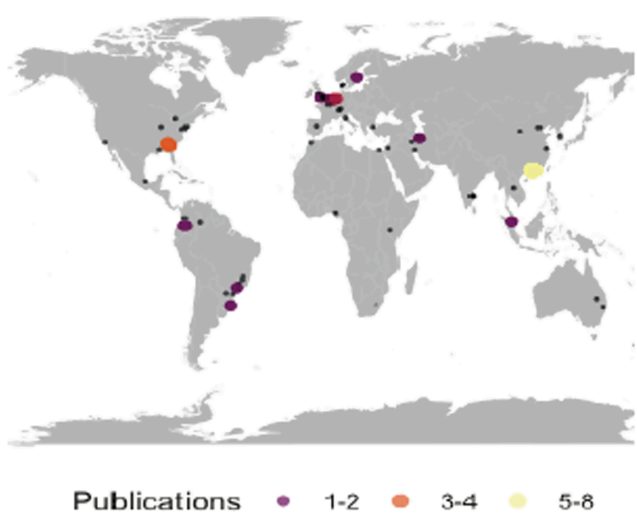

Fig. 2. Selected papers distribution by country.

3.2.1. *Behavior/Environmental monitoring*

In this category (Table 3), the selected papers numbering about 57 (61.29 %) focused on systems that remotely monitor chicken behavioral characteristics, i.e., feeding, resting, running, and environmental parameters (temperature, relative humidity). This intervention's main idea is to add value to poultry farmers by facilitating automated acquisition of relevant data using IoT technologies (i.e., sensors, cameras, microphones, mobile phones) and transmitting such to a server or cloud for instant processing and visualization. These automated monitoring systems facilitate the continuous measurements of broilers in a non-intrusive and non-invasive way.

To support farmers in welfare issues especially in risk evaluation, these studies highlight broilers physiological responses, i.e., respiratory rate and cloacal temperature (Bloch et al., 2020; Branco et al., 2020; Carpentier et al., 2019; Hernández-Julio et al., 2020), gender determination (Cuan et al., 2022a; Yao et al., 2020), posture and activity monitoring (Aydin, 2017; Banerjee et al., 2012; Cheng et al., 2019; de Alencar Nääs et al., 2020; Feiyang et al., 2016; Kashiha et al., 2014; Li et al., 2021; Nasiri et al., 2022; Neves et al., 2015; Sirovnik et al., 2021; Van Hertem et al., 2018; J. Wang et al., 2020; Zaninelli et al., 2018) for comprehensive behavioral expression assessments.

Others sought to monitor real-time changes in body weights (Amraei et al., 2017a; Amraei et al., 2017b; Fontana et al., 2015; Mollah et al., 2010; Mortensen et al., 2016), oviposition events (You et al., 2021), feed or water consumption and feed conversion ratio optimization of poultry birds (Aydin et al., 2015; Aydin & Berckmans, 2016; Huang et al., 2021; Kakhki et al., 2019; Kashiha et al., 2013; Li et al., 2020a; Li et al., 2020b). Comin *et al.* (2019) identified and interpreted the associations between housing system, rearing facilities, farm management, and welfare indicators in laying hens; and speculated about the potential causative role of variables directly and indirectly associated with the welfare status of the flock.

Similarly, studies such as those from Debauche et al. (2020), Fernández et al. (2018), Lashari et al. (2018), Lin et al. (2016), and Rico-Contreras et al. (2017) monitored and controlled changes (i.e., temperature, moisture and faeces content, humidity, ammonium, and pest species monitoring) in the poultry environment. Also, Kashiha et al. (2013) monitored the automated broiler house to detect problems and report malfunctioning feeders and drinkers.

3.2.2. *Disease predictive analytics*

Identifying diseases early enough to avoid disease spread is a big challenge in the poultry business. However, studies abound that introduced technologies to facilitate accurate, rapid detection and diagnosis of poultry diseases to decrease the time and effort needed to manage large livestock numbers. In this category (Table 4), the selected papers were 24, representing 25.81 % of the reviewed articles. These articles discussed strategies for efficient disease management in poultry. For instance, studies such as those from Banakar et al. (2016), Carpentier et al. (2019), Cuan et al. (2020), Du et al. (2018), Golden et al. (2019), Ismail et al. (2016), Okinda et al. (2019), Rizwan et al. (2016), Zhang and Chen (2020), and Zhuang et al. (2018) were interventions to decrease the need for manual observations and human decision making regarding disease detection.

Poultry diseases and infections commonly examined are Newcastle Disease Virus (Aziz & Othman, 2017; Banakar et al., 2016; Carroll et al., 2014; Cuan et al., 2022b; Mahdavian et al., 2021), avian influenza (Banakar et al., 2016; Cuan et al., 2020; Huang et al., 2019; Ismail et al., 2016; Qiang & Kou, 2019; Xu et al., 2017), bursal diseases (Fang, 2019), Salmonella (Hwang et al., 2020), hock burn (Hepworth et al., 2012), and *Listeria spp* prevalence (Golden et al., 2019). Standard methods for identifying sick birds include analyzing eating patterns (Li et al., 2020b), poultry movement patterns and postures (Banerjee et al., 2012; Fang et al., 2021; Zhuang & Zhang, 2019), weight checking (Amraei et al.,

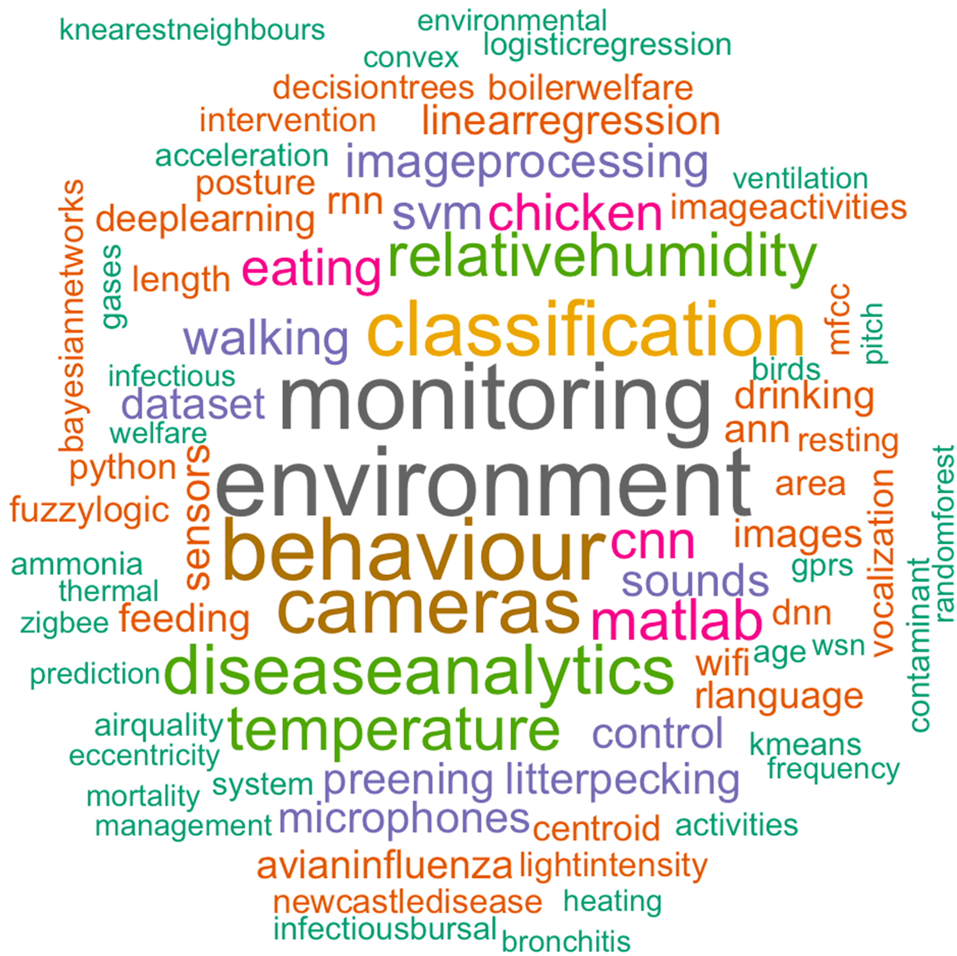

Fig. 3. Word Cloud of key IoT and AI applications in poultry.

2017b), and poultry sound analysis (Aydin et al., 2015; Carpentier et al., 2019; Du et al., 2018; Rizwan et al., 2016).

3.2.3. *Control intervention in poultry health management*

Proper monitoring of environmental parameters, i.e., temperature, humidity, ventilation, and lighting in poultry houses, is essential to guarantee optimal rearing conditions. In addition, their simultaneous supervision and control will reduce energy consumption and increase productivity (Sitaram et al., 2018). Studies (12, 12.90 %) in this category (Table 5) highlight the use of sensors to monitor and control environmental conditions by activating appropriate devices, i.e., ventilations, lightning, cooling, and heating systems (Choukidar & Dawande, 2017; Demmers et al., 2010; Gunawan et al., 2019; Lahlouh et al., 2020; Li et al., 2020a; Lorencena et al., 2020; Mirzaee-Ghaleh et al., 2015; So-In et al., 2014). For instance, Zhang and Chen (2020) developed an automatic detection system for sick chickens based on the ResNet residual network (accuracy of 93.70 %) to monitor broilers' behavioral physiology and production performance.

Also, Lorencena et al. (2020) proposed a framework to control and supervise temperature and humidity to aid optimal decision-making in poultry farming. In the same vein, Gunawan et al. (2019) developed a system to maintain the optimum environmental conditions, where ammonia and carbon dioxide levels were regulated using exhaust DC fans. Similarly, humidity and temperature were controlled by DC fans and heat lamps. Water quality management in poultry farms is essential for chicken growth and for controlling bacterial diseases. Thus, Choukidar and Dawande (2017) connected sensors to a Raspberry Pi to control the water level and other parameters, i.e., temperature, smoke, gas, and food dispensing in a poultry farm. Furthermore, So-In et al. (2014) developed a low computational complexity system of 80.00 % accuracy to automatically adjust the poultry environmental behavior using temperature, humidity, light intensity, and population density.

In addition, feeding systems optimization is necessary for improved production efficiency and animal welfare to promote leg health in broiler chickens. Thus, control strategies to optimize feeding over the entire period of growth to reduce the feed intake and cost have been developed (Demmers et al., 2010, 2018; Kakhki et al., 2019; Klotz et al., 2022). Finally, Lahlouh et al. (2020) developed a system with a 97.00 % accuracy to control hygro-thermal parameters (temperature and relative humidity) and contaminant gases to provide appropriate conditions suitable for efficient poultry production.

3.3. *AI/ML techniques for poultry health and welfare management*

Research in machine learning (ML) has been concerned with building computer programs to construct new knowledge or improve already possessed knowledge by using input information (Michalski et al., 2013). Thus, ML-based techniques generally consist of feature extractors that transform raw data (i.e., pixel values of images) into feature vectors and learning subsystems that regress or classify patterns in the extracted features. However, constructing feature extractors in conventional ML requires laborious adjustment and considerable technical expertise, which limits their applications (LeCun et al., 2015). In contrast, deep learning techniques, developed from conventional ML techniques, are representation-learning methods that can automatically discover features (or data representation) from raw data without extensive engineering knowledge on feature extraction (LeCun et al., 2015). Different deep learning architectures available are deep neural networks,

Table 3
IoT and ML for poultry behavior and environment monitoring.

Reference	Metric	IoT devices	Algorithms	Measures	Purpose
Amraei et al. (2017a)	R-Squared 0.98	Cameras	ANN	Poultry activity images	Broiler body weight
Amraei et al. (2017b)	R-Squared 0.98	Cameras	SVM	Poultry activity images	Broiler body weight
Aydin (2017)	R-Squared 0.99	Cameras	Classification	Speed, step frequency, step length, body oscillation	Predict lameness
Aydin et al. (2015)	Accuracy 86.00	Sensors, WS	LR	Pecking sound, appearance, feed uptake	Monitor feed intake
Aydin and Berckmans 2016	R-Squared = 0.97	Microphones	LR	Pecking sounds, feed intake	Feeding behavior
Banerjee *et al.*(2020)	Accuracy 82.60	Sensors	DT, NB, ANN	Accelerometer data	Broiler activity recognition
Bloch et al. (2020)	Accuracy 0.27 °C	Thermal sensors	Lasso	Age, temperature	Heat stress
Branco et al. (2020)	–	Sensors, Cameras	GSP	Eating, walking, litter pecking, dust bathing	Heat stress
Cao et al. (2021)	Accuracy 93.80	Cameras	CNN	Eating, drinking, and jumping	Estimate chicken density
Cheng et al. (2019)		Cameras	CNN	Poultry activity images	Estimate chicken density
Comin *et al.* (2019)	–	Historical data	ABN	Lighting, air quality, housing variables, flock information	Analyze housing and hens' welfare
Cuan et al. (2022a)	Accuracy 91.25 %	Digital voice recorder, Camera	CNN, LSTM, GRU	Sound	Gender detrmination
Dawkin *et al.* (2021)	–	Cameras	BMLR	Activities	Monitor boiler welfare
De Alencar *et al.* (2020)	Accuracy 91.00	Cameras	DT	Walking speed, acceleration, genetic strain, sex	Lameness prediction
Debauche et al. (2020)	–	Sensors	GRU	Temperature, RH, CO, CO_2, light intensity, water level	Air quality prediction (NH3 rate)
Diez-Oliva *et al.* (2019)	Accuracy > 81.00	GPRS, sensors	RF	Humidity, temperature	Estimate lame, mortality, and weight
Du et al. (2018)	Accuracy 74.70	Microphones		Flock's number of vocalizations, location	Monitor layers' abnormal sound
Fang et al. (2020)	MTPE 0.73	Cameras	DNN	Movement speed	Target tracking
Fang et al. (2021)	Accuracy94.00 (eating) ,96.00 (resting)	Cameras	DNN, NB	Activities	Pose estimation, behavior classification
Feiyang et al. (2016)	kappa 0.78	Sensors, WS	K-means	Eating, resting, moving	Classify activities
Fernández et al. (2018)	R^2 0.70	Cameras	LR	Feeding, drinking, resting	Evaluate welfare risk issues
Fontana et al. (2015)	R^2 0.98	Microphones	LR	Hens voice data	Growth estimation
Geffen et al. (2020)	Accuracy 89.60	Cameras	CNN	Broiler image	Detect and count laying hens
González et al. (2017)	PCC 0.90	Cameras	LR	Movement	Monitor poultry activities
Guo et al. (2020)	R-Squared 0.99	Cameras	ANN, K-means, FuzzyC	Activities	Chicken floor distribution analysis
Hernández-Julio et al. (2020)	R-Squared 0.99	Historical data	FL, Fuzzy-Genetic	Bulb temperature, stress duration (days)	Estimate cloacal temperature
Huang et al. (2021)	Accuracy 96.00	Microphones	RNN	Poultry, wings flapping, trampling sounds	Classify eating and normal vocalizations
Johansen et al. (2019)	RMSE 66.80 g	Sensors/Historical	DNN	Heating, ventilation, temperature, RH, light intensity	Weight, feed/water consumption
Jung et al. (2021)	Accuracy 75.80	Microphones	CNN	Voice data of laying hens	Recognize laying hens sounds
Kashiha et al. (2013)	Accuracy 95.20	Cameras	LR	Feeding, drinking, movement	Report faults in broiler houses
Kashiha et al. (2014)	Accuracy 95.90	Cameras	–	Hens movement, occupancy	Monitor ammonia aversion
Küçüktopcu and Cemek (2021)	R-Squared 0.86	Sensors	Neuro-fuzzy, ANN	Temperature, RH, airspeed, litter moisture	Estimate ammonia concentration
Lashari et al. (2018)	Unspecified	Sensors	–	Temperature, RH, CO, CO2, NH3	Monitor poultry environment
Li et al. (2020a)	Accuracy 89.10	Cameras	CNN	Moving heads of hens drinking	Detect drinking behavior
Li et al. (2020b)	Accuracy 93.00	Cameras	LR	Broiler behaviors	Monitor feeding/drinking behaviors
Li et al. (2021)	Accuracy 99.50	Cameras	CNN	Chicken image	Detect stretching birds
Lin et al. (2016)	R-Squared 7.00	Sensors	–	RH, temperature	Measure ammonium
Ma et al. (2020)	RE 3.00	Cameras, WS	ANN	Daily weight gain, day-age, average velocity, weight	Broiler body weight
Mehdizadeh et al. (2015)	R-Squared 0.99	Cameras	LR	Broiler image	Detect broiler feeding behavior
Mollah et al. (2010)	R-Squared 0.99	Cameras	LR	Broiler image	Predict broiler body weight
Mortensen et al. (2016)	RE 7.80 %	Cameras	LR, ANN, BANN	Broiler image	Predict broiler body weight
Nasiri et al. (2022)	Accuracy 97.50 %	Cameras	CNN-LSTM	Broiler image	Lameness recognition
Neves et al. (2015)	R-Squared 0.74	Cameras	GLM	Activities images	Assess feeders' effects on behavior
Pereira et al. (2013)	Accuracy 70.30 %	Cameras	DT	Activities image	Broiler behavior
Pereira et al. (2020)	R-Squared 0.90	Sensors	Least Squares	Temperature, RH, luminosity	Monitor ecological parameters
Pu et al. (2018)	Accuracy 99.20 %	Cameras	CNN	Activity images	Recognize chicken behavior
Reboiro-Jato et al. (2011)	RE 1.02	Historical data	DT, ANN	Feed consumption, mortality indices, feeder types	Feed utilization
Ribeiro et al. (2019)	Unspecified	Sensors/Historical	ANN	Ventilation, environment control, spraying, heating	Action plans for pen management
Rico-Contreras et al. (2017)	R-Squared 0.93	Historical data	ANN, FL	Density, temperature, days, feeder type, drinker type	Predict litters moisture content

(*continued on next page*)

Table 3 (*continued*)

Reference	Metric	IoT devices	Algorithms	Measures	Purpose
Roberts et al. (2012)	Unspecified	Cameras	BN	Activity images	Broiler welfare
Sirovnik et al. 2021	Unspecified	Cameras, Sound	GLM	Activity images	Chickens movement manipulate onto elevated platforms for roosting
Van Hertem et al. (2018)	R-Squared 0.92	Cameras	LR, PCA	Age, walking speed and acceleration, genetic strain, sex	Lameness recognition
Wang et al. (2016)	Precision 92.10 %	Cameras	SVM	Activity images	Track layers
Wang et al. (2020)	Accuracy 96.90 %	Cameras	CNN	Activities- feed, stand, fight, spread, mate, drink	Track layers, abnormal behavior
Yao et al. (2020)	Accuracy 96.00 %	Cameras	CNN	Drinking water, eating, waving wings	Gender classification
Sibanda et al. (2020)	Precision 92.10 %	Sensors	K-means	Housing variables, flock information	Resource usage
Zaninelli et al. (2018)	Sensitivity 95.70 % Specificity 95.40 %	Sensors, Cameras		Hens images	Track layers/detect nests occupancy

Table 4
IoT and ML for poultry disease analytics.

Reference	Metric	IoT devices	Algorithms	Measures	Purpose
Aziz and Othman (2017)	Accuracy 93.80	Cameras	SVM	Chickens' excrement image	Diagnose respiratory problems
Banakar et al. (2016)	Accuracy 91.20	Microphones	SVM, DST	Sound	Diagnose respiratory problems
Belkhiria et al. (2020)	AUC > 0.70	Historical data	RF, ME	Location, viral subtypes, broiler species & density	Diagnose respiratory problems
Carpentier et al. (2019)	Precision 88.40	Microphones	LD	Sneezing sounds	Detect sneezing in chickens
Carroll et al. (2014)	Accuracy 73.40	Cameras, sensors	DT	Sound, activities, temperature, RH	Detect rales
Cuan et al. (2020)	Accuracy 97.40	Microphones	RNN, CNN	Sound, swab samples	Diagnose respiratory problems
Cuan et al. (2022b)	Accuracy 98.50	Cameras	BiLSTM	Sound, images	Diagnose respiratory problems
Fang (2019)	–	Sensors	Logistic, ANN	RNA microarray	Diagnose respiratory problems
Golden et al. (2019)	AUC 0.91	Sensors	RF, GBM	Faeces/soil sample, temperature, RH, wind speed	*Listeria spp* prevalence
Hemalatha & Maheswaran (2014)	Accuracy 96.60	Sensors, Cameras	SVM, ELM	Postures and activities	Diagnose Fowlpox
Hepworth et al. (2012)	Accuracy 0.78	Historical data	SVM; Logistic	Stocking density, mortality rates, average weight	Diagnose Hock burn
Huang et al. (2019)	Accuracy 90.00	Microphones	SVM	Chicken sound	Diagnose respiratory problems
Hwang et al. (2020)	AUC 0.88	Cameras, sensors	RF	Faeces/soil sample, temperature, RH, wind speed	Salmonella prevalence
Ismail et al. (2016)	Precision 0.99	Historical data	K-means, RCE	Type, subtype, segment, sequence length	Diagnose respiratory problems
Mahdavian et al. (2021)	Accuracy 83.00	Acoustic box	SVM	Sound	Diagnose respiratory problems
Okinda et al. (2019)	Accuracy 98.80	Cameras, sensors	ANN, Logistic, SVM	Mobility, posture shapes	Diagnose respiratory problems
Qiang and Kou (2019)	AUC 0.99	Historical data	SVM, BN, kNN	Avian Influenza isolates	Diagnose respiratory problems
Raj and Jayanthi (2018)	–	Sensors, Cameras,	kNN	Temperature, RH, HN3; movements	Diagnose respiratory problems
Raj and Jayanthi (2019)	Accuracy 95.10	Cameras, Sensors	kNN, SVM, Logistic, DT	Chicken image, sound	Diagnose respiratory problems
Rizwan et al. (2016)	Accuracy 97.60	Microphones	SVM, ELM	Chicken sound	Detect rales
Xu et al. (2017)	–	Historical data	Association rule; SPM	Farm, city, bird category, number of birds	Diagnose respiratory problems
You et al. (2021)	AUC 0.94	RFID/Historical	DNN	Time, real-time weight, target weight, feed intake	Identify non-laying birds
Zhuang and Zhang (2019)	Precision 99.70	Cameras	CNN	Chicken images, feather texture, postures	Diagnose respiratory problems
Zhuang et al. (2018)	Accuracy 99.50	Cameras	SVM	Postures	Diagnose respiratory problems

recurrent neural networks, deep belief networks, convolutional neural networks, autoencoders, generative adversarial networks, and deep reinforcement learning. Critical factors for deep learning networks' success include deeper architectures to capture invariant properties of data, regularisation techniques to support robust optimization for enhanced performance, massive datasets availability, and efficient computing hardware to solve complex problems (Oyedele et al., 2021). Convolutional neural network is one of the most representative deep learning algorithms in digital image processing (Zhuang & Zhang, 2019).

Table 5
IoT and ML for poultry control and intervention.

Reference	IoT devices	Algorithms	Measures	Purpose
Choukidar and Dawande (2017)	Sensors	–	Temperature, RH, climate quality, water level, gases	Control environmental parameters/food
Demmers et al. (2010)	WS, sensors	RNN	Weights, temperature, RH, light intensity, feeding	Optimize feeding system
Demmers et al. (2018)	WS sensors	DRNN	RH, light intensity, feed amount	Control feed intake for growth
Gunawan et al. (2019)	Sensors	–	Ammonia, CO_2, humidity, temperature	Optimum control of DC fan and heat lamp
Kakhki et al. (2019)	–	neuro-fuzzy, GA, PSO	Digestible lysine levels, sulfur amino acids, threonine	Optimize body weight/feed conversion ratio
Klotz et al. (2022)	Sensors	LSTM, GA	Temperature (min, mea, max, RH(min, mean, max), day	Optimize body weight/feed conversion ratio
Lahlouh et al. (2020)	Sensors	MIMO FL	Temperature, RH and contaminant gases NH_3, CO_2	Poultry house climate.
Lorencena et al. (2020)	Sensors	–	Temperature, RH	Control thermal comfort
Mirzaee-Ghaleh et al. (2015)	Sensors	FL	Temperature, RH, contaminant gases	Maintain indoor parameters
So-In et al. (2014)	Cameras, sensors	*K*–Means, Fuzzy *C*, MS, logic	Temperature, RH, light intensity	Perform environmental control operation
Youssef et al. (2015)	Cameras, sensors	–	Ambient air, temperature	Control activity level and position of broiler
Zhang and Chen (2020)	Cameras	*CNN*	Broiler images	Automatic detection of sick chickens

Most ML models use historical data as input to predict new output values. ML is classified as either supervised or unsupervised (Milosevic et al., 2019), with many learning models (i.e., classification, regression, clustering) and learning algorithms (i.e., ANN, SVR, random forest, CNN, GLM). Supervised learning algorithms use labelled data in their development for accurate classifications or predictions. Unsupervised learning, on the other hand, uses no pre-assigned labels in unravelling unique patterns in datasets. ML techniques, i.e., deep learning (22 %), SVM (13 %), linear regression (9 %), neural networks (8 %), random forest (4 %), decision trees (4 %), logistic (4 %), k-means (4 %), and fuzzy logic (3 %) have, in reality, seen increasing usage in the poultry welfare management domain. A brief discussion on studies that have applied ML techniques for poultry health and management follows.

Primarily, monitoring of poultry farm environmental parameters, i.e., temperature, humidity, levels of ammonia, and luminosity, are desirable to ensure efficient control of the indoor condition by controllers. ML techniques employed to monitor environmental parameters (temperature, humidity, carbon dioxide, and ammonia) include linear regression (Pereira et al., 2020), fuzzy logic (Lahlouh et al., 2020; Mirzaee-Ghaleh et al., 2015), neuro-fuzzy and ANN (Küçüktopcu & Cemek, 2021) and deep learning (Debauche et al., 2020).

Also, the heat stress of broilers in commercial broiler-houses negatively affects poultry farm productivity and profitability. ML techniques adopted in estimating the body temperature (heat stress) of broilers include Lasso regression (Bloch et al., 2020), Fuzzy-GA (Hernández-Julio et al., 2020), and generalized sequential pattern (Branco et al., 2020). Furthermore, monitoring poultry welfare and behavioral activities, i.e., eating, drinking, preening, and resting, are important as good welfare promotes healthy chicken growth and improves production. Consequently, ML techniques used in monitoring welfare and behavioral activities include linear regression (Aydin et al., 2015; Li et al., 2020b; Neves et al., 2015) and decision trees (Reboiro-Jato et al., 2011) for monitoring feed and water utilization. Also, Kakhki et al. (2019) employed neuro-fuzzy techniques to optimize feed consumption in poultry farms.

In addition, Banerjee et al. (2012) compared the predictive performance of decision trees, ANN, Naïve Bayes, and radial basis function for poultry activity monitoring, Pereira et al. (2013) also used decision trees, Fang et al. (2020) utilized deep learning techniques, while Zhang *et al.* (2016) employed k-means clustering for poultry activity monitoring. Linear regression technique (Dawkins et al., 2021; Fernández et al., 2018) and Bayesian regression (Roberts et al., 2012) were also used to monitor and evaluate the risk of welfare issues. In the density map estimation of crowded chicken, Cheng et al. (2019) used deep learning to estimate the density and counting of poultry in farms. ANN was used to generate action plans for broiler house management (Ribeiro et al., 2019) and k-means for evaluating resource usage (Sibanda et al., 2020). Also, Rico-Contreras et al. (2017) used ANN and fuzzy logic to predict litters' moisture content, while So-In et al. (2014) employed k and fuzzy-C means to manage poultry population density.

Furthermore, weight is an essential parameter for estimating poultry farms' growth and feed conversion efficiency. Consequently, ML techniques, i.e., linear regression (Fontana et al., 2015; Kashiha et al., 2013; Mollah et al., 2010), support vector regression (Amraei et al., 2017b), and Bayesian artificial neural network (Mortensen et al., 2016) have been used for broilers' growth estimation. Other ML techniques used are deep learning (Demmers et al., 2010; Huang et al., 2021; Johansen et al., 2019), ANN (Amraei et al., 2017a; Ma et al., 2020), and quantile regression forests (Diez-Olivan et al., 2019). Likewise, lameness is one of the causes of poor welfare in poultry and early detection of lameness will allow farmers and veterinarians to take timely management actions in time. ML techniques for detecting lameness in broilers include decision trees (de Alencar Nääs et al., 2020) and linear regression (Van Hertem et al., 2018).

The occurrence of poultry diseases affects poultry welfare and production, food safety, and zoonotic infections. Hence, ML techniques have been employed for the timely detection of these diseases. For instance, Raj and Jayanthi (2019) evaluated the predictive performance of KNN, SVM, logistic decision, linear and quadratic discriminant techniques in detecting avian influenza. Qiang and Kou (2019) also benchmarked support vector machines, Bayesian networks, and kNN to predict avian flu. Other studies using ML techniques to detect avian influenza are SVM (Aziz & Othman, 2017; Huang et al., 2019; Zhuang et al., 2018), random forest, and maximum entropy (Belkhiria et al., 2020), deep learning (Cuan et al., 2020, 2022a) and association rules and sequential pattern mining (Xu et al., 2017).

Also, in monitoring Newcastle disease, a severe infectious disease, Banakar et al. (2016) used SVM and Dempster-Shafer, while Okinda et al. (2019) benchmarked the performance of neural networks, SVM, and logistic regression. Furthermore, KNN (Raj & Jayanthi, 2018), Rapid Centroid Estimation and k-means clustering (Ismail et al., 2016), and deep learning techniques (Zhuang & Zhang, 2019) have been employed to detect Newcastle disease. Other ML techniques, i.e., decision trees (Carroll et al., 2014) and deep learning (Rizwan et al., 2016), have been used to predict infectious bronchitis, a highly contagious, acute poultry infection characterized by nasal discharge, coughing, and rales in poultry farms. Other poultry diseases managed by ML techniques include infectious bursal, diagnosed using neural network and logistic regression techniques (Fang, 2019). In addition, in detecting poultry

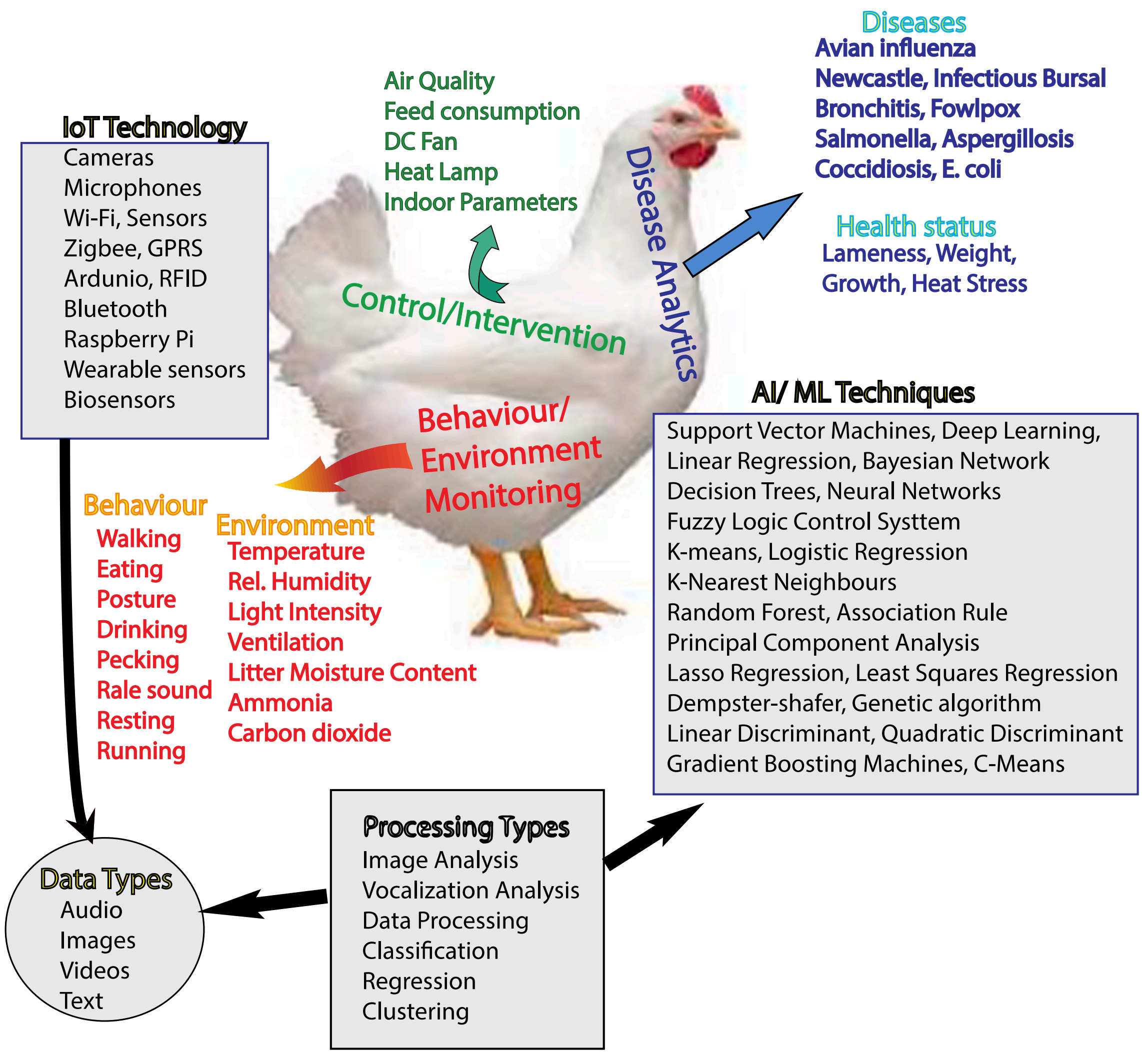

Fig. 4. Overview of IoT and ML in poultry health management.

diseases, random forest (*Salmonella spp*, *Listera spp*) and gradient boosting machines (*Listera spp*) have been used (Golden et al., 2019; Hwang et al., 2020). Also, Hemalatha and Maheswaran (2014) (Hemalatha & Maheswaran, 2014) diagnosed fowlpox with SVM and extreme learning machine (ELM), while (Hepworth et al., 2012) detected hock burn disease using SVM and logistic regression.

3.3.1. Progress of deep learning techniques in poultry health and welfare management

Deep learning (DL) is widely used in different fields. For example, it has proven to be an efficient method commonly used in various agriculture-related areas (Yao et al., 2020). The great advantage of using deep learning is the reduced need for feature engineering since deep neural networks are directly involved in the extraction of intrinsic attributes, i.e., color, shape, and texture information (LeCun et al., 2015).

The use of deep learning in poultry health and welfare management is on the rise, especially, DL-based approaches, including Faster R-CNN, You Only Look Once (YOLO), and Single Shot multibox Detector (SSD) have been applied for object detection in poultry in recent years. For instance, Cao et al. (2021) proposed an automated chicken counting method with Dense CNN. Jung et al. (2021) developed CNN models to automate the classification of vocalizations of laying hens and cattle. In addition, Zhuang and Zang (2019) implemented a deep learning variant-improved Single Shot MultiBox Detector, to automatically diagnose broilers' health status. The proposed algorithm achieved 99.70 % mean average precision. Similarly, Huang et al. (2021) used combined RNN, LSTM, and GTU to detect poultry eating behavior based on vocalization signals with an accuracy of 96.00 %, while Cheng et al. (2019) used fully convolutional networks for density estimation and poultry counting. Zhang and Chen (2020) also designed an automatic detection system for sick chickens using an improved residual Network (ResNet), which resulted in 93.70 % recognition accuracy. Also, You et al. (2021) developed a DNN model to predict oviposition events for individual broiler breeders for efficient bird management with the area under the receiver operating characteristic (ROC) curve at 0.94.

Also, Yao et al. (2020) used deep neural networks (DNNs) to estimate the gender ratio of chickens, and the experimental results achieved an average accuracy of 96.90 %. Similarly, a performance comparison of CNN, LSTM, and GRU was performed to determine chicken gender, with CNN obtaining the highest accuracy of 91.25 % (Cuan et al., 2022a). Also, Geffen et al. (2020) used the Faster R-CNN method to detect and count laying hens in battery cages with 89.60 % accuracy of a validation dataset of 2000 images. These studies on deep learning confirm its reliability and efficiency in poultry welfare management. GANs application in poultry welfare is a gray area. However, GANs and autoencoders can be combined for robust image classification to provide an unsupervised data augmentation method for poultry-related computer vision problems. In addition, GANs can synthesize additional realistic images that resemble those in the training set.

From the papers reviewed, the applications of a few DL techniques in poultry welfare management are basically for object detection (Geffen et al., 2020; Zhang & Chen, 2020), growth prediction (Demmers et al., 2018), disease management (Zhuang & Zhang, 2019), acoustic analysis (Jung et al., 2021), tracking (Cao et al., 2021; Fang et al., 2021; Li et al., 2021; Pu et al., 2018), and habitat monitoring (Debauche et al., 2020).

Deep Reinforcement Learning (DRL) is an advanced and active research field in ML that combines deep and reinforcement learning to solve impossible problems (Lei et al., 2020). Moreover, it promises to solve more complex problems in robotics, resource management, and other fields requiring decision-making capabilities. But unfortunately, deep reinforcement learning is yet to be applied in poultry welfare and health management. Huang et al. (2021) also opined that fully functional robots developed and implemented in the poultry production system are limited. However, in poultry welfare management, DRL would be an essential ingredient for interactive perception, mainly for object segmentation, object recognition, or categorization tasks. In addition to perception capability, DRL will facilitate planning and executing low-productivity tasks, reasoning, and communication capabilities to support optimal decision-making by production managers. Fig. 5 describes the current state of DRL applications in poultry health and welfare management.

3.4. Processing techniques

This subsection presents an overview of the poultry data processing types regarding computer vision and vocalization techniques. Consequently, classification, regression, and clustering algorithms in poultry health and welfare management were briefly discussed.

3.4.1. Computer vision

Computer vision combines mathematics, computer science, and software programming to provide image-based automated process control (Okinda et al., 2020). Similarly, it comprises hardware and software (image processing and analysis algorithms), with the hardware consisting of computers, cameras, and lighting units (Abd Aziz et al., 2021; Nyalala et al., 2021) to track and monitor the behavior and health status of chickens. The advantages of computer vision systems lie in their non-invasive, non-invasive, and low-cost animal monitoring (Li et al., 2021). Fig. 6 depicts the components of computer vision for poultry health and welfare management. Cameras are one of the core components of computer vision systems, and they are classified into 2D and 3D cameras (Abd Aziz et al., 2021). Digital 2D cameras are common and cheap (Fernández et al., 2018; Van Hertem et al., 2018). They operate with a light-sensing chip (charge-coupled device) to detect the brightness of three filtered color channels (red, green, and blue) at each pixel. The 3D cameras, though more expensive and with fewer pixels per area, allow for broader application as they can capture additional information, i.e., depth (the vertical distance between target and camera), and are less prone to darkness and environmental influences (Okinda et al., 2020).

Camera types immensely used in poultry farms for objective quality measurements are visible light cameras, infrared/thermal, and depth (Kashiha et al., 2014; Mehdizadeh et al., 2015; Neves et al., 2015). Visible light cameras enable light detection in the pure visible light spectrum, typically from 400 to 750 nm, and their use in poultry welfare management abound. For instance, de Alencar Nääs et al. (2020), Mollah et al. (2010), and Neves et al. (2015) deployed Sony Cyber-shot, Sony DCR-TRV330, and Handycam Memory Flash PJ200 (Sony Corporation, Tokyo, Japan) for lameness prediction, broiler's weight estimation, and behavior monitoring. Similarly, Amraei et al. (2017b) used an SM-N9005 camera (Samsung Electronics, Suwon, South Korea) for chicken weight prediction, while Mehdizadeh et al. (2015) deployed Mikrotron Eosens MC1363 cameras (Mikrotron GmbH, Bavaria, Germany) to evaluate chickens' beak and head motion during feeding. Also, studies such as those from Fang et al. (2021) and Zhuang et al. (2018) deployed Logitech C922 camera (Logitech International, Lausanne,

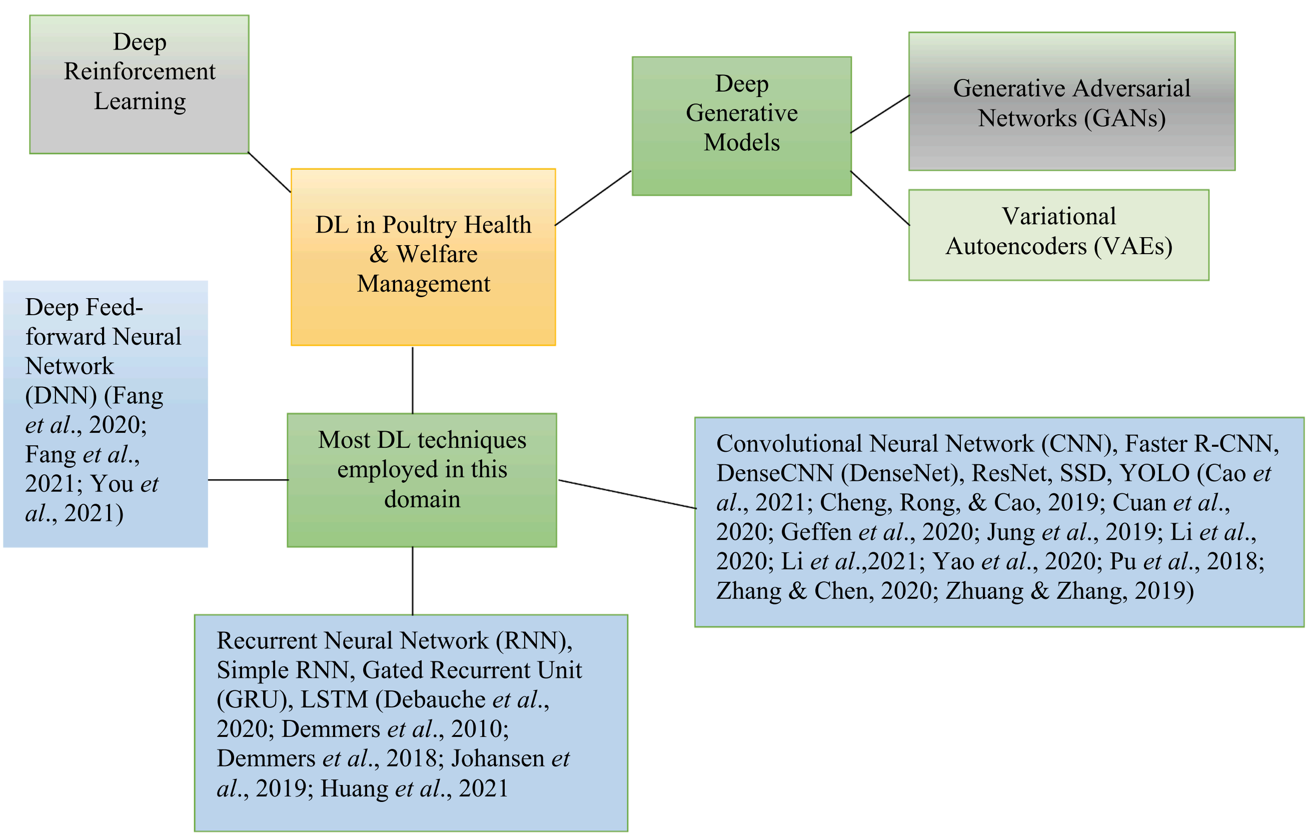

Fig. 5. DL applications in poultry welfare management.

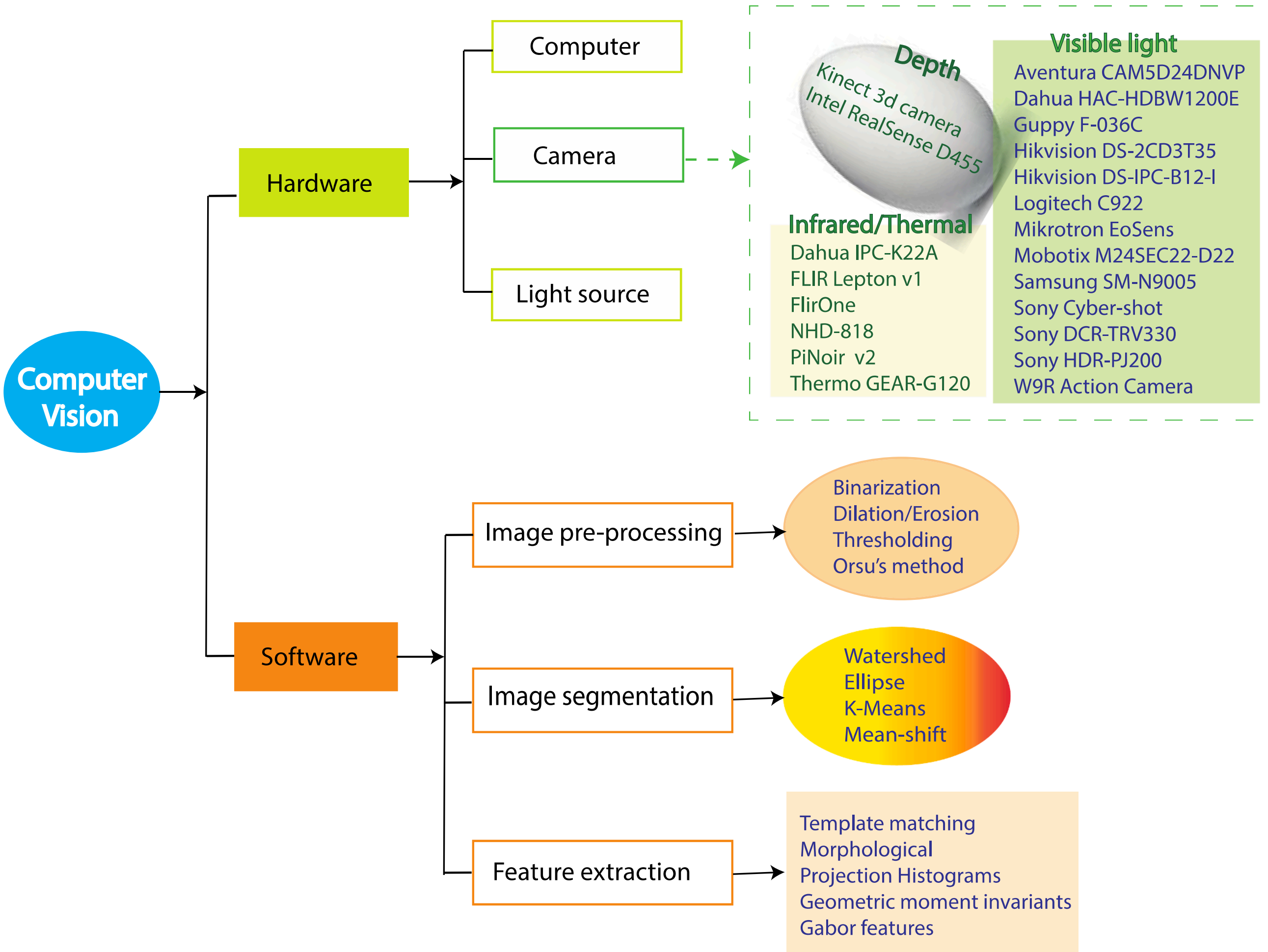

Fig. 6. Computer vision components in poultry welfare management.

Switzerland) for pose estimation and sick broilers detection. In addition, a Guppy FO36C camera (Allied Vision Technologies, Stadtroda, Germany) was deployed to detect the lameness of broilers (Aydin *et al.*, 2017). Additionally, studies by Cao et al. (2021) and Okinda et al. (2019) used Hikvision cameras (Hangzhou Hikvision Digital Technology, Hangzhou, China) to automate the chicken counting process and detect sick chickens, respectively.

The thermal or infrared cameras create images using infrared radiation and are sensitive to wavelengths between 1,000 and 14,000 nm. Examples of these cameras as deployed for broilers' behavioral pattern recognition and monitoring include FLIR Lepton (FLIR Systems, Inc., Oregon, USA) for temperature measuring (Bloch et al., 2020) and activity monitoring (González et al., 2017). Similarly, Dahua IPC-K22A (Dahua Technology, Hangzhou, China) was used to assess pullets' drinking behaviors (Li et al., 2020a). Also, Li et al. (2021) utilized NHD-818 cameras (Swann Communications, Santa Fe Springs, USA) to measure broiler stretching behaviors. Likewise, a PRO-1080MSFB camera (Swann Communications, Santa Fe Springs, USA) was used to monitor chicken floor distribution (Guo et al., 2020), while Zaninelli et al. (2018) used Thermo GEAR-G120 cameras (NEC Avio Infrared Technologies, Tokyo, Japan) to monitor laying hens and detect multiple nest occupations.

Depth cameras create a 3D image of the targeted scene or object and offer more discerning information to recover postures and recognize actions. Thus, they have been deployed to monitor poultry's behavior and health status. For instance, studies such as those from Aydin *et al.* (2017), Mortenson *et al.* (2016), and Okinda et al. (2019) deployed Kinect cameras (Microsoft Corporation, Washington, USA) for broilers' lameness detection, weight prediction, and detection of sick chickens, respectively. Also, Nasiri et al. (2022) used Intel RealSense D455 (Intel Corporation, Santa Clara, California, USA) for broilers pose estimation.

The lighting units (i.e., LED and Halogen) illuminate the pen or poultry house to ensure that the illumination intensity is within an acceptable range (typically between 15 and 20 lx) (Wang et al., 2016), for improved image processing and analysis operations. From the software perspective, it is a set of programs or routines associated with computer system operations, and its development plays an essential role in computer vision (Abd Aziz et al., 2021). Software forms in computer vision include image pre-processing for image quality enhancement, image segmentation, and feature extraction, which extracts meaningful information from images.

Image pre-processing methods employed in past studies include dilation and erosion (Amraei et al., 2017a; Kashiha et al., 2014; Mollah et al., 2010), scaling (Fang et al., 2020; Zhuang & Zhang, 2019), data augmentation (Zhang & Chen, 2020), Otsu's method (Kashiha et al., 2014; Okinda et al., 2019), gaussian filter (Mortensen et al., 2016; Raj & Jayanthi, 2019) binarization (Amraei et al., 2017a; Aydin, 2017; Guo et al., 2020; Neves et al., 2015; Okinda et al., 2019; Raj & Jayanthi, 2019), and thresholding (Amraei et al., 2017a; Amraei et al., 2017b; Mehdizadeh et al., 2015; Mollah et al., 2010; Youssef et al., 2015).

Image segmentation partitions images into multiple segments and labels the segments with known classes to facilitate accurate classification (Abd Aziz et al., 2021; Zhuang et al., 2018). Though this field has a long research history, deep learning networks have delivered models with remarkable performance for segmentation and have thus become the new standard for image segmentation (Okinda et al., 2020). Techniques for image segmentation (i.e., extracting a chicken body from a background image) in poultry welfare management include the Watershed algorithm (Cao et al., 2021; Mortensen et al., 2016) and the Ellipse model (Kashiha et al., 2014; Zhuang et al., 2018). Others are Mean-shift clustering (Fang et al., 2020) and K-Means clustering (Zhuang et al., 2018).

Feature extraction algorithms transform raw data into a suitable internal representation to enhance ML models' predictive ability (LeCun et al., 2015). Thus, extracting features from images helps to correlate objects to a specific bio-response or bio-process under investigation (Okinda et al., 2020). Consequently, after the pre-processed and segmented operations, selected features of images are extracted for classification purposes. Common features used for conventional image analysis in poultry include age (1D), morphological features (i.e., length, breadth, area, perimeter), and 3D (volume and surface area) (Abd Aziz et al., 2021; Okinda et al., 2019, 2020). For instance, Mollah et al. (2010) used 1D and morphological features to examine the relationship between manual body weight and the number of surface-area pixels in the image. Features such as area are mostly used to estimate the broiler body size. The area was computed by summing pixels within a contour constituting the broiler image to analyse broiler behavior (Pereira et al., 2013). Aydin (2017) also used 1D features in detecting lameness in broilers. Morphological features have also been used to measure feed intakes (Aydin et al., 2015; Mehdizadeh et al., 2015; Neves et al., 2015) and strentching (Li et al., 2021) of broilers. Amraei et al. (2017b) also used 2D (morphological) features for the broiler weight estimation. Debauche et al. (2020) also used morphological features for poultry monitoring. Mortensen et al. (2016) used age, morphological features, and 3D to determine optimal ways to control food, water supplies, and circadian rhythm of broilers for optimal growth patterns.

Commonly used image analysis software for the studies reviewed includes MATLAB, (Mathworks, Inc. MA, USA) (Amraei et al., 2017a; Aydin, 2017; Bloch et al., 2020; Fernández et al., 2018; Guo et al., 2020; Hemalatha & Maheswaran, 2014; Kashiha et al., 2013, 2014; Li et al., 2020b; Ma et al., 2020; Mehdizadeh et al., 2015; Mortensen et al., 2016; Neves et al., 2015; Okinda et al., 2019), R Programming Language (R Development Core Team, Vienna, Austria) (Hwang et al., 2020; Mollah et al., 2010; Qiang & Kou, 2019; Zaninelli et al., 2018), Python (Dawkins et al., 2021; Fang et al., 2021; González et al., 2017; Li et al., 2020a; You et al., 2021), Minitab (Minitab Inc, PA, USA) (Mehdizadeh et al., 2015; Neves et al., 2015), Weka (University of Waikato, New Zealand) (Branco et al., 2020; Carroll et al., 2014; Pereira et al., 2013), SPSS (IBM, Armonk, New York, USA) (Okinda et al., 2019), and Rapidminer Studio (Rapidminer Inc, Boston, MA, USA) (de Alencar Nääs et al., 2020; Fernández et al., 2018). In addition, however, libraries, i.e., OpenCV (Intel Corporation) (Debauche et al., 2020; González et al., 2017; Pu et al., 2018; Wang et al., 2016; Zhuang et al., 2018; Zhuang & Zhang, 2019), TensorFlow (Google Brain Team) (Li et al., 2020a, 2021), Pytorch (Meta AI, New York, USA) (Cao et al., 2021), and Keras (You et al., 2021; Zhuang & Zhang, 2019) are recently gaining grounds.

Examples of computer vision applications to poultry breeding farm processes (health and welfare management) include chicken behavior analysis (Cheng et al., 2019; C. Fang et al., 2020, 2021; Fernández et al., 2018; González et al., 2017; Mehdizadeh et al., 2015; Neves et al., 2015; D. Pereira et al., 2013; So-In et al., 2014), welfare and resource management (Fernández et al., 2018; Kashiha et al., 2013; Roberts et al., 2012), and hen tracking (Fang et al., 2020; Kashiha et al., 2013; Wang et al., 2016; Zaninelli et al., 2018). Others are disease detection and diagnosis (Aydin, 2017; Aziz & Othman, 2017; Hemalatha & Maheswaran, 2014; Okinda et al., 2019; Qiang & Kou, 2019; Raj & Jayanthi, 2019; Van Hertem et al., 2018; Zhang & Chen, 2020; Zhuang et al., 2018; Zhuang & Zhang, 2019), and weight or growth prediction (Amraei et al., 2017b; Diez-Olivan et al., 2019; Johansen et al., 2019; Kashiha et al., 2013; Ma et al., 2020; Mollah et al., 2010).

Finally, the gender ratio of free-range chickens is considered a major welfare problem in commercial broiler farming. Thus, systems to support free-range chicken producers have been developed for chicken counting (Cao et al., 2021) and identifying chicken gender for flock economic value (Yao et al., 2020).

3.4.2. Vocalization analysis

Analysis of broiler vocalizations can yield valuable insights into poultry welfare and how diseases manifest and progress over time. In addition, this technique can play an important role in detecting infection with pathogenic *microorganisms*, threat signals, information about feeding, activity monitoring, and population estimation. The key advantage of the technology is the continuous non-invasive audio measurements of the poultry environment at a relatively low cost (Jung et al., 2021). Thus, vocalization analysis applications in poultry welfare management abound. The following are some examples.

The frequency of rales produced by infected chickens was used to detect respiratory infection and initiate remedial actions to inhibit further infection or spread before clinical signs manifestation (Carroll et al., 2014; Cuan et al., 2020; Rizwan et al., 2016). Also, Carpentier et al. (2019) presented an algorithm with a precision of 88.40 to monitor the chicken sneezing sounds from multiple broilers' vocalizations in a noisy environment, while Banakar et al. (2016) proposed a system with a 91.20 % accuracy for detecting and diagnosing respiratory diseases. Du et al. (2018) developed a system to detect anomaly poultry status at night by monitoring the number of vocalizations and area distributions. The proposed approach (74.70 % accuracy) is a practical and feasible method for poultry behavior and welfare, especially in stress detection. Feeding behavior detection of broiler chickens is vital in distinguishing healthy from infected birds. Furthermore, pecking sounds have been used to monitor the feed intake of broilers by a real-time sound processing technology (Aydin et al., 2015; Aydin & Berckmans, 2016). Also, Fontana et al. (2015) proposed a method to automatically measure the growth rate of broiler chickens by sound analysis ($R^2 = 0.98$). Cuan et al. (2022a) obtained a classification accuracy of 91.25 % for chicken gender determination, while Jung et al. (2021) developed a strategy (75.80 % accuracy) for chicken gender identification for economic value estimation.

In summary, these studies have revealed potential applications of vocalization analysis due to its good performance and low computational cost to optimize conditions of the poultry environment and detect behavioral problems, i.e., feather pecking, feed intakes, infections, and stress. Thus, sound technology has real potential for practical commercial implementation to improve health and poultry welfare. Features commonly used in previous studies (i.e., Aydin et al., 2015; Aydin & Berckmans, 2016; Banakar et al., 2016; Fontana et al., 2015) for detecting and classifying poultry vocalization data include pitch, frequency, and time–frequency. Similarly, studies such as those from Carroll et al. (2014), Cuan et al. (2022b), Cuan et al. (2022a) and Jung et al. (2021) used the Mel frequency cepstrum coefficients (MFCCs) to represent the acoustic sound of hens to recognize behavioral meanings from those sounds.

3.4.3. Data processing

This subsection briefly describes data pre-processing techniques for poultry audio and image data.

Data processing involves collecting and manipulating data to produce meaningful information, and pre-processing of high-dimensional features is a general and robust method for improving the learning algorithm performance (Hastie et al., 2009). Data in the context of this study refers to text and multimedia data, i.e., images, audios, and videos employed in poultry welfare management. Consequently, data processing comprises techniques to improve data further to eliminate noise or unwanted frequencies and increase measurement precision and analysis reliability (Cuan et al., 2022a; Pereira et al., 2013; Huang et al., 2021).

For instance, in computer vision problems, the primary purpose of this process is to enhance the image quality for the segmentation step, especially in separating a digital image into distinct areas (Nyalala et al., 2021). Standard pre-processing techniques include filtering, normalization, approximation, enhancement, and cancellation of points (Okinda et al., 2020). In addition, many of these pre-processing methods used in poultry welfare management include dilation and erosion (Amraei et al., 2017a; Kashiha et al., 2014; Mollah et al., 2010; So-In et al., 2014), thresholding (Kashiha et al., 2013; Mehdizadeh et al., 2015; Neves et al., 2015; Okinda et al., 2019; Youssef et al., 2015), Otsu's method (Kashiha et al., 2014; Okinda et al., 2019), gaussian filter (Mortensen et al., 2016; Raj & Jayanthi, 2019), and binarization (Guo et al., 2020; Li et al., 2020b; Neves et al., 2015; Okinda et al., 2019; Pereira et al., 2013). Others include image cropping to emphasize a particular subset of a larger image (Li et al., 2021) and image size reduction (Li et al., 2020a), as large image sizes can decrease detection speed when input into CNN detectors. Also is data augmentation (Zhang & Chen, 2020), to increase the amount of data by adding slightly modified copies of already existing data or newly created synthetic data from existing data.

Also, in poultry vocalization analysis, studies such as those from Huang et al. (2021), Klotz et al. (2022), and Pereira et al. (2013) used data normalization, a technique to convert data from spatial domain to frequency domain with either fast Fourier transform or Discrete cosine transform techniques (Cuan et al., 2022b; Huang et al., 2021; Mahdavian et al., 2021). Similarly, the uses of pre-emphasis and micro-analysis techniques are standard pre-processing techniques used on audio signals (Jung et al., 2021; Huang et al., 2019; Huang et al., 2021).

3.4.4. Classification

This subsection briefly describes the classification technique as one of the key processing techniques in poultry welfare management.

The classification technique categorizes data into classes to identify primarily the category under which new data or objects belong (Okinda et al., 2020), and it is the most used technique for delineating classes of output (usually categorical) based on some set of input features (Ajayi et al., 2020). Also, the classification task is essential for computer vision and vocalization analysis (Amraei et al., 2017b; Aydin, 2017; Aydin et al., 2015; Aydin & Berckmans, 2016) as it helps to identify objects and tasks performed by those objects. For example, given an image or sound, classification techniques can help discriminate between healthy and sick broilers or determine whether a chicken is laying eggs, walking, or drinking. Examples of classification techniques include CNN, SVM, ANN, DNN, random forests, logistic, and decision trees. However, the high CNN classification accuracy makes it a promising approach, especially for classifying animal sounds (Jung et al., 2021). As revealed in this study, typical classification applications in poultry welfare management are activity recognition and disease detection. A few examples are presented.

For activity recognition, Banerjee et al. (2012) compared decision trees, Naïve Bayes, and neural networks for broilers' activity recognition and reported that neural networks had the best overall accuracy of 82.10 %. Similarly, Pereira et al. (2013) employed the classification tree algorithm to identify hen white broiler breeder behavior and reported an overall success rate of 70.30 % on the validation set. Also, Rizwan et al. (2016) compared extreme learning machine and SVM classifiers to detect rales (a gurgling sound that is a symptom of respiratory diseases in poultry) and reported a classification accuracy of SVM (97.60 %) over the extreme learning machine technique. Pu et al. (2018) developed an automatic CNN-based method (accuracy of 99.17 %) to recognize the chicken behavior within a poultry architecture. Also, a CNN classification model, with a classification accuracy of 75.78 % on the validation dataset, was used to effectively recognize the sounds of laying hens (Jung et al., 2021). Geffen et al. (2020) used Faster R-CNN detection and tracking algorithms to detect hens in cages with an 89.60 % accuracy at cage level. Li et al. (2020a) used CNN to detect drinking behaviors of pullets in a lighting preference test system, and they reported a classification accuracy of 89.10 %. Also, Fang et al. (2021) used a Naive Bayesian model to classify and identify the poses of broiler chickens. They reported the test precision of behavior recognition at 0.75 (standing), 0.51(walking), 0.63 (running), 0.94 (eating), 0.96 (resting), and 0.93 (preening). Lastly, Li et al. (2021) used a faster R-CNN method to detect broiler stretching behaviors with an accuracy of 99.50 % on the testing dataset. Nasiri et al. (2022) developed a CNN-LSTM-based model for skeleton-based lameness recognition in broilers, and the model achieved a per-class classification accuracy of 97.5 %, while Cuan et al. (2022a) obtained a classification accuracy of 91.25 % for chicken gender determination.

Similarly, timely disease detection is paramount in poultry production (Zhang & Chen, 2020). The following are a few examples of classification models in poultry disease detection and diagnosis. Huang et al. (2019) developed an audio analysis-based detection method to detect avian influenza in chickens using SVM (a binary classification) and reported an accuracy rate between 84.00 % and 90.00 %. Also, Cuan et al. (2020) proposed a CNN model to detect chickens with avian influenza from chicken sound extracts and reported the highest accuracy of 95.84 %. Also, Okinda et al. (2019) compared the performance of an SVM classifier with ANN and logit regression to establish a correlation of broiler feature variables with their health status. The authors reported that an SVM classifier outperformed all other models with an accuracy of 97.80 %. Zhang et al. (2018) developed a system to analyze broilers' postures and detect sick broilers with an SVM classifier. The authors reported an accuracy rate of 99.47 % on the test samples. Also, Zhuang and Zhang (2019) proposed a CNN-based recognition model with a 99.70 % mean average precision (mAP) for detecting the health status of broilers to support efficient flock management. Similarly, Zhang and Chen (2020) developed an automatic detection system for sick chickens based on ResNet residual (a CNN architecture) classifier. They reported accuracy of 93.70 % on the test set.

3.4.5. Regression

Regression techniques predict an output variable according to known input variables (Milosevic et al., 2019). They are mainly used for modeling regression problems consisting of one or more dependent variables and a set of predictors (Küçüktopcu & Cemek, 2021; Milosevic et al., 2019). For example, in regression problems for chicken welfare systems, dependent variables commonly used are weight, litter moisture, and contaminant gases concentration (Küçüktopcu & Cemek, 2021; Mortensen et al., 2016). In contrast, predictor variables employed are the object's surface area, 2D, 3D image features, sound frequency, broiler's age, and environmental parameters, i.e., light intensity, temperature, and relative humidity (Küçüktopcu & Cemek, 2021; Mehdizadeh et al., 2015; Mortensen et al., 2016; Okinda et al., 2019).

This methodology often used to describe relationships between independent and dependent variables, is a formula usually represented as a line to make predictions, including interpolations and extrapolations (Hastie et al., 2009). Multivariable regression uses more than one independent variable to predict an outcome (Küçüktopcu & Cemek, 2021). The two modes of tackling regression problems are linear and nonlinear regression methods. Linear regression models are simple and often provide an adequate and interpretable description of how the inputs affect the output (Hastie et al., 2009). The nonlinear models are complex and used for modeling the nonlinear pattern relationship between predictor and response variables. Regression methods mostly applied in poultry monitoring include linear, logistic, lasso, SVM, ANN, RNN, DNN, and tree model regression (Okinda et al., 2020).

Body weight is an essential indicator for determining poultry's growth and health status as it is closely related to production performance (Johansen et al., 2019). Consequently, with respect to poultry, regression-based models have been used to analyze poultry growth curves (Amraei, Abdanan, et al., 2017; Demmers et al., 2010, 2018; Fontana et al., 2015; Johansen et al., 2019; Mollah et al., 2010;

Mortensen et al., 2016). For example, linear regression was applied to estimate chicken weight, with a relative error in weight estimation of chicken, expressed in terms of percent error of the residuals from surface area pixels between 0.04 and 16.47 (Mollah et al., 2010). Mortensen et al. (2016) applied Bayesian ANN regression for broiler weight estimation and reported a relative mean error of 7.8 % for the proposed model. Amraei et al. (2017a) used neural networks to estimate the live body weight of broilers and reported an R-Squared value of 0.98. Amraei et al. (2017b) used support vector regression (SVR) to estimate the weight of life broiler chickens with an R-Squared value of 0.98. Also, Fontana et al. (2015) proposed a method to automatically measure the growth rate of broiler chickens by sound analysis (R2 = 0.98).

Ammonia is a primary air pollutant in poultry farms, adversely affecting the ecosystem, environment, birds, and human health (Küçüktopcu & Cemek, 2021). Therefore, estimating NH3 concentration is essential for proper litter management and protecting environmental, human, and animal health (Debauche et al., 2020; Küçüktopcu & Cemek, 2021). Hence, Küçüktopcu and Cemek (2021) performed a performance comparison of four models (i.e., multilayer perceptron, integrated adaptive neuro-fuzzy inference systems with grid partitioning and subtractive clustering (ANFIS-GP and ANFIS-SC), and multiple linear regression analysis) to estimate ammonia concentration in poultry. They reported that ANFIS-SC was more accurate, with an R-Squared value of 0.86 on the validation set.

Also, Lin et al. (2016) developed an ammonia monitor for a poultry farm and reported a relative error (RE) of the monitor averaged 7 %. Debauch et al. (2020) also developed a system to monitor and predict the air quality in poultry using GRU and reported improvements in both the training and prediction speeds. Other applications of regression-based models are for analyzing litter moisture content (Rico-Contreras et al., 2017), evaluating chicken gender ratio (Yao et al., 2020), and counting birds in poultry farms (Cao et al., 2021; Cheng et al., 2019; Geffen et al., 2020).

3.4.6. Clustering

This subsection presents a brief highlights of clustering techniques and their application in poultry welfare management.

The clustering technique divides data into a group of similar objects that are different from objects of other groups (Ismail et al., 2016). The clustering technique is often one of the first steps in data mining analysis and therefore supports the development of population segmentation models (Zhang et al., 2018). Examples of clustering techniques include K-means, Gaussian mixture, K-Medoids, and Fuzzy C-Means. However, K-means application is more common in poultry welfare management (Carroll et al. (2014; Feiyang et al., 2016; Küçüktopcu & Cemek, 2021). The K-means technique aggregates similar objects concerning their characteristics based on a distance measure, i.e., Euclidean distance (Hastie et al., 2009).

Application of clustering techniques in poultry health and welfare management include monitoring chicken floor distribution (Guo et al., 2020), behavior monitoring (Feiyang et al., 2016), diagnosing diseases (Ismail et al., 2016), and optimizing the segmentation process (Zhuang et al., 2018).

For instance, Carroll et al. (2014) used the k-means algorithm to cluster the vectors of MFCCs from chicken audio data into 60 clusters, to yield a single cluster index for each time slice when detecting that detecting chicken making rales sound. Feiyang et al. (2016) used the K-means method to classify poultry into sick, normal, and active to boost a classifier while analyzing chicken behavior characteristics, i.e., speed, ability to snatch food, and resting time. Thus, ensuring that chicken diseases are timely detected and the accurate growth states of chickens are immediately known. Clustering is a useful technique for discovering data distribution and patterns in the underlying data. Guo et al. (2021) developed a model to discover chicken distribution and compared a method integrating the GB (Green/Blue) color space and two-dimensional Otsu processing with K-means and Fuzzy C-Means techniques concerning the processing time and target extraction. The Fuzzy C-Means method was reported to extract individual broiler from original images with a reasonable visualization efficiency (e.g., clearness and completeness of chicken areas). Ismail et al. (2016) evaluated the rapid centroid estimation (RCE), a lightweight swarm clustering algorithm with k-means to cluster the Newcastle disease dataset, and reported that RCE shows better external clustering quality measures than K-means.

Similarly, while estimating the ammonia concentration in poultry farms, Küçüktopcu and Cemek (2021) used a subtractive clustering technique to determine optimal input parameters for the regression model. Zhuang et al. (2018) also proposed a real-time poultry segmentation algorithm based on K-means clustering and the ellipse model for automated diagnoses of broilers' health status.

3.5. Sensor technologies in poultry welfare

Recently, tremendous advances have been achieved in sensing technologies in terms of diversity, accuracy, and affordability. Sensors, if appropriately deployed, can provide a timely diagnosis of diseases in animals, eventually decreasing economic losses. Furthermore, the primary environmental conditions to control in the poultry buildings are the hygro-thermal parameters (temperature and relative humidity) and contaminant gases, i.e., ammonium and carbon dioxide (Lahlouh et al., 2020). Therefore, such devices are particularly useful for poultry health management (Carpentier et al., 2019). In this regard, a tool for data visualization, as shown in Fig. 7, was created to summarize the relevant and tested sensor-based applications and sensor types used in the studies reviewed. The innermost circle represents the unifying name for the devices, whereas the outer circle represents the sensor types, and the outermost circle represents specific sensors.

Sensor types include environmental, acoustic, Kinect, thermal, camera, weight, and lighting.

Environmental sensors are primarily used to monitor environmental conditions, i.e., temperature, humidity, and air quality, to provide the appropriate conditions suitable for the significant efficiency of animal production. Importantly, inadequate temperature, relative humidity, and the length of exposure have substantial impacts on broiler welfare, mortality, and performance (Debauche et al., 2020; Diez-Olivan et al., 2019). Furthermore, exposure to elevated levels of noxious gases like

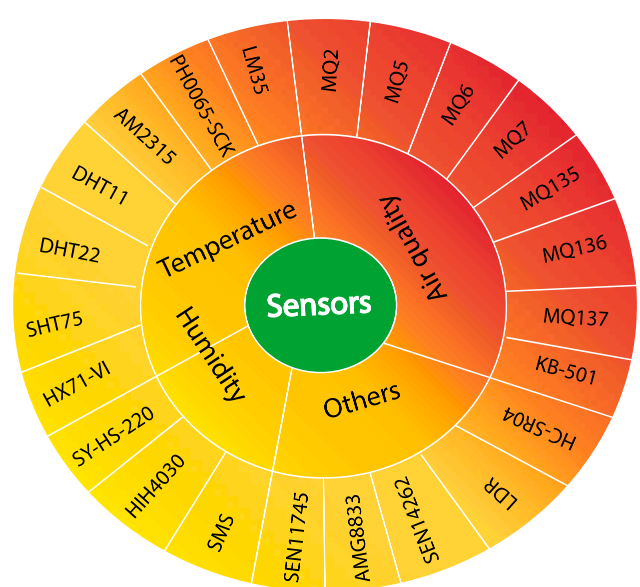

Fig. 7. Sensor types used in poultry welfare management. DHT11, DHT22, SHT75, and HX71-VI sensors can all be used to monitor temperature and humidity.

carbon dioxide and ammonia can reduce weight, feed conversion, overall viability, and loss of profit in the poultry industry (Küçüktopcu & Cemek, 2021). Thus, efforts to monitor and control environmental conditions will directly impact bird welfare and permit the development of systems for precise control of the production environment. Several wireless-based sensors and use IoT tools to monitor environmental parameters have been proposed as a promising tool in PLF (Debauche et al., 2020; Gunawan et al., 2019; Lahlouh et al., 2020; Lashari et al., 2018; Lin et al., 2016; Lorencena et al., 2020; Mirzaee-Ghaleh et al., 2015; Pereira et al., 2020; So-In et al., 2014).

Examples of environmental sensors employed in the reviewed studies include DHT22 (Pereira et al., 2020; Raj & Jayanthi, 2018; So-In et al., 2014), LM35 (Choukidar & Dawande, 2017; Lahlouh et al., 2020; Mirzaee-Ghaleh et al., 2015; Youssef et al., 2015), AD590 (Mirzaee-Ghaleh et al., 2015) for measuring temperature. Similarly, sensors used to measure relative humidity include HIH4030 (Lahlouh et al., 2020; Mirzaee-Ghaleh et al., 2015), DHT22 (Raj & Jayanthi, 2018; So-In et al., 2014) SY-HS-220 (Choukidar & Dawande, 2017). Although, the following sensors DHT11, DHT22, SHT75, and HX71-VI, can all be used to monitor both the temperature and humidity. Also, sensors for measuring contaminant gases, i.e., CO, CO_2 NH_3 concentrations, include MQ7 (Debauche et al., 2020), MG811 (Lahlouh et al., 2020; Mirzaee-Ghaleh et al., 2015), and MQ137 sensors (Debauche et al., 2020; Mirzaee-Ghaleh et al., 2015; Pereira et al., 2020). In addition, Youssef et al. (2015) used the EE576 sensor to measure air ventilation.

Acoustic sensors are used to measure the characteristics of sounds emitted by hens. Analysis of acoustic data can serve as a reliable stress indicator (Du et al., 2018), measure food intake (Aydin et al., 2015), and disease detection (Cuan et al., 2020; Huang et al., 2019). Avian influenza poses a potential health threat to both chickens and humans. Banakar et al. (2016) developed an avian influenza monitoring system to simulate the spread of highly pathogenic avian influenza viruses in chickens. Results showed the sensor's capability to detect the virus accurately. In addition, other respiratory diseases can be timely detected using appropriate sound technologies (Carpentier et al., 2019). Raj and Jayanthi (2019) used an acoustic sensor, SEN-14262, for the real-time identification of infected hens.

Infrared or thermal sensors (i.e., FLIR Lepton (FLIR Systems, Inc., Oregon, USA, Thermo GEAR-G120, Kinect cameras (Microsoft Corporation)) are non-invasive welfare devices to assess the body's superficial temperature distribution from the infrared radiation emitted by objects. For example, systems incorporating FLIR Lepton cameras have been proposed to measure broiler temperature (Bloch et al., 2020; Hernández-Julio et al., 2020). In addition, the movement of layers across perches and other housing equipment is a risk factor for bone breakage, a typical condition of poor welfare. Thus, Kinect sensors were used to monitor and study different aspects of the movement of broilers and layers (Aydin, 2017; Feiyang et al., 2016; Pu et al., 2018). Also, Banerjee et al. (2012) used the MTS510 accelerometer (Crossbow Technology, Inc., San Jose, California), placed in laying hens to monitor their movement. Other sensors, i.e., FSR402 weight sensors (Interlink Electronics, Camarillo, California), were used to assess the average broiler weight (Lahlouh et al., 2020), and Light Dependent Resistor (LDR) was used to monitor luminosity (Lahlouh et al., 2020).

In summary, sensors can be implanted on chickens to measure body temperature (Bloch et al., 2020; Hernández-Julio et al., 2020); observe behavior and movement (Banerjee et al., 2012; Feiyang et al., 2016), and detect stress (Branco et al., 2020). Also, they are used for sound analysis (Carroll et al., 2014; Cuan et al., 2020; Du et al., 2018; Fontana et al., 2015; Huang et al., 2019) and disease prevention (Cuan et al., 2020; Huang et al., 2019). In addition, they can detect the presence of viruses and pathogens (Golden et al., 2019), predict moistures in litters (Rico-Contreras et al., 2017), and regulate environmental parameters (Mirzaee-Ghaleh et al., 2015; Pereira et al., 2020).

4. Key challenges in poultry welfare management

Although there are several studies relating to poultry welfare management, researchers have also improved the method of measuring the pen house atmospheric conditions, health, behavior, weight, and growth of chickens. However, there are still several issues to be addressed. The section describes the issues and challenges in poultry management, including the quality of raw data, the precision of image segmentation, and the reliability of prediction or classification.

(i) New datasets to support further challenging tasks: - although researchers have collected several datasets recently for everyday welfare management tasks, there is a need for new large-scale datasets for more challenging tasks. These new tasks include responding to sudden disease outbreaks, handling new insects and vermin, efficient nutrient utilization, and optimizing feed for improved production. The increasing availability of large data sources and data sets, obtained through sensors will encourage more initiatives, projects and new ventures in the poultry health and welfare management.

(ii) Raw data quality: - Challenges in ensuring raw data quality are related to physical actions affecting changes in postures, orientations, and the diversity of birds' body dimension measurement. Besides, images could be poor due to dust bathing of hyperactive broilers when stretching out wings. Also, image dimension varies due to factors affecting chicken locations (i.e., below cameras, feather level, lighting, image threshold values, and the distance of chickens from cameras). Some researchers omitted the head and tail positions during the feature extraction phase to overcome this challenge (Mortensen et al., 2016). However, this strategy will lead to underestimating the broiler's body weight and behavior compared to the actual.

(iii) Deep learning and adversarial perturbations: -in another direction, deep models are fragile to adversarial perturbation on inputs (Papernot et al., 2016). Those changes in data distribution can unpredictably trigger weak features. Thus, leading to a slight decline in performance and ultimately causing deep learning models to make wrong predictions with high confidence. For instance, imperceptible pixel differences in images can trick deep learning models. Such adversarial attacks are an important obstacle to the successful deployment of deep learning, especially in applications involving a proactive response to sudden poultry disease outbreaks. Though some early solutions have been proposed (i.e., distillation, feature aggregation, applying denoising autoencoders on data, using multi-scale networks,) a significant challenge is to develop effective defence mechanisms against these attacks.

(iv) Interpretable of deep learning models: - While DL models have achieved promising performance in various challenging problems, their limitation regarding interpretability (" black-box" problem), which aims to explain their output, is a challenge. For example, why a model outperforms another model on one dataset but underperforms on other datasets? What exactly have DL models learned? What is a minimal architecture for achieving a definite accuracy on a given dataset? Although attention and self-attention mechanisms, widely used in many fields because of their ability to distinguish features, can provide some insight toward answering these questions, a detailed study of these models' underlying behavior and dynamics is still lacking. Nevertheless, a thorough understanding of their theoretical aspects can help develop enhanced models for various poultry health and welfare management analysis scenarios.

(v) The conventional fuzzy-logic controllers deployed in studies such as those from Lahlouh et al. (2020) and Mirzaee-Ghaleh et al. (2015) are heavily reliant on the user's knowledge of the system and complicated rules. Besides, conventional controllers (i.e., proportional integral derivative (PID), fuzzy logic, predictive controller optimized by genetic algorithm, particle swarm optimization) deployed in studies such as those from Hernández-Julio et al. (2020), Kakhki et al. (2019), Küçüktopcu and Cemek (2021), Lahlouh et al. (2020) and Mirzaee-Ghaleh et al. (2015) suffer from the inability to learn in real-time. However, to overcome this shortcoming, recent technologies such as reinforcement learning (RL), a hotspot in artificial intelligence, and ML techniques can be deployed to design intelligent systems to optimize a policy for complex tasks.

(vi) Robust and accurate processing techniques: - The next problem is image processing techniques, i.e., segmentation and feature extraction used in convectional ML techniques. These techniques are confronted with problems (i.e., noise, contrast issues) that affect classification models' accuracy. In addition, the strong dependence on domain knowledge for designing features makes these methods difficult to generalize to new tasks. Finally, these models cannot take advantage of large amounts of training data because the features are pre-defined. However, for DL, the tasks of segmentation, feature extraction, and feature selection are eliminated using CNNs. Similarly, variational autoencoders, based on their ability to learn model parameters through the encoder-decoder path automatically, are commonly used to create compact data representations for efficient decision-making. As a result, DL techniques have achieved much success in animal monitoring systems.

5. Proposed poultry welfare framework

Having reviewed existing interventions by other researchers in poultry welfare management, a scalable, resilient, extensible, and secured framework is presented to support the precision livestock farming concept for smart poultry health and welfare in addressing some of the challenges in the existing systems. The critical components of the framework (Fig. 8) include the deep learning (DL) module, Digital Twin module, cloud edge computing (cloud-fog-based) module, communication, security, and user-interface module.

(i) DL module comprises robust deep learning techniques, i.e., CNN (for classification operations), RNN (for regression operations), GAN/AE (for data analysis and feature learning), and RDL (to control poultry KPI parameters through actuators). All DL modules reside in the cloud to take advantage of storage and computation speed. CNN has proven to perform well on image and audio classification tasks on large datasets. The GAN and AE techniques combined will automatically learn signatures and dependencies in the poultry data (images and audios) and create compact data representations for efficient decision-making in an unsupervised manner. RDL is a transfer reinforcement learning agent trained to accomplish multiple tasks, generalize its knowledge and transfer it to new tasks. This agent regulates the controller by helping to take actions to control environmental parameters and the poultry house.

(ii) The device module consists of all devices for performing detection, monitoring, and controlling. They are controllers, actuators (i.e., heaters, fans, lightings, humidifiers, dehumidifiers), and sensors (i.e., humidity, temperature, cameras, microphones) for monitoring humidity, temperature, movement, gait, preening and sand bathing behaviors, water level, food level, and air quality.

(iii) The communication module transmits data and signals in the network. The communication mode between components (Cloud,

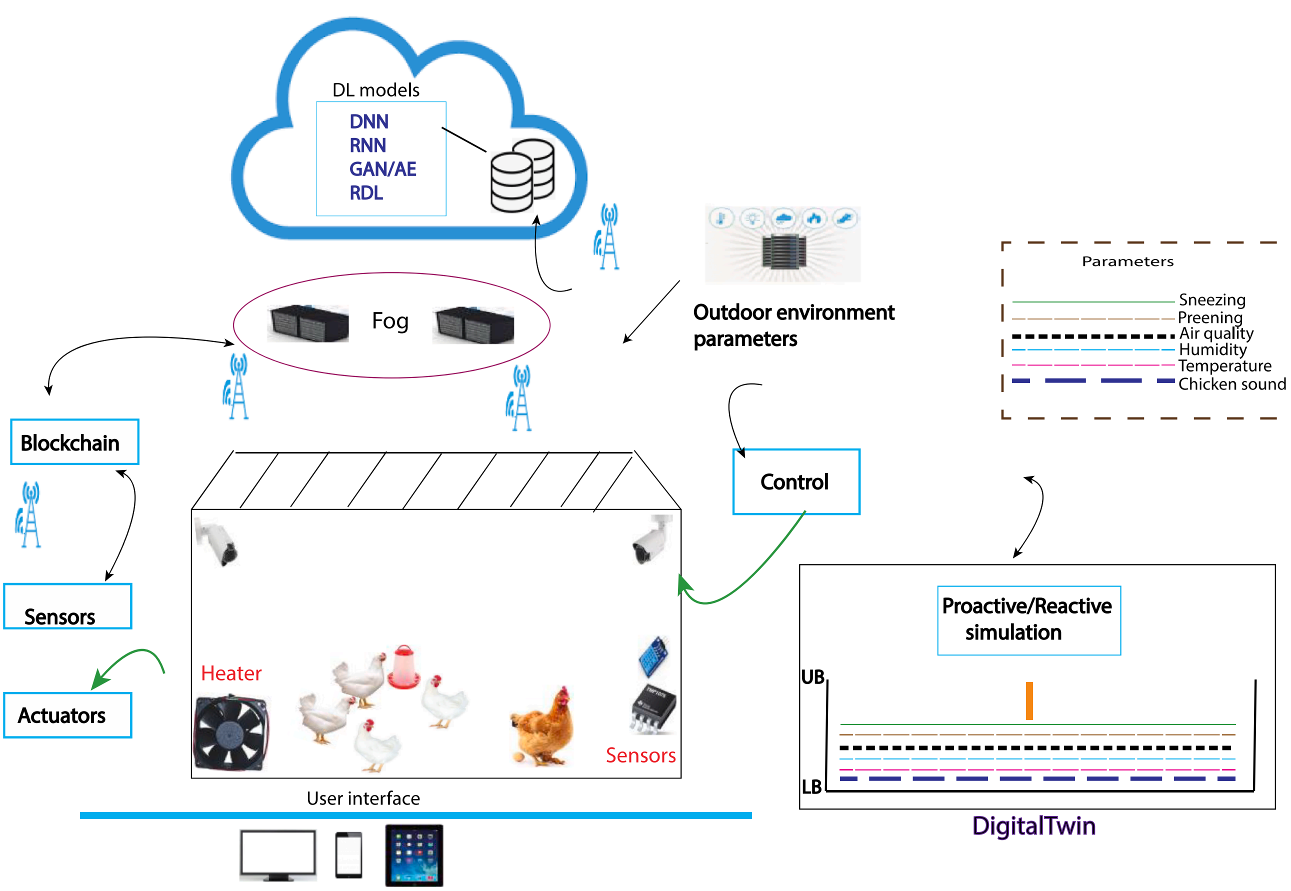

Fig. 8. Smart poultry health and welfare management framework.

blockchain, edge, sensors, and users) is wireless and mobile, as shown in Fig. 8.

(iv) Cloud-Edge computing-The successful deployment of a smart poultry welfare solution depends on this technology. The cloud-fog-based module stores DL models, databases, and datasets due to better data management. The execution of DL models is carried out in fog computing nodes for increased network performance due to reduced latency.

(v) Security module: - The recurrent news about security breaches, private data leaks, and inappropriate use of data has recently made the security of the IoT platforms necessary. Thus, the blockchain techniques will be deployed to secure the poultry welfare network platform due to the multitude of devices, sensors, and services involved in data collection and transmission.

(vi) Digital-twins module will support real-time data processing and simulations of complex dynamic processes in poultry production with environmental and behavioral-based parameters (i.e., preening, chicken sound, temperature, humidity, ammonia) by advanced deep learning techniques. This module will facilitate better business decisions, improve poultry health and welfare-being, and maximize the return from agricultural resources.

(vii) The user interface module allows users to interact with the system. Through this module, users can receive alarms, visualize data in real-time, perform prospective analysis, and validate actions carried out by the RBL agent in controlling actuators.

5.1. Implications for practitioners and academics

The need for transparent, efficient, and sustainable poultry production systems is driving the digital transformation in poultry welfare both for ethical and economic reasons. The stakeholders, therefore, need to reassess their present position concerning the emerging technologies disrupting the agro-industry. Furthermore, with the increasing demand for poultry meat and eggs, and the incessant poultry disease outbreak, which has continued to be a threat and economic burden to the poultry industry, there is a need for a massive deployment of digital technologies to improve poultry disease management and productivity. The review reveals enormous benefits of IoT and ML to poultry welfare. Furthermore, it suggests how contemporary AI and IoT techniques can be harnessed to confront current challenges in poultry welfare to increase efficiency.

Based on the discussions in this study, the following areas need further investigation from researchers. First, more studies on how AI and IoT algorithms can facilitate the optimal use and utilization of resources in poultry welfare are required. Similarly, studies on identifying the relationships between the various barriers to implementing AI-based IoT systems for commercial poultry farming are required. The identification of the driving and dependence barriers will help in expediting the AI-based IoT implementation.

6. Conclusion

In this article, a comprehensive and systematic review of the applications of AI and IoT in poultry health and welfare management, especially for poultry production, has been provided. Also presented were the latest applications of AI-enabled IoT using various representative studies highlighting processing techniques, data, hardware, and software parts used in poultry welfare systems. In addition, this study illustrated the significant divisions of IoT/AI interventions in poultry and presented a reliable, robust, and extendable framework for poultry welfare, specifically in realizing robust poultry disease outbreak prevention. This study contributes to knowledge by helping stakeholders understand and better harness advanced digital technologies and critically analyse the limitations of poultry farms in recognizing the possible applications and patterns of technological advances in the domain. Also, information regarding technologies for poultry welfare management and optimization of its production process will help facilitate reaching a high quality, short process time, and low-cost production in poultry. Thus, the review will stimulate new lines of reasoning that will improve productivity and profitability in the poultry farming industry.

Declaration of Competing Interest

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Data availability

No data was used for the research described in the article.

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