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Artificial intelligence in animal farming: A systematic literature review

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ABSTRACT

Some scientific researches have been conducted recently based on Artificial Intelligence (AI) to solve animal welfare and health related problems. However, no review study was conducted to assess the potential of AI in solving the diverse application problems in several animal species including ruminants, pig and poultry. To fill in this gap, this paper provides a systematic review on scientific research advancement in AI related animal farming based on 131 research publications over the past four decades. It was shown that the number of related studies has increased significantly since 2016, and the most intensive studies were focused on animal behavior detection and recognition, and concentrated mostly on farm animal species of pig (37.95%), cattle (37.44%), and poultry (16.92%); Also, most scientific research in animal farming driven by sensors and AI models were focused on data collection, processing, assessment, and analysis in the areas of animal behavior detection, disease monitoring, growth estimation, and environment monitoring at the experimental stage; Moreover, some technical challenges on AI like the accuracy and cost need to be improved before it could come into use in the commercial animal farming.

1. Introduction

In the intensive animal farming, the Artificial Intelligence (AI) technology takes importance role on assisting a smart farming in the field of animal health and welfare improvement, so as to achieve good economic benefit. Although some scientific researches have been conducted using the AI, no literatures review that covers most AI related researches on multiple livestock species was reported to provide good references for research and farming. To fill in this gap, the literature review was provided to answer the questions of how and where are the AI used in the smart farming process, to solve the main concerns (i.e., costs and disease) and to improve animal production efficiency.

Solutions focus on the quality of animal care as well as the state of animal welfare are considered as the effective ways to achieve an optimal and sustainable animal farming. To some extent, it is not easy to achieve good animal welfare (Hemsworth et al., 2015) that covers with various condition of health, safety, behavioral and emotional expression with traditional measures. Fortunately, the emerging AI technology are sought to have the potential to cope with and improve animal welfare for improving production performance in animal farming (Alves et al., 2021).

In recent years, a wide range of researches in sensors, data processing and transmission, AI models of machine learning (ML), deep learning (DL), artificial neuro networks (ANN), etc., are attempted to solve problems that related to animal identification (e.g. (Hu et al., 2020)), behavior detection (e.g., (Riaboff et al., 2021)), disease monitoring (e.g., (Volkmann et al., 2021)), environment control (e.g., (Gautam et al., 2021)) and so on.

Besides the scientific researches, some reviews on animal farming concentrated on specific species in a limited application field have also been presented. For example, sensors (Neethirajan, 2020) and IoT (Astill et al., 2020) used for poultry welfare (Ben Sassi et al., 2016); pig precision farming (Vranken and Berckmans, 2017); deep learning (Chen et al., 2021) for cattle and pig behavior detection; data modeling for animal production (Ellis et al., 2020).

However, to the best of author's knowledge, no comprehensive review that covers most AI application for several farm animal species (poultry, swine and ruminants) in a literature was found. Therefore, the objective of this review is to provide a systematic review and in-depth discussion on the AI technology used currently and in the future that have the potentials to provide advanced, economic and sustainable animal farming, and to present some critical references for researchers and engineers who are interested in smart animal farming.

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Nomenclature

AI	Artificial intelligence
ANFIS	Adaptive neural fuzzy inference system
ANN	Artificial neuro networks
ANN-RBF	Artificial neuro networks combined with radial basis function
CNN	Convolutional neural networks
CNN-LSTM	Convolutional neural networks combined with long short-term memory
DL	Deep learning
DNN-HMM	Deep neuro network combined with hidden Markov model
IMU	Inertial measurement units
LSTM	Long short-term memory
MFCC	Mel frequency cepstrum
ML	Machine learning
PLF	Precision livestock farming
RBF	Radial basis function
R–CNN	Region convolutional neural networks
RFID	Radio frequency identification
PR	Pattern recognition
VGG-Face	Visual geometry group – Face
WMFCC	Weighted Mel frequency cepstrum
YOLO-MRM	You Only Look Once combined with multiple regression model

The following sections were organized as: Methodology, it covers with systematic review protocol, research questions, search and selection criteria, quality assessment and data extraction and analysis; Overview of the research area and survey results, it presents the characteristics of this research area, and its chronological and geographical research advancement and statistical analysis, and reveals the major AI models, simulation tools and measurement devices; Application domain, it develops insights into AI technology and its popular application domain on different animal species; and Challenges and future needs, it discusses AI technologies with potential, research trends and future needs in agriculture animal farming.

2. Methodology

2.1. Systematic review protocol

The protocol of this systematic literature review (SLR) followed a standard process in plaining, execution, and discussing phase to achieve a credible and comprehensive review result (Staples and Niazi, 2008), also the selection criteria were referenced from the review literature (Awan et al., 2021c) and survey (Awan et al., 2021a). The flowchart describing the proposed methodology was shown in Fig. 1.

2.2. Research questions

This paper is intended to identify, evaluate and interpret published studies that tackled the AI technology applied in the aspects of animal welfare and health conditions. For this purpose, four specific research questions have been addressed: (1) what are the various applications of AI distributed in or focused on animal farm? (2) what are the AI technologies used in a certain field of animal farming? (3) what are the limitations and advantages of AI models in animal farming? (4) what are the challenges and future need for the AI technology in animal farm?

2.3. Search and selection criteria

The referenced research papers and reports were retrieved from international digital libraries such as ScienceDirect, Scopus, IEEE and Web of Science. Search strings like, "animal behavior", "animal farm", "pig", "cattle", "sheep", "poultry", "livestock", "big data", "artificial intelligence", "deep learning", "machine learning", "machine vision", "sensors", "RFID", etc., were used in combination based on title, abstract and keywords.

The referenced publication must meet the criteria (Awan et al., 2021c) were considered: (1) cover both the intelligent technology and farm animal, (2) be published in refereed journals or peer-reviewed conference publications, (3) report original findings. There were 194 papers meet the inclusive criteria.

2.4. Quality assessment

The assessment were made to evaluate the quality of each individual study and help to filtering the poor quality and irrelevant studies from five aspects (Kitchenham, 2007): (1) well-designed and practical experiments with sufficient datasets, (2) appropriate research methods and simulation platforms, (3) clear research objectives, (4) accurate and critical discussion and analysis, (5) good significant to knowledge and technology advancement. The papers were considered for the referenced literatures only they were fulfilled two aspects or more that mentioned above. There were 131 articles selected as the referenced publications according to the quality assessment.

2.5. Data extraction and analysis

The research activity of the review extended along the period between 1980 and 2021. The first author's affiliation was regarded as the country for statistical analyses. The data of the referenced publications including, title, authors, publishing year, country, published journals, animal species, application domains, AI techniques, software and tools were extracted and write into the summarized excel file (Microsoft Excel, 2016). To facilitate the statistical analysis, the review statistic data of geographical, chronological, the percentage of the AI models and animal species were counted and generated from the worksheets. Also, the excel commands of count, countif, sum, average, etc., were used to calculate the number of the reviewed literatures that meet the searching

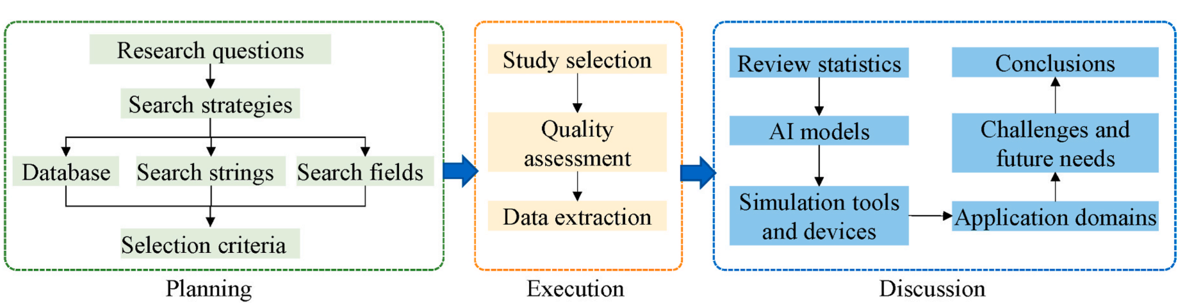

Fig. 1. Flowchart of the systematic review methodology.

parameters in the summarized excel files. Moreover, the statistical figures (Figs. 3–5) were generated according to the statistical results in the excel file.

3. Overview of the research area and survey results

3.1. Interdisciplinary research

AI in animal farming is a technology and application requirement interdisciplinary research field (Fig. 2). It solves the sustainable production needs on animal welfare, behavior, disease, and environment management. Advancement in this research field has been driven by the contributions and collaborations of computer scientist, animal scientists, agricultural engineers, environmental scientists, and veterinarians. Research on the technology has focused on some non-structured (e.g., image, video, voice) and structured (e.g., textual) data collection, analysis (Awan et al., 2021b), processing, recognition, and modeling that are related to animal behavior, welfare, diseases, as well as animal building designs and environmental management.

3.2. Review statistics

3.2.1. A geographical view

The referenced papers from thirty-two countries in Asia, America, Europe, Africa and Australia have been contributed to AI related research on animal farming (Fig. 3). The number of the referenced papers reported by researchers in China was 57. The UK (16) and the USA (16) ranked second among all contributing countries. Germany (11), Iran (9), Belgium (9), and Korea (8) have also been very active in the AI related scientific research. Only one study was reported in Africa (Omomule et al., 2020).

There were 37.44% referenced paper (73) were focused on the AI related scientific research in dairy or beef cattle, 34.23% of them (25) were mainly contributed by five Asia countries (i.e., China, Iran, India, Korea, and Japan), and 19.18% of them (14) were from European countries (i.e., the UK, Germany, Belgium, Italy and France). Also, there were 37.95% referenced papers (74) were concentrated on the smart pig farming, most of them were contributed by Asia countries (e.g., China, Korea, Japan). Moreover, there were 16.92% research on poultry (33), most of them were from Asian countries (China, Iran, India).

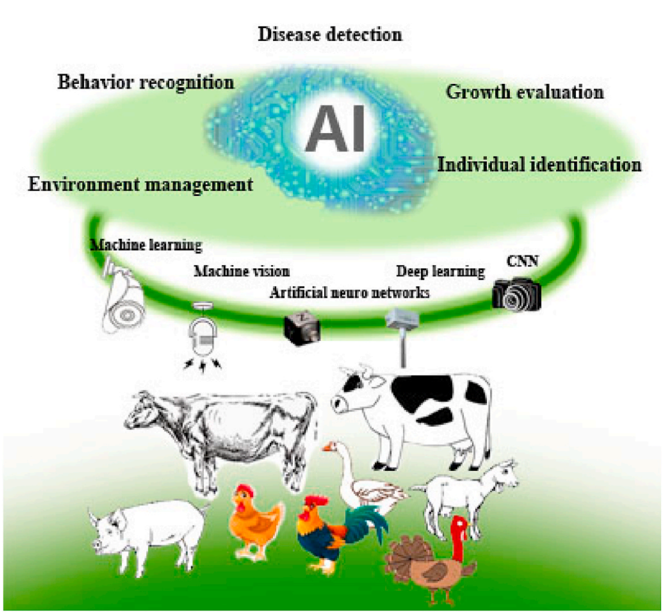

Fig. 2. AI applied in animal farming.

3.2.2. A chronological view

The AI related research is a popular scientific and engineering area, it is believed to have originated since the Dartmouth Conference in 1956. The earliest AI-based animal farming can be traced back to 1970s with the expert's system being used to determine vitamin B6 deficiency in chicks by electroencephalogram (EEG) analysis in America.

In 1980s, the research was followed by computer based head move image recordings and analysis (Lecas and Dutrieux, 1983). A modeling approach to simulate animal and habitat interactions was established (Saarenmaa et al., 1988) to implement a hierarchical decision-making model of behavior. Also, an expert's system was proposed for dairy herd management to improve feeding, culling, mastitis control (Spahr et al., 1988).

In the 1990s, the AI in animal farming became popular with weight evaluation and estimation (Schofield, 1990), health and metabolic status (Mottram, 1997). The pig weight estimation was conducted from specific areas and dimensions that measured directly from the top view using digital images and estimated a pig weight within 5% accuracy.

Since 2000s, especially, over the past five years, studies on smart animal farming have been increased dramatically, the number of reviewed papers increased from 13 to 64 since 2016 to 2020 (Fig. 4), especially, in China, there has been a surge since 2018. They have been in a wide range of disease detection (18), behavior recognition (71), individual identification (12), barn environmental control (21) and monitoring (34) (Fig. 4).

3.3. AI models

AI models that frequently used for modeling, prediction, and management of animal farming include Artificial Neural Network (ANN), Convolutional Neural Networks (CNN), Deep Learning (DL), Adaptive Neural Fuzzy Inference System (ANFIS), Machine Learning (ML), and Pattern Recognition (PR) (Fig. 5). In the reviewed papers, AI models of CNN, DL, ML were in a large percentage and popular in the recent years.

3.3.1. Convolutional Neural Networks (CNN)

The CNN models were constructed by feed forward neural networks with convolution computation and depth structure to imitate the biological visual perception mechanism. In the reviewed papers, CNN models (48) took for 26.52%, which mainly focused on animals' behavior recognition and individual identification (Table 1) by means of image, video and audio processing.

The CNN models were sensitive under different conditions of daylight and night time (Zhang et al., 2019a) when used for behavior recognition on posture, location (Ye et al., 2020) and tracking (Cowton et al., 2019). Also, on the purposes of welfare, feeding and growth monitoring, CNN models were established for individual identification including face and body recognition, and weight estimating. They provide a non-invasive automatic identification method instead of invasive RFID tags (Table 1).

3.3.2. Machine learning (ML) and deep learning (DL)

Models of ML (30) and DL (29) ranked the second and the third in percentages of 15.78% and 15.26%, respectively, in the reviewed papers. ML models mainly included algorithms of decision tree (Warner et al., 2020), clustering (Gauthier et al., 2021), support vector machine (Mito et al., 2020), and Markov chain model (Kalantari and Cabrera, 2012). They focused on the disease detection, behavior recognition for postural classification, and also on sound detection of animals (Table 1).

DL models extract the inherent law and represent the sample data on images (Kumar et al., 2018), video (Jiang et al., 2019), and audio (Nasirahmadi et al., 2020) for animal's location (Riekert et al., 2020), tracking (Fang et al., 2020) and behavior recognition (Wang et al., 2021c) (Table 1). Sometimes, the two AI models of DL and ML were combined with and compared to in one study and formed a hybrid AI model.

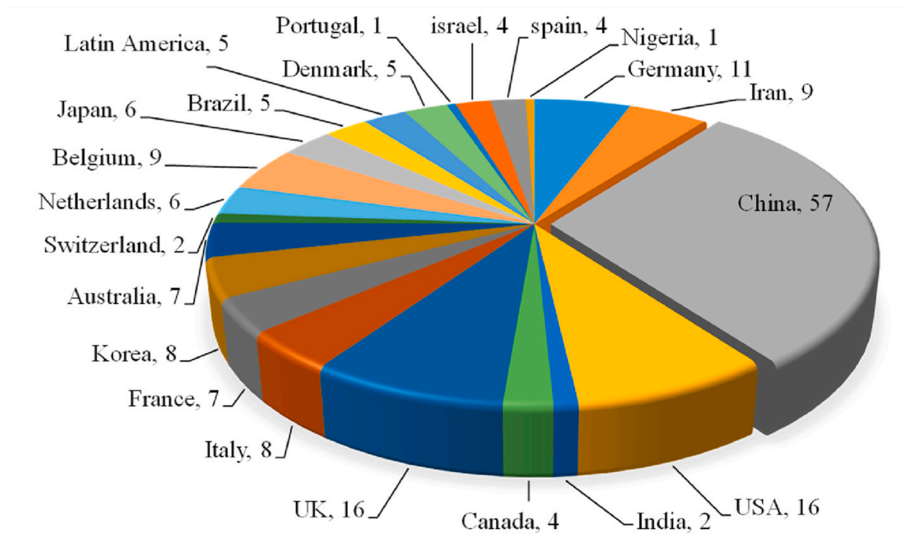

Fig. 3. Geographical distribution of the numbers of reviewed AI related publications.

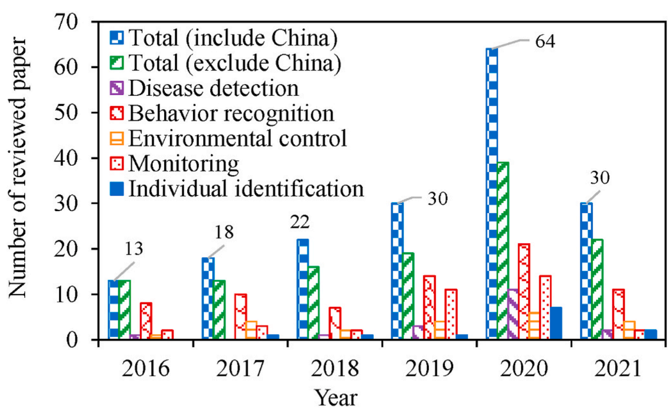

Fig. 4. The referenced papers in recent five years.

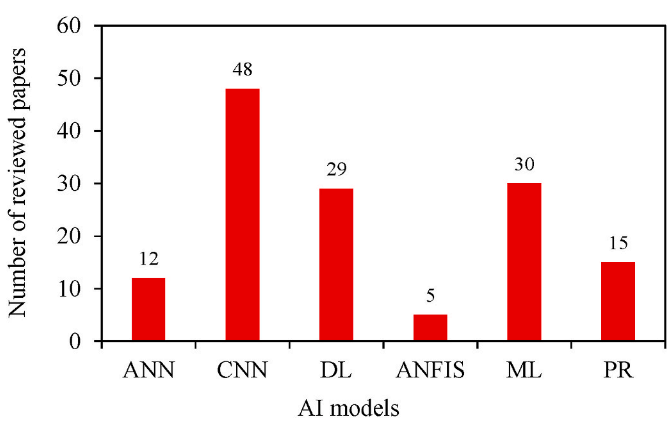

Fig. 5. AI models of reviewed papers.

3.3.3. Artificial Neural Network (ANN)

ANN was the most recurrent AI model in the previous years. Different ANN algorithms including Back Propagation (BP) (Ahmad, 2009), Radial Basis Function (RBF) (Amid and Mesri Gundoshmian, 2017), and feed-forward (Heald et al., 2000) were found in the reviewed literatures. In recent years, the publications of ANN decreased compared with those in the early 2000s. The ANN models mainly concentrated on the animal disease detection, growth performance estimation and environmental condition monitoring and control (Table 1).

3.3.4. Adaptive Neural Fuzzy Inference System (ANFIS)

ANFIS is another research direction of AI in recent years, which combines fuzzy logic and neural network. The ANFIS models focused on ammonia (Xie et al., 2017) or greenhouse gas concentration and emission prediction for environment control in swine buildings, energy output (Amid and Mesri Gundoshmian, 2017) and consumption (Sefeedpari et al., 2014) in the broiler or cattle farm, biogas production from the cow manure (Zareei and Khodaei, 2017), and the relations between feeding intensity of geese and reeds damage (Salski and Holsten, 2009).

3.3.5. Pattern recognition (PR)

PR can process and analyze information from images, videos and sounds in the way of brain like intelligence by biological perception and computer realization to describe and identify individual behaviors, meat quality (Masferrer et al., 2018) and growth performances (Philipsen et al., 2018). A typical PR model was proposed by Chelotti et al. (2018) with Chew-Bite Intelligent Algorithm (CBIA) in attempting to improve the recognition of jaw movements by sound signal derived from ruminant feeding behavior, and the recognition rate of 90% was achieved.

3.3.6. Hybrid models

The hybrid models that integrated different AI algorithms aimed at eliminating the shortcomings or improving the performance of separated single model. Obviously, most hybrid AI models improve the performances compared with the single models. Moreover, it was noticed that most hybrid models (Table 2) were used to solve a specific problem. However, the CNN-LSTM model was used to improve the multiple behavior-related recognition of drinking, feeding, aggressing, egg quality detection and engagement. Therefore, it indicated that most AI hybrid models grew vertically, some hybrid models should be constructed to solve more horizontal problems as possible as it could.

3.4. Simulation tools and devices for measurement

3.4.1. Simulation tools

AI software platforms and libraries provide necessary tools to solve the problems in animal farm management. MATLAB is the most common used software, particularly in the training and testing on models of ANN and ANFIS for animal production (e.g. (Omomule et al., 2020),) and environment prediction (e.g. (Xie et al., 2017),). Another commonly used analysis and simulation tool is SPSS, an IBM software being used to

Table 1
Summary of referenced literature with different AI models in different application area.

Application area	Sub area	CNN	DL	ML	ANN	PR	ANFIS
Disease detection	–	–	(Jorquera-Chavez et al., 2021; Xudong et al., 2020; Zhuang and Zhang, 2019)	(Mito et al., 2020; Probo et al., 2018; Vandermeulen et al., 2016; Volkmann et al., 2021; Warner et al., 2020; Zhao et al., 2020)	(Heald et al., 2000; Hemati Matin et al., 2013)	–	–
Behavior recognition	Posture	(Achour et al., 2020; Chen et al., 2020d; Li et al., 2020, 2021; Peng et al., 2019; Wang et al., 2021c; Yang et al., 2018)	(Fuentes et al., 2020; Li et al., 2019; Nasirahmadi et al., 2019a; Wang et al., 2021a; Yin et al., 2020; Zhang et al., 2019b)	(Adamczyk et al., 2017; Borchers et al., 2017; He et al., 2021; Ren et al., 2021; Riaboff et al., 2020; Williams et al., 2016)	–	(Chelotti et al., 2018; Riaboff et al., 2021; Zaninelli et al., 2017)	–
	Location and tracking	(Psota et al., 2019; Zhang et al., 2019a; Zin et al., 2020)	(Fang et al., 2020; Zheng et al., 2018)	Smith et al. (2020)	–	–	–
Individual identification	Body Identify	(Achour et al., 2020; Che et al., 2020; Gomez Villa et al., 2017; Hu et al., 2020, 2021; Zin et al., 2020)	(Andrew et al., 2021; Sun et al., 2019)	Monteils and Sibra (2019)	–	Kashiha et al. (2013)	–
	Face Identify	(Hansen et al., 2018; Marsot et al., 2020; Wang et al., 2020)	Noor et al. (2020)	–	–	–	–
Growth performance estimation	Weight	(Dohmen et al., 2021; Jun et al., 2018; Samperio et al., 2021)	Cang et al. (2019)	(He et al., 2021; Weber et al., 2020)	(Ma et al., 2020; Tahmoorespur and Ahmadi, 2012)	Masferrer et al. (2018)	–
	Body score	–	Sun et al. (2019)	Nasirahmadi et al. (2019b)	–	–	–
Environment control and monitoring	–	–	–	(Dohmen et al., 2021; Gorczyca and Gebremedhin, 2020)	(Amid and Mesri Gundoshmian, 2017; Hosseinzadeh-Bandbafha et al., 2017)	–	(Salski and Holsten, 2009; Sefeedpari et al., 2014; Xie et al., 2017)

Table 2
Analyses of hybrid models in the reviewed literatures.

Literature	Hybrid model	Objective	Results
Amid and Mesri Gundoshmian (2017)	ANN-RBF	To develop predictive models for determining input (fuel, feed, and electricity) and output (broilers and manure) parameters in broiler production.	✓ ANN-RBF was the best predictor of outputs. ✓ ANN-RBF had a higher R2 of 0.996 and 0.995 for broiler and manure, respectively; and lower RMSE of 0.016 and 0.02 for broiler and manure, respectively.
Ye et al. (2020)	YOLO-MRM	To improve the accuracy and efficiency of broiler stunned state recognition, and applied to the recognition of the broiler stunned states.	⋄ YOLO -MRM algorithm achieved good performance with an accuracy of 96.77%. ⋄ YOLO -MRM can complete the detection task of more than 180,000 broilers per hour. ⋄ Compared with the traditional method, the recognition accuracy and speed are improved obviously.
(Chen et al., 2020a, 2020b, 2020c, 2020d; Turkoglu, 2021; Wang et al., 2021c; Wu et al., 2021)	CNN-LSTM	To develop a CNN-LSTM algorithm to recognize or classify pig (or cow) behaviors of feeding, drinking, aggressing, movement, posture, and enrichment engagement (EE); defective egg detection.	✓ The recognition accuracy was 98.4%, sensitivity was 98.8%, specificity was 98.3% and precision was 95.9%. ✓ The classification accuracy in the body and head regions of interest was 87.2% and 92.5%, respectively. ✓ Aggressive episodes could be recognized with an accuracy of 97.2%. ✓ The proportion of EE with each object of blue ball, golden ball and wooden beam was 75.8%, 6.0% and 18.2%, respectively. ✓ The average precision, recall and specificity of five basic behaviors were 0.971, 0.965 and 0.983, respectively. ✓ The accuracy on the test dataset on 500 new videos was 90.60%. ✓ A defective detection accuracy score of 99.17% was achieved.
Zhao et al. (2020)	DNN-HMM	To construct an acoustic model for continuous pig cough sound recognition to detect the respiratory	⋄ The average Word Error Rate (WER) of each group in DNN-HMM was 3.45% lower than that of GMM-HMM

(continued on next page)

Table 2 (*continued*)

Literature	Hybrid model	Objective	Results
		disease in the early stage.	⋄ The best result of the DNN-HMM model was obtained with the lowest WER of 7.54%.
Chung et al. (2013)	SVDD-SRC	To propose an efficient data mining solution for the detection and recognition of pig wasting diseases using sound data in audio surveillance systems.	✓ A combination of MFCC and SVDD can automatically detect pig wasting diseases using cough sounds at an accuracy level of 94%. ✓ The SRC classified pig wasting diseases at an accuracy average of 91.0%.
Peng et al. (2019)	LSTM-RNN	To develop a RNN with a LSTM model to monitor and classify cattle behavior patterns using inertial measurement units (IMU).	⋄ Achieved the best performance when using a window-size of 64 (accuracy, precision, recall, f1-score all were 88.7%). ⋄ With a window-size 64, classification accuracy of feeding, lying, ruminating-lying, ruminating-standing, licking salt, moving, social licking, head butt was 97.8%, 88.7%, 88.4%, 92.9%, 94.4%, 84.8%, 80.3%, and 81.9%, respectively.

perform statistical analysis of correlations between inputs and outputs (e.g., pattern recognition in egg production (Omomule et al., 2020), ruminating and eating of cows (Zehner et al., 2017)). R software is used to edit and analyze datasets, particularly in sensor data analysis on animal activity related prediction (Rutten et al., 2017). Python language is used to simulate AI models, which contains Tensor Flow along with other libraries such as, OpenCV (Nasirahmadi et al., 2019a), RoIPool (Li et al., 2019), and Keras (Wang et al., 2020).

3.4.2. Devices for measurement

Devices used for data measurement in animal farming can be summarized into two categories: (1) fixed-installed non-invasive devices (e.g., camera (Zaninelli et al., 2017), microphone (Alex and Joseph, 2018)) and (2) sensor-based animal attached devices (e.g., accelerometer (Giovanetti et al., 2016), ear tag (Rutten et al., 2017), nose band sensor (Zehner et al., 2017)). The fixed-installed devices are used to track, locate, identify, and detect the behaviors of feeding and drinking for the individuals. The sensor-based animal attached devices are used for animal movements or posture classification and recognition by various technological solutions (Table 3). While, non-invasive devices are promising for smart animal farming, further studies are needed for improving the accuracy, stability, and adaptability of the measurements under the complex farm conditions.

4. Application domains

4.1. Individual identification

Individual identification enables the farm managers to treat animals as individually tailored diets and environmental control for an optimal productivity. Also, it is an important step for the traceability of animal products through the supply chain. Up to date, ear tags and RFID technology are commonly used for individual identification of pigs (Cappai et al., 2018), ruminants (i.e., cattle, sheep) (Rutten et al., 2017), and poultry (Sales et al., 2015). However, ear tag is an invasive method which could bring some stress on animals, also, it is too easy to be contaminated for number reading. Although, the RFID identification system could overcome the reading problem of ear tag, it still has some limitations of battery supply and signal interference, and costly for current practical applications.

To avoid these problems mentioned above, non-invasive recognition of machine vision was attempted. Cameras are usually installed in front of feed troughs to capture face images. The analysis software and algorithms perform the tasks of extracting and recognizing the acquired face images. For example, Hansen et al. (2018) conducted an on-farm pig face recognition by steps of visual data capturing, data cleaning and implementing (Fig. 6). In their study, an accuracy rate of 96.7% was achieved based on 1553 images.

Indeed, machine vision-based pig face recognition can provide an inexpensive solution for individual identification on farm environment, however, the uncontrolled variables (e.g., position, pose, lighting and dirty conditions) will affect the recognition accuracy; also, the algorithms of image processing and recognition are too complex to be performed on the onsite devices. Therefore, the efficiency and accuracy of pig face recognition need to be further improved before it can be applicable in the commercial pig production.

4.2. Behavior monitoring

Animal behaviors (Zheng et al., 2018) are always monitored by means of camera (Nasirahmadi et al., 2019a), microphone (Aydin et al., 2015), and accelerometer (Giovanetti et al., 2016) for the purpose of inspecting animal health and welfare conditions. The eYeNamic camera-based system is usually installed on top of the animal activity zone to generates a top-down visualization perspective. Some software (e.g., Phython, Matlab, Tensorflow, etc.) and algorithms (e.g., CNN, ML, DL, etc.) are used to translate or classify the visual or acoustic information from the acquired images into certain behaviors.

4.2.1. Feeding behaviors

Among most behaviors, the feeding behavior of animal individuals is an important indicator reflecting its healthy status. Water meters provide accurate water consuming information, it is considered as a simple and effective way to monitor the drinking performance. Video surveillance or video recorder was used for automatic monitoring on individual feeding (Yang et al., 2018) and drinking (Chen et al., 2020b) behaviors of the group-housed pigs and ruminants (Giovanetti et al., 2016). Sensor-based devices of nose band pressure (Zehner et al., 2017), accelerators (Barker et al., 2018), HOBO logger (Rayas-Amor et al., 2017), microphones (Chelotti et al., 2016), were used for automatic measurement of ruminants feeding behavior (including eating, chewing, swallowing, and ruminating) (Fig. 7).

Feature extraction (e.g., color moments feature, geometric features) (Zhu et al., 2017) is key point to identify individual feeding or drinking behavior from the video sequences to establish the accurate mathematical models (e.g., CNN, LSTM) (Chen et al., 2020b). Currently, to facilitate precious feeding decisions on farms, the accuracy rates of feeding behavior recognition still need to be improved although it could be achieved above 90% at the experimental level.

4.2.2. Aggressive behaviors

Abnormal behavior of aggression is regarded as the most important welfare problem in group-housed pigs (D'Eath and Turner, 2009) because it could results in injury of skin trauma, infection and even to death, which could increase the potential of lowering productive performance. However, the studies on automatic aggressive behavior

Table 3
Sensors or devices for measurement in the reviewed literatures.

Study	Sensor or device	Type	Location	Objective
Wijaya et al. (2019)	Sensor array: MQS gas sensors and a temperature-humidity sensor	MQ135, MQ136, MQ2, MQ4, MQ6, MQ9, DHT22	On top of the sample chamber.	Detect gasses produced by mesophilic bacteria in the process of beef spoilage.
(Ruuska et al., 2016; Zehner et al., 2017)	RumiWatch pressure-based noseband sensor	–	Attached on the nose of dairy cow.	Measure eating, rumination and drinking time of dairy cow.
Giovanetti et al. (2016)	Tri-axial accelerometer sensor; camera	Camera: Sanyo Xacti VPC-TH1, Sanyo Electric Co., Ltd. OSAKA, Japan.	Tri-axial accelerometer sensor positioned under the lower jaw of the sheep.	Measure behavioral parameters of dairy sheep at pasture.
Benaissa et al. (2019)	Accelerometer sensor	–	Neck and leg.	Automatically classify cows' behaviors of lying, standing, and feeding by comparing leg- and neck-mounted accelerometers.
Riaboff et al. (2021)	3-D accelerometer; GPS sensor; datalogger	3-D accelerometer: LSM9DS1; GPS sensor: EVA-7M-0; datalogger: RF-Track;	Neck	Identify behavioral and movement variables of dairy cows at pasture that could discriminate lameness scores.
Rutten et al. (2017)	Agis SensOor sensors	Agis Automatisering B.V., Harmelen, The Netherlands	Attached to the ear tag of the cow.	Acquire synthesized cumulative activity, rumination, feeding, and temperature to help the prediction for calving.
Bloch et al. (2021)	Cameras	5 MP, DS-2CD2652F–I, HikVision, China	On arms placed 4 m above the feeding area.	Rank cows by their feed conversion efficiency in commercial farms.
Barker et al. (2018)	Neck-mounted mobile sensor	Xtrinsic MMA8451Q 3-Axis	Attached to the neck of the cow.	Monitoring behaviors such as time spent feeding.
Arcidiacono et al. (2020)	Tri-axial accelerometer	Kionix KXTJ9	In a SensorTag that fixed to the hind leg.	Detect cow's oestrus activity.
Zaninelli et al. (2017)	Thermografic camera	Thermo-GEAR-G120, AVIO, Nippon Avionics Co., Ltd., Tokyo, Japan	The sensor was installed 2.5 m above the floor.	Automatic detecting the presence of hens.
Ju et al. (2018)	Kinect depth sensor	Microsoft Kinect	3.8 m above the floor.	Provide a low-cost device for separating touching-pigs.
(Küster et al., 2020; Nasirahmadi et al., 2019a)	Cameras	VTC249/IRP/W, VIVOTEK IB836BA-HF3, and Hikvision DS-2CD2142FWD-	On top of the pens.	Capture two-dimensional images, help detecting the movement activity, standing and lying postures of pigs.
Alex and Joseph (2018)	IoT and sensors (thermal sensor, microphone controller sensor, RGB camera)	Thermal sensor: AMG8833, microphone: SEN-14262, Camera: SEN 11745–728 × 488	Mounted at the 2 m height.	Use IoT and sensors to analyze and identify the infected hen.
González-García et al. (2021)	Radio frequency identification ear tags; WoW prototype	Tru-test XR3000 WoW Scales	Installed in the corridor at the exit race of the electronic static scale.	Using an automated walk-over-weighing (WoW) prototype to measure daily LW changes in dairy ewes without human intervention.
Wang et al. (2021b)	Sensors of temperature, humidity, heart rate, blood oxygen saturation.	Temperature and humidity sensors: DHT22; skin temperature sensor: MLX90614; heart rate and blood oxygen:photoplethysmogram (PPG), MAX30102	–	Evaluation and prediction of environmental comfort to ensure the quality and safety of mutton sheep.
Ginovart-Panisello et al. (2020)	Handheld recorder, directional microphone	Handheld recorder: Zoom H5, Microphone: Behringer ultra-voice XM 1800S.	One meter high from the ground and at the center to the house.	Evaluate the relation between traditional indicators (death, weight, and CO2) as well as acoustical metrics.

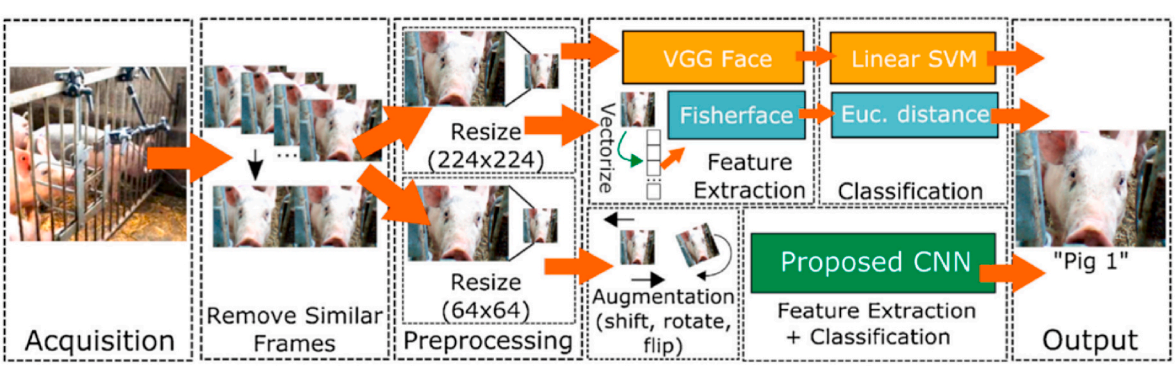

Fig. 6. Processing pipeline showing the acquisition, pre-processing steps, feature-extraction and classification for pig face recognition (Hansen et al., 2018).

recognition are still limited. In recent year, some machine vision-based aggression studies were conducted on aggressive interactions (Viazzi et al., 2014), aggressive behaviors (Chen et al., 2018), and motion features (Chen et al., 2017).

4.3. Live weight estimation

Live weight is used for assessing the health condition and growth performances of farm animals. Traditionally, the live weight was measured by pass-over scale. To avoid the injury and stress caused by

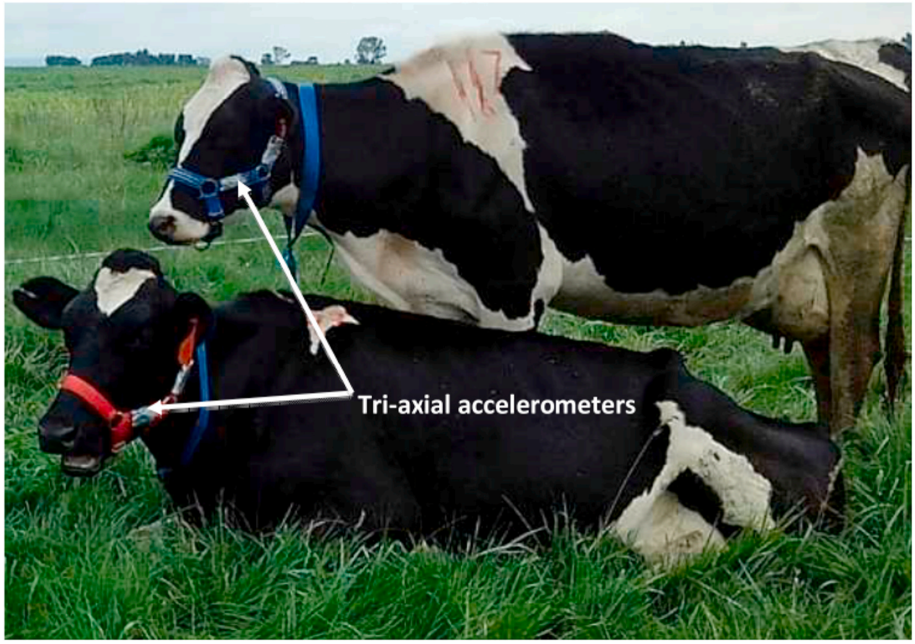

Fig. 7. Data loggers were attached consistently in a harness to lateral-medial side of the jaw (Rayas-Amor et al., 2017).

the direct weighing, non-contact weighing methods using cameras of RGB (Shuai et al., 2020), depth (Wang et al., 2018), or binocular (Jun et al., 2018) for pig size or volume calculation based on images have increased. Most studies focused on the live weight estimation (Tahmoorespur and Ahmadi, 2012) by means of image processing algorithm (e.g., edge detection, image segmentation) and deep learning (FLYOLOv3, CNN) in complex farm environment (Cang et al., 2019). However, the accuracy of the weight estimation largely depends on the posture features, the models therefore need to be improved to increase its applicability.

4.4. Health monitoring and detection

4.4.1. Coughing detection

Respiratory problems, frequent presenting symptoms in the grouped pigs and poultry farm, may be caused by poor living space environment, or some disease infection. Berckmans' lab developed some algorithms and tools for pig cough detection for on-farm application (Exadaktylos et al., 2007) and scientific research (Guarino et al., 2005).

Coughing detection followed with the steps of sound data collection, meaningful information extraction (i.e., audio feature extraction), and sound data classification. The most commonly used method of acoustic features extraction is Mel Frequency Cepstrum Coefficients (MFCC). Comparatively, it is noted that recent trends on animal coughing detection have been implemented by a variety methods of deep learning (e.g. (Zhao et al., 2020),) and machine learning (Liu et al., 2020) (Fig. 8).

Only if the ability of detecting and positioning on cough sounds be improved, it could be used as an automatic detection indicator for animal welfare and health conditions to provide a good reference for the veterinarians or the farmers.

4.4.2. Disease detection

In poultry industry, it is common of some diseases such as Infectious Bronchitis, Avian Influenza, and Infectious Sinusitis. With the progress of AI technology, more studies were conducted on disease detection for sick bird (Hemati Matin et al., 2013) (Alex and Joseph, 2018). The sick bird could be identified by some symptoms of abnormal body temperature (Okada et al., 2009) measured by wearable wireless sensor (Segovia et al., 2013), decreased feed intake and movement, different sound patterns. Although the wearable sensing technology could achieve a good abnormal body temperature detection, it can only be used as early-stage warning because it cannot determine by which disease the birds were infected, at the same time, now it was still not practicable due

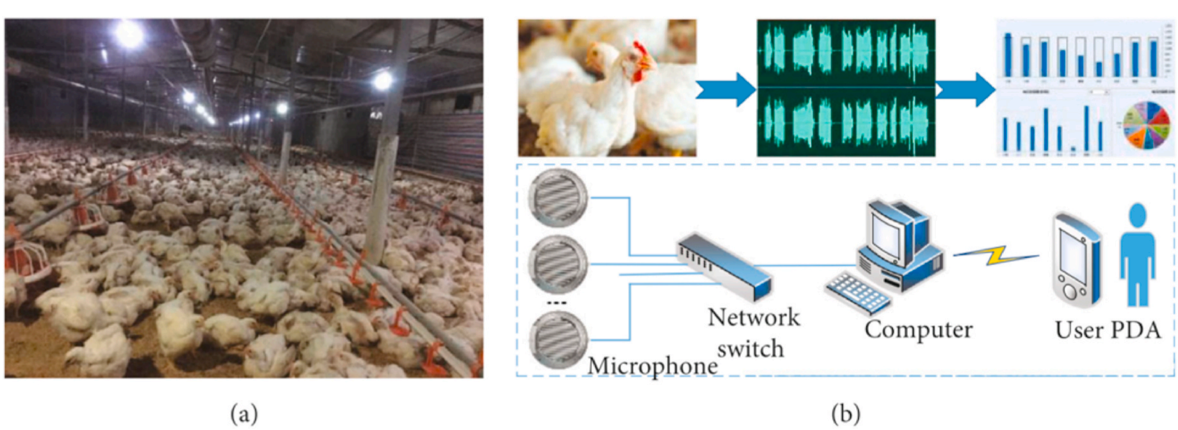

Fig. 8. System structure. (a) Interior of the broiler building; (b) system model (Liu et al., 2020).

to its high cost being equipped in such a large poultry flock.

In the milk production, bacteriologic status of the mastitis in dairy herds could be analyzed and predicted using ANN and ANFIS models with complex data as the input variables to improve probabilities of diagnosing (Heald et al., 2000).

4.5. Activity detection and classification

Activity characteristics (e.g., lying, standing, and walking) of animals can be used as indicator of oestrus and welfare states. In order to detect the activity and to assess environmental conditions, some machine vision-based systems and sensor-based devices can be integrated with WiFi networks, Bluetooth, radio frequency methods and GPS.

It was most a common method that inertial devices (Fig. 9) are embedded with an 3D-accelerometer or uniaxial-accelerometer (Arcidiacono et al., 2020) being attached to animal's leg (Benaissa et al., 2019), neck (Nóbrega et al., 2020), jaws (Giovanetti et al., 2016), or ear (Rutten et al., 2017) to acquire activity data. Some algorithms of machine learning (e.g., support vector machine (Benaissa et al., 2019), random forest (Borchers et al., 2017), clustering (Adamczyk et al., 2017)) and deep learning (Yin et al., 2020) are used for activity classification based on acceleration threshold values in axis of X, Y, or Z. The activity detection system using accelerometer combined with the RFID tags showed potentials in ruminants movement monitoring, as well as some limitations like battery life, attachment methods and stability of the device, the accuracy of the classification, needs to be overcome.

Recently, machine vision-based activity detection and classification for pigs, ruminants and poultry become more popular, since it provides an automated, low cost, non-contact and non-stressful way to achieve activity monitoring (Wu et al., 2021), individual counting (Xu et al., 2020) and detecting (Noor et al., 2020) to support famers generating judgments and early warnings for animal's health conditions on large scale farm.

4.6. Production prediction

Animal farm production can be measured with comprehensive factors such as performance (e.g., quantity and quality of the milk and egg), reproductivity and mortality of animals. Computational models of ANFIS (Shahinfar et al., 2012), ANN (Ince and Sofu, 2013), non-linear pattern recognition (Zhang et al., 2014), clustering (Bonora et al., 2018), and automatic systems could help to predict the breeding values of milk quality and fat yield, herd optimization (Demeter et al., 2011), insemination outcomes (Shahinfar et al., 2014), oestrus (Arcidiacono et al., 2020), abortion (Keshavarzi et al., 2020), energy consumption (Hosseinzadeh-Bandbafha et al., 2017) and environment related physiological responses (Gorczyca and Gebremedhin, 2020). With the AI technology being widely used in all the aspects in animal farming, the production performance and automatic management will be improved increasingly.

5. Challenges and future research needs

Obviously, in the past few years, some technologies for data collecting and processing, modeling algorithms and tools have been developed and integrated for assessing animal health and welfare states. Although some of them are not integrated enough to be implemented under commercial conditions, in fact, they have shown great potential to enhance the farming efficiency on decision making based on the technologies supporting environmental sustainability and cleaner production during the growing cycle. To describe the future research directions further, a conceptual model was established (Fig. 10) from the literature review.

5.1. Animal welfare-based research needs

In the aspects of addressing specific animal welfare issues, sensors, automatic system and AI based models have shown great advantage in examining and monitoring environmental factors (including temperature, humidity, harmful gas concentrations), behaviors (movement, feeding, drinking, posture, gait, aggression), growing or productive performances (weight gain, milking, reproductions), and individual identification.

5.1.1. Environmental control

Under the concept of animal welfare, a comfortable living environment need to be assured to facilitate a better welfare, health, cleaner and sustainable production performance. It is common to install some sensors to collect the multiple environmental factors such as temperature, humidity, and harmful gas contents. Thus, a precise, fast, low-cost and automatic control measures for cleaner environment conditions need to be developed during the production process. Importantly, appropriate data collection interval needs to be considered not only for an optimal and continuous control but the volume of environmental dataset. A large volume of environmental dataset may not be helpful unless data are processed adequately in order to extract relevant and meaningful information for the end users. At the same time, environmental control strategies also need to be optimized in terms of the coupling characteristic of the multiple environmental factors for energy saving to maintain a sustainable production, especially in some typical climate

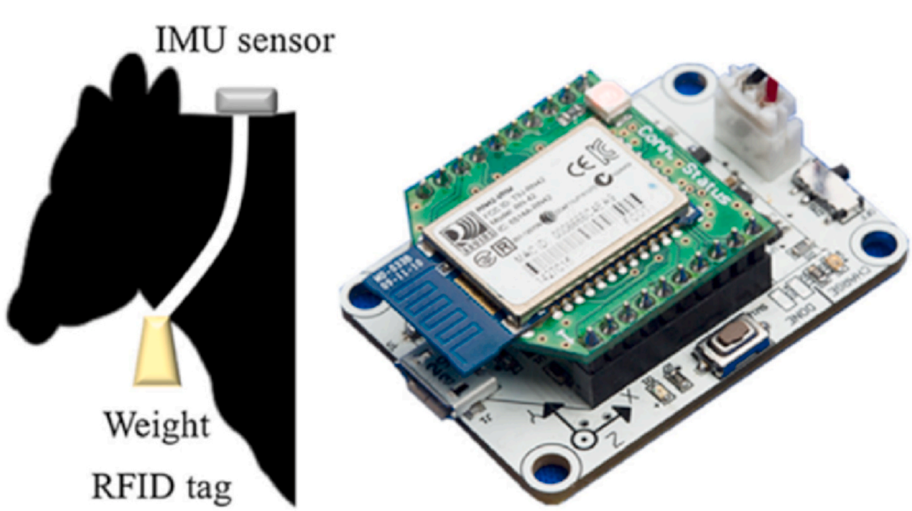

Fig. 9. Inertial measurement units (IMU) sensor installed on the neck (Peng et al., 2019).

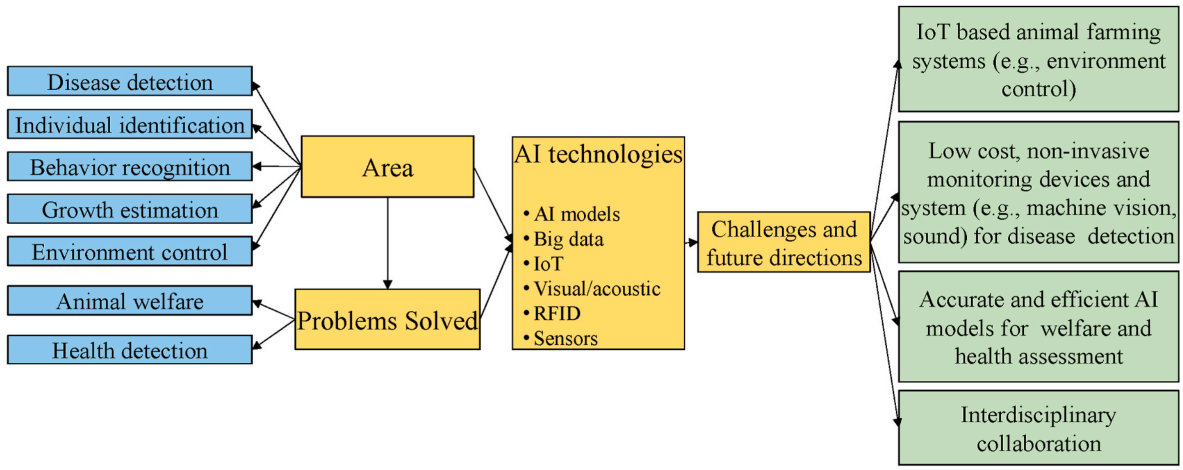

Fig. 10. A conceptual model for future research directions.

areas (extremely cold, hot or humid).

Moreover, Internet of Things (IoT) has far reached implications in agriculture and will be a part of smart animal farming in the very near future. IoT consists of several components including hardware for environmental data collection, connectivity for data transmission, platform for data storage, analyzing and processing, and interface for users to interact with. IoT provides for animal farming a capability of automatic and efficient management practices through communication between sensors and control devices installed on the farms. Notably, to facility automatic environment control, an easily and friendly used software installed on some smart phones will also help the PLF challenge in improving real time online environmental conditions monitoring for farmers.

5.1.2. Animal behavior detection

Many researches have shown that sensors like accelerometer can be useful in investigating the basic welfare states of animals based on their movement characteristics and gait abnormalities. However, the most sensor-based devices for behavior monitoring are wearable by attaching to animals (e.g., leg, neck, wing, ear), to some extent, they may exert some uncomfortable feel or stress to animals.

Further opportunities could lie in the development of machine vision-based systems for monitoring animal behaviors, individual or group features on farm conditions in the non-invasive and low-cost way. However, large data are produced by 2D or 3D cameras monitoring animal behaviors, data analyzing and retrieving is challenging for most researchers when evaluating animal behavior.

Therefore, in the future, a standard database or method for animal behavior data cleaning and selecting is needed for decreasing the time consuming and costs on data process. Moreover, a greater effort should be focus on more effective and practical application of machine vision-based algorithms to improve the accuracy and sensitivity of animal behavior classification and detection.

5.2. Animal health detection research needs

At the health level, the studies on audio (e.g., coughing, sneering, pecking, rumination) and visual (e.g., infrared thermal image, optical flow) show that such technology can be applicable in detecting respiratory disease symptoms and health conditions for early-stage warning. It is estimated that disease caused about 10%–15% losses of production performance in poultry farms (Ben Sassi et al., 2016). A future implementation of these technologies at commercial level should be focused on an accurate prediction in identifying a specific disease by means of monitoring and analyzing sound or visual data.

Automatic individual identification is essential for PLF on individual animal monitoring. Currently, the RFID technology provides more reliable way than image analysis (e.g., animal face identification) in farm environment since individuals in a group are very similar in their shape, behavioral expression, face, color or size. However, due to a higher cost for large number of the RFID tags in a large flock or group, in the future, the image-based individual identification has a great potential to be applied in a commercial farm for its advantages of low-cost and non-invasive as long as more accurate algorithm or technology is developed.

All in all, in the aspects of monitoring animal welfare and health conditions for a sustainable and cleaner animal farming production, in the future, the smart farms should integrate technologies of sensing, RFID, visual and audio processing and analytic into an entire plug-in device. In this system, a welfare precise automatic assessment, intelligent management, disease early-stage warning at a commercial level will be achieved based on multiple scales of behavior expression to assist farmers to make an early right decision for management of sustainable production. Therefore, there is a strong demand for interdisciplinary collaboration among researchers, engineers, economists, consumers, farmers, and technicians to achieve the real PLF with great efforts, even though, currently, these examples of technological developments are still at an experimental phase.

6. Conclusions

According to the literature review, a systematic application involving the basic data collection devices, data processing, and smart algorithms needs to be developed to facilitated the overall animal farming. Especially, the costless IoT based data collection system and high time-efficiency AI models were very necessary to achieve a smart animal farming.

Moreover, some limitations of the AI technology to be applied in the commercial animal farming were pointed out, they were mainly caused by traditional farming production method, accuracy and cost of sensors and devices. Great efforts need to be done to overcome these limitations of the AI technology in farm productions in the future.

The findings of this SLR answered the four research questions to help the researchers, government authorities, animal farm managers to well understand how and where the animal farming will be going globally by using the AI technology, also, they were expected to give some contributions to guide a sustainability and cleaner animal farm production and management, and to facilitate rules making for smart animal farming and present some references for potential environment crisis caused by animal farming.

(1) The AI application mostly distributed in or focused on cattle (37.95%) and pig (37.44%) farms. The application of animal

behavioral detection, grow performance estimation, individual identification, and disease detection were mostly concentrated on. The reports on animal behavior detection took the highest percentage of 45.51%.

(2) The AI models of CNN were most used for animal behaviors classification and recognition based on both visual or audio data collected by camera or microphone. Also, sensor-based devices like RFID tags and accelerometer were most used for individual identification and activity detection in animal farming.

(3) Different AI models have different limitations and advantages in animal farming. Although CNN models exhibited some advantages of higher accuracy in animal identification and recognitions, some limitations of sensitive to environmental conditions and animal postures were also existed. While, hybrid models showed their better performance compared with the single model.

(4) Non-invasive AI technology or systems based on video or audio show great potential in solving the issues of assessing animal welfare and health conditions in the future smart animal farming, however, some limitations like the accuracy, costs, and stability are still need to be improved.

CRediT authorship contribution statement

Jun Bao: Conception and design of study, Reviewing and editing - original draft.

Qiuju Xie: Conception and design of study, Acquisition of data, Analysis and/or interpretation of data, Writing - original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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