Computers and Electronics in Agriculture 200 (2022) 107227

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Barriers to computer vision applications in pig production facilities

Jiangong Li [a,g,*], Angela R. Green-Miller [a], Xiaodan Hu [b], Ana Lucic [d], Mahesh Mohan M.R. [b], Ryan N. Dilger [c], Isabella C.F.S. Condotta [c], Brian Aldridge [e], John M. Hart [f], Narendra Ahuja [b]

[a] Department of Agricultural and Biological Engineering, University of Illinois at Urbana-Champaign, 1304 W Pennsylvania Ave, Urbana 61801, IL, United States
[b] Department of Electrical and Computer Engineering, University of Illinois at Urbana-Champaign, 306 N Wright St, Urbana, IL 61801, United States
[c] Department of Animal Sciences, University of Illinois at Urbana-Champaign, 1207 W. Gregory Dr., Urbana, IL 61801, United States
[d] Applied Research Institute, University of Illinois at Urbana-Champaign, 2100 S Oak St, Champaign, IL 61820, United States
[e] Department of Veterinary Clinical Medicine, College of Veterinary Medicine, University of Illinois at Urbana-Champaign, Urbana, IL, 61802, United States
[f] Coordinated Science Laboratory, University of Illinois at Urbana-Champaign, 1308 W. Main St., Urbana, IL 61801, United States
[g] College of Animal Science and Technology, China Agricultural University, Beijing, PR China

ARTICLE INFO

Keywords:
Computer vision
Precision livestock farming
Behavior
Deep learning
Dataset
Swine

ABSTRACT

Surveillance and analysis of behavior can be used to detect and characterize health disruption and welfare status in animals. The accurate identification of changes in behavior is a time-consuming task for caretakers in large, commercial pig production systems and requires strong observational skills and a working knowledge of animal husbandry and livestock systems operations. In recent years, many studies have explored the use of various technologies and sensors to assist animal caretakers in monitoring animal activity and behavior. Of these technologies, computer vision offers the most consistent promise as an effective aid in animal care, and yet, a systematic review of the state of application of this technology indicates that there are many significant barriers to its widespread adoption and successful utilization in commercial production system settings. One of the most important of these barriers is the recognition of the sources of errors from objective behavior labeling that are not measurable by current algorithm performance evaluations. Additionally, there is a significant disconnect between the remarkable advances in computer vision research interests and the integration of advances and practical needs being instituted by scientific experts working in commercial animal production partnerships. This lack of synergy between experts in the computer vision and animal health and production sectors means that existing and emerging datasets tend to have a very particular focus that cannot be easily pivoted or extended for use in other contexts, resulting in a generality versus particularity conundrum.

This goal of this paper is to help catalogue and consider the major obstacles and impediments to the effective use of computer vision associated technologies in the swine industry by offering a systematic analysis of computer vision applications specific to commercial pig management by reviewing and summarizing the following: (i) the purpose and associated challenges of computer vision applications in pig behavior analysis; (ii) the use of computer vision algorithms and datasets for pig husbandry and management tasks; (iii) the process of dataset construction for computer vision algorithm development. In this appraisal, we outline common difficulties and challenges associated with each of these themes and suggest possible solutions. Finally, we highlight the opportunities for future research in computer vision applications that can build upon existing knowledge of pig management by extending our capability to interpret pig behaviors and thereby overcome the current barriers to applying computer vision technologies to pig production systems. In conclusion, we believe productive collaboration between animal-based scientists and computer-based scientists may accelerate animal behavior studies and lead the computer vision technologies to commercial applications in pig production facilities.

* Corresponding author at: Department of Agricultural and Biological Engineering, University of Illinois at Urbana-Champaign, 1304 W Pennsylvania Ave, Urbana 61801, IL, United States.
E-mail address: jli153@illinois.edu (J. Li).

https://doi.org/10.1016/j.compag.2022.107227
Received 23 December 2021; Received in revised form 8 June 2022; Accepted 16 July 2022
Available online 30 July 2022

1. Introduction

Over the past five decades, the global swine industry has responded to market demands through enterprise consolidation and a significant system shift by which most of the pig production occurs in large, intensive pig production systems rather than many small farm enterprises (McBride and Key, 2013; Pedersen, 2018; Woonwong et al., 2020). While this shift in scale has significantly advanced efficient, low-cost animal production, it has also introduced new challenges regarding maintaining optimal animal health and welfare (Norton et al., 2019). On the one hand, most pig production systems consist of massive units containing large numbers of pigs, overseen by a small number of relatively low-skilled caregivers. In addition, the size and efficiency of these production system units limit the amount of time that workers can observe and interact with each animal (Norton et al., 2019; Neethirajan and Kemp, 2021). On the other hand, the general consumer base for pork products displays an increasing preference for meat products from systems that value individual animal health and well-being and are committed to reducing the environmental impact of livestock production (Miranda-de la Lama et al., 2019; Alonso et al., 2020; Rauw et al., 2020). In the current economic climate and human resource shortages, pig production systems face significant challenges in hiring enough skilled laborers (either full-time or part-time) to provide high-quality care to the pigs (Benjamin and Yik, 2019; Lee et al., 2019; Norton et al., 2019; Albernaz-Gonçalves et al., 2021; Larue, 2022). This situation results in an increasing gap between societal and production demands.

Paying closer attention to an individual animal positively impacts animal welfare and health and can also increase the producer's ability to achieve a more sustainable system while still reaching production needs (Rauw et al., 2020). Developing solutions for precision livestock farming is one way of bringing the animals closer to the producers in these expanding systems (Berckmans, 2017). In these solutions, technology is used to enable better interaction between animals and farmers despite the challenges they face (Benjamin and Yik, 2019; Norton et al., 2019). Sensors automatically interpret individual animals' behavior and physical conditions. With that, it is possible to generate data that feeds real-time monitoring and warning systems for producers to take immediate management actions when a problem, such as a disease, injury, or stressor, is detected (Norton and Berckmans, 2018; Tzanidakis et al., 2021). These systems enable farmers to make better decisions from both a production and a welfare standpoint. The results are a better and more effective use of resources, including antibiotics, grains, and water; improved animal welfare; and better insight into new facility design as well as genetic evaluation and selection (Matthews et al., 2016; Wurtz et al., 2019; Yang and Xiao, 2020; Sharma et al., 2021).

The use of principles and technologies of process engineering to manage livestock can provide producers with information on the herd's health, welfare, and production, helping them identify animals' individual needs and management problems (Norton and Berckmans, 2018; Salau et al., 2016). Computer vision applied to livestock systems, a fast-growing research area, is an example of these technologies that shows great potential to improve livestock farming practices and enable better animal care on large farms with reduced labor requirements.

As a non-invasive system, cameras can reveal behavioral details of animals (Wurtz et al., 2019; Qiao et al., 2021). Similarly, computer vision has been used to automate a number of pig operation tasks, such as pig counting (Oczak et al., 2016; Tian et al., 2019), localization of animals within the pen(Kulikov et al., 2014; Nasirahmadi et al., 2016), identification of marked pigs (Kashiha et al., 2013b; Seo et al., 2019, 2020), division of pig growth stage (Shi et al., 2020), animal measures (Wu et al., 2004; Condotta et al., 2018; Wang et al., 2018), water usage assessment (Kashiha et al., 2013a; Zhu et al., 2017), as well as body weight measurement (Schofield, 1990; Ramaekers et al., 1996; Brandl and Jørgensen, 1996; Schofield et al., 1999; Stajnko et al., 2008; Wang et al., 2008; Kashiha et al., 2013a; Kongsro, 2014; Wongsriworaphon et al., 2015; Shi et al., 2016; Condotta et al., 2018; Jun et al., 2018; Pezzuolo et al., 2018).

Additionally, computer vision technology has been used to determine animal behaviors by creating a digital representation of pigs, such as postures (lying, sitting, standing, etc.) (Shao and Xin, 2008; Nasirahmadi et al., 2016; Lao et al., 2016; Zhang et al., 2019; Yang et al., 2020; Riekert et al., 2020; Zhu et al., 2020; Kasani et al., 2021), as well as determine particular activities (lameness, tail-biting, aggressiveness, mounting, etc.) (Kashiha et al., 2013a; Viazzi et al., 2014; Gronskyte et al., 2015, 2016; Stavrakakis et al., 2015; Nasirahmadi et al., 2016; Condotta et al., 2020; Chen, 2020; Chen et al., 2020b; Liu et al., 2020a). This rapid growth in precision livestock farming has shown that computer vision methods can provide effective alternatives to certain manual observations in livestock farming in order to provide better conditions for animals and improve their well-being.

The growing research in this area has also revealed several problems, especially concerning transferring the research results into commercial applications. For example, to understand the status of an animal, more than one type of information (e.g., identification, biometrics, and behaviors) and typically more than one type of computer vision tasks (detection, recognition, segmentation, etc.) are required (Neethirajan and Kemp, 2021). The combination of techniques requires a system that can identify an animal through a video stream, recognize their behavior, and include other input (such as outside temperature and humidity conditions, as well as pig's morphological features). The integration of computer vision algorithms into systems for pig management is lacking in the current research landscape. Such a demonstration is necessary to guide the development of computer vision applications and optimize the usage of computing and storage resources (Lee et al., 2019; Seo et al., 2020).

Current studies in precision livestock farming particularly need support from interdisciplinary teams, such as animal scientists, veterinarians, computer scientists, and engineers, to translate phenotypic information into animal status. This information has the potential to help farmers manage their herds. Several animal science studies revealed the relationship between behavioral patterns (feed intake, inactivity) and the health status of pigs (Chijioke Ojukwu et al., 2020; Zhu et al., 2020), defined comfort and well-being (Liu et al., 2020a), and detected unusual behaviors (Viazzi et al., 2014; Haladjian et al., 2017). However, there are still many unsolved questions involving the interpretation of animal responses that can be answered with computer vision. With more interpretable behaviors, computer vision would have broader applications such as optimizing labor, permitting greater resiliency in operational logistics, and improving animal caregiving and facility design.

There are also several knowledge gaps concerning computer vision application to animal research. For instance, there is no handbook that can help translate animal behavior into computer vision tasks. Studies discussing how to convert computer vision results (boolean, segmentation, numeric) to the measures of interest for animal operators (occurrence, frequency, duration) are limited in scope. For example, Zhu et al. (2017) applied machine vision methods to recognize the drinking behavior of pigs. In particular, the recognition of drinking behavior required a combination of computer vision tasks, which are detection of pig within the zone (result: yes/no), distance measurement between pig and drink nipple (results: numerical), and pig feature extraction (color moments, area, perimeter, etc.). To estimate the duration of drinking behavior for one pig, the video should be screened and analyzed by specific sampling rate or by every frame.

This paper aims to address some of the problems and gaps and provide possible directions to promote the development of computer vision solutions that can be applied to commercial pig production systems. The second section identifies and defines several concepts commonly used in interdisciplinary research but with different resonances depending on the discipline. The third section explains the computer vision purpose and associated challenges concerning the application of computer vision tasks to pig behavior analysis. The fourth section summarizes the existing computer vision algorithms and potential directions in pig management. The fifth section highlights the challenges of preparing image & video data in pig farm applications and proposes an annotation methodology.

2. Interdisciplinary research and terminology

Precision livestock farming is defined as the "management of individual animals by continuous, automated, and real-time monitoring of health, welfare, production/reproduction, and environmental impact" (Berckmans, 2017). This can be done by integrating cutting-edge techniques in data science with management systems that automate animal care and farm operations. Such an emerging area requires a close collaboration of researchers working across several disciplines. As shown in Fig. 1, the students and professors from animal science, agricultural engineering, computer science, and veterinary clinical medicine are working together on precision livestock farming at the Center for Digital Agriculture of the University of Illinois at Urbana-Champaign. In our regular communication as an interdisciplinary research team, we noticed that the terms *annotation* and *label* have different resonances across different disciplines. In particular, the phrase *image annotation* can mean different things to researchers from computer and animal science. For example, a contour of an object or entity represented in an image can be delineated using different graphic annotation methods (for example, key point, bounding box, polygon, semantic segmentation), but we can also provide additional information about the object or entity in the image in forms of labels—or, alternatively, *annotations*—that describe the type or attributes of an object or entity. Both types of annotation (graphic annotation and labeling) are needed for automating animal management tasks and for the collaboration of computer-based scientists and animal-based scientists. To better separate these two related but distinct tasks, we decided to refer to the process of delineating a shape of an object or animal in images and videos as *graphic annotation* or *annotation* and to the process of providing additional information about the objects/entities in the image as *labeling*. We provide here a more detailed meaning of these phrases:

- Graphic annotation: refers to key point, bounding box, polygon segmentation, semantic segmentation of objects such as drinkers and feeders as well as animals.
- Labeling tasks: we differentiate between several types of labeling tasks in this paper:
- Body parts or body shape labeling: refers to the process of naming animal body parts or their shape;

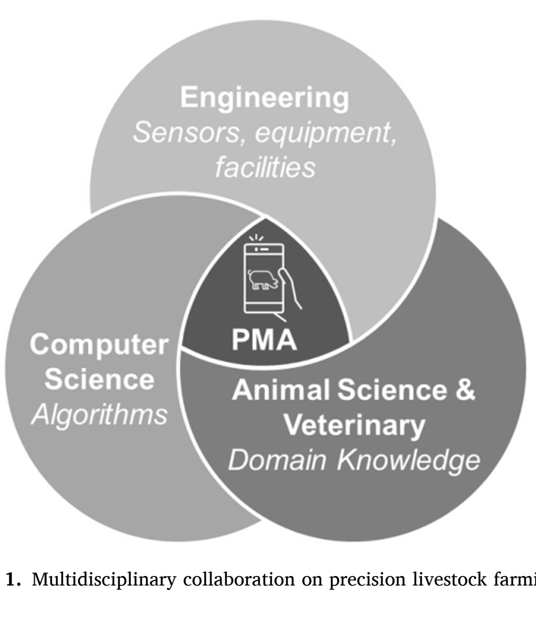

Fig. 1. Multidisciplinary collaboration on precision livestock farming.

- Behavior labeling: refers to the process of identification and naming animal behavior associated with a sequence of digital images;
- Posture labeling: refers to the process of identification and naming animal posture associated with individual or a sequence of digital images.
- Computer vision tasks: refers to the extraction of numerical or symbolic information from digital images (e.g., detection, segmentation, identification, motion tracking, etc.).
- Animal management tasks: refers to routine farm management tasks that may or may not be replaced by computer vision tasks for the animal care staff (e.g., pig counting, physical examination, artificial insemination, etc).

All animal images shown in this paper were collected from the animal research facilities of the University of Illinois at Urbana-Champaign.

3. Challenges and opportunities in pig behavior analysis

Observation of pig behavior has long been a tool used by caregivers to indicate pig status. Through visual observation, well-trained operators can understand an animal's responses to a variety of stimuli, including both internal (e.g. disease status, thermoregulation, etc.) and external factors (e.g. thermal environment, air quality, noise, etc.). In turn, caregivers can respond accordingly in order to consider management of environment, health, and production.

3.1. Animal behavior recognition by human

Referred to as an "ethogram" in scientific studies and "signs of sickness" in a practical setting, the visual observation of animal behavior provides input for a subjective interpretation of an animal's state. Scientists in research and workers on a farm often need long-term observation and continuous training to recognize and correctly interpret some nuances of varied behaviors. Several pig postures can be directly classified from a single image by a human and even computer vision algorithms, such as lying, standing, sitting, and kneeling (Nasirahmadi et al., 2019; Kasani et al., 2021). However, most animal behaviors cannot be distinguished from a single image but require a sequence of images taken over a period of time (Liu et al., 2020a; Yang et al., 2021). In other words, the visual recognition of behaviors requires a human's comprehensive abilities. The complex judgments require long-term memory, several reviews, and more than one type of human intelligence (induction, deduction, and prediction).

With the growing threat of contagious disease and climate change, there is an urgent need to develop real-time systems that can evaluate pig responses to their health status in a shorter time (Cadenas-Fernández et al., 2019; Robbins et al., 2020). The collection and processing of pig behavior is time-consuming and requires highly skilled observers and analysts. A valid animal behavior study will generate a large quantity of video footage containing similar animals in different treatments (e.g. chemical treatment, feed treatment, etc.). Reviewing and recording animal behavior by individuals is an inherently time-consuming process. The ethogram needs to be validated, and investigators should be trained, evaluated, and retrained to ensure observer reliability. A behavioral observation often requires more than one investigator blinded to treatments and video sequences (Fleming et al., 2019; Miller et al., 2019; Robbins et al., 2020). These steps are designed to ensure consistent behavioral labeling but are costly for current animal behavior research. In the past, animal behavior analysis was too time-consuming and costly for real-time systems to assess the improvement of management, technologies, medication, and feed formula as pig genetics changed over time (Torrey and Widowski, 2004; Elmore et al., 2010; Meizhi et al., 2017).

Computer vision can accelerate the progress of animal behavior research by automating animal behavior recognition. Animal studies frequently use target labels (predictable behaviors) and examine the duration or frequency of these labels (Küster et al., 2020; Riekert et al., 2020). The exploratory behavior analyses may not use target labels but may track clear signs of individual characteristics (tag identifier, coat color/patterning, anatomical points of interest, regions of interest, activity levels, etc.) (Dan et al., 2021; Yang, 2018). These tasks can be adapted for either supervised or unsupervised learning tasks (machine learning with/without labeled datasets). Computer vision may achieve higher accuracy rates than those performed manually, as in computer vision tasks with relatively consistent experimental setups and sampling frequencies.

Given that the expertise needed to accurately label postures and behaviors are often overlooked in many computer-vision studies, it is necessary to create standard definitions that can be summarized visually. Conventional tenets of animal behavioral recognition cannot be directly applied in the research of automated recognition and analysis of animal behaviors. Liu et al. (2020) explained one reason for a failure of tail-biting recognition by computer vision: there is a challenging distinction between the “relative location of one pig’s head and one pig’s tail” and “one pig wiggles its head around another pig’s tail.” Animal scientists are translating their perceptions into a language-based definition, which is valid for a specific study. However, there are no standard descriptions of animal behaviors and no benchmark rules to define or name them. For example, “eating” or “feeding” behavior was defined as “piglet is standing at the feeder, ingesting feed” (Byrd et al., 2019) and “head in or above and tilted down toward feeder” (Elmore et al., 2010) in different research studies. These differences in definitions may be influenced by the viewing angle for behavior observation, as well as differences in age/size of pigs, types of facilities/furnishings, and occlusions. As shown in Fig. 2, a computer vision algorithm may treat all three metrics shown (proximity to feeder, intersection between feeder and pigs, and interacting with feed) as “feeding behavior.” Computer vision relies on quantitative descriptions (e.g., distance, intersection), which have not typically been useful metrics (and thus not collected or reported) in past animal studies (Tscharke and Banhazi, 2016).

3.2. Classification of health and welfare based on animal behavior

Pig practitioners (e.g., animal feeding workers, veterinarians, equipment designers) may find value in a continuous pig monitoring system that would provide decision-support for caretakers to satisfy the pigs’ needs. Computer vision-based animal identification is potentially more affordable to farmers than other sensor-based solutions and can link animal data to build “digital representations” for traceability of animals for meat production (Benjamin and Yik, 2019; Norton et al., 2019). The application of computer vision methods could provide sufficient information on each animal, guiding animal caretaking practices and offering consumers a high degree of confidence in pig products regarding animal welfare. Computer vision systems are able to link animal behaviors to external stressors (e.g., temperature, dust, abusive handling, overcrowding, etc.), detect pigs’ preferences on environmental enrichment, test medicine efficacy, which automatically provide information to support the decision-making of farm operations (Matthews et al., 2017; Chen, 2020; Chen et al., 2020a). Kashiha et al., (2013c) introduced an automated systems to detect anomalous events in a broiler house. In the future, computer vision may be integrated into automatic environmental controller that provide precise thermal needs to animals (Shao and Xin, 2008).

Through transforming the findings and knowledge from animal behavior research, the application of computer vision can indicate pig health status (Joosen et al., 2019; Wang et al., 2021b). Certain animal behaviors have the diagnostic value as subclinical signs of sickness and welfare problems. Experienced farmers can detect sick pigs based on loss of appetite, droopy ears, and humped back (Taylor and Field, 2007). Pig behaviors need to be recognized successfully over a long period to enable the quantification of behaviors through time budget or frequency and the later differentiation between the normal and abnormal condition of a pig (Matthews et al., 2017). Fernández-Carrión et al. (2020) used computer vision for tracking animal motion to indicate the connection between behavior and fever caused by African Swine Fever. Similarly, the spatial distribution of pigs within a pen could indicate thermal comfort and individual preferences of pigs (Shao and Xin, 2008). Although it is not currently possible to directly diagnose specific animal sickness from behavior analysis, it might be possible to link maladaptive and abnormal behaviors to specific sicknesses in the future.

3.3. Challenges in multidisciplinary studies

Given that the use of computer vision in animal husbandry is an interdisciplinary area of study, it requires strong collaboration between researchers with varied backgrounds; however, the communication and knowledge gaps can lead to significant misunderstandings. For example, the visual condition, animal density, and technique interests are different in an experimental laboratory, research farm, and commercial farm settings. The formulation of domain-specific (animal science, agricultural engineering, or veterinary medicine) research to computer vision tasks is an iterative process of testing, which requires input from all expert areas. For example, Huang et al (2021) defined two types of occlusion (body-separated occlusion and partmissing occlusion) based on the application scene and labeled pig centers with pig polygons to improve the pig recognition under occlusion. The initial assumption of the application scenes and technical requirements may be adjusted or verified depending on outcomes of algorithms. Sometimes, the application could restrict the algorithm development concerning computation resources (bandwidth, memory, cores) and performance (speed, accuracy, complexity). Sa et al. (2019) summarized previously published studies’ data size and image types. Images with low resolution can save computation time and bandwidth and represent a promising approach for pig detection and behavior recognition tasks. However, this is not a good solution for specific detection and recognition tasks that may require delineation of individual body parts, characterization of lameness, or nuanced behaviors that happen infrequently.

Many complex behaviors (e.g., exploratory, social, and sickness-

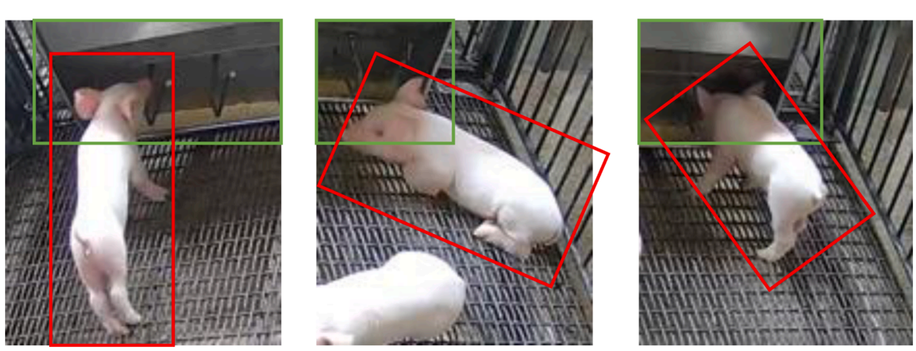

Fig. 2. Examples of “feeding” behavior from different definitions: proximity to feeder, intersection between feeder and pigs, and interacting with feed.

related) haven't been defined in a way that is useful for application of computer vision. It is necessary to close the knowledge gap between animal management tasks and computer vision tasks. An animal management task can be formulated through various computer vision directions. For example, the detection of belly-lying and side-lying can be either formulated through detection tasks (belly, shoulder, and hoofs touching the ground) or classification tasks (lying: sternal or lateral).

Finally, the education programs and practitioners in pig industry should adapt to the new knowledge and skills. Several new master programs (computer science + animal science, information science + animal science, etc) that have developed or are being developed in the United States and abroad as a result of realizations that a combination of domain science and computer science is needed in a variety of areas, such as, computer vision, animal science, veterinarian, biomedicine etc. The ways of collaboration are also changed between domain experts and technology providers (Pedersen, 2018). For example, animal specialists may need to see several key elements (such as body parts or motion) to label a behavior under poor visual conditions, whereas computer scientists may be able to improve the image quality and remove obstruction to assist the behavior recognition. Serval algorithms have been

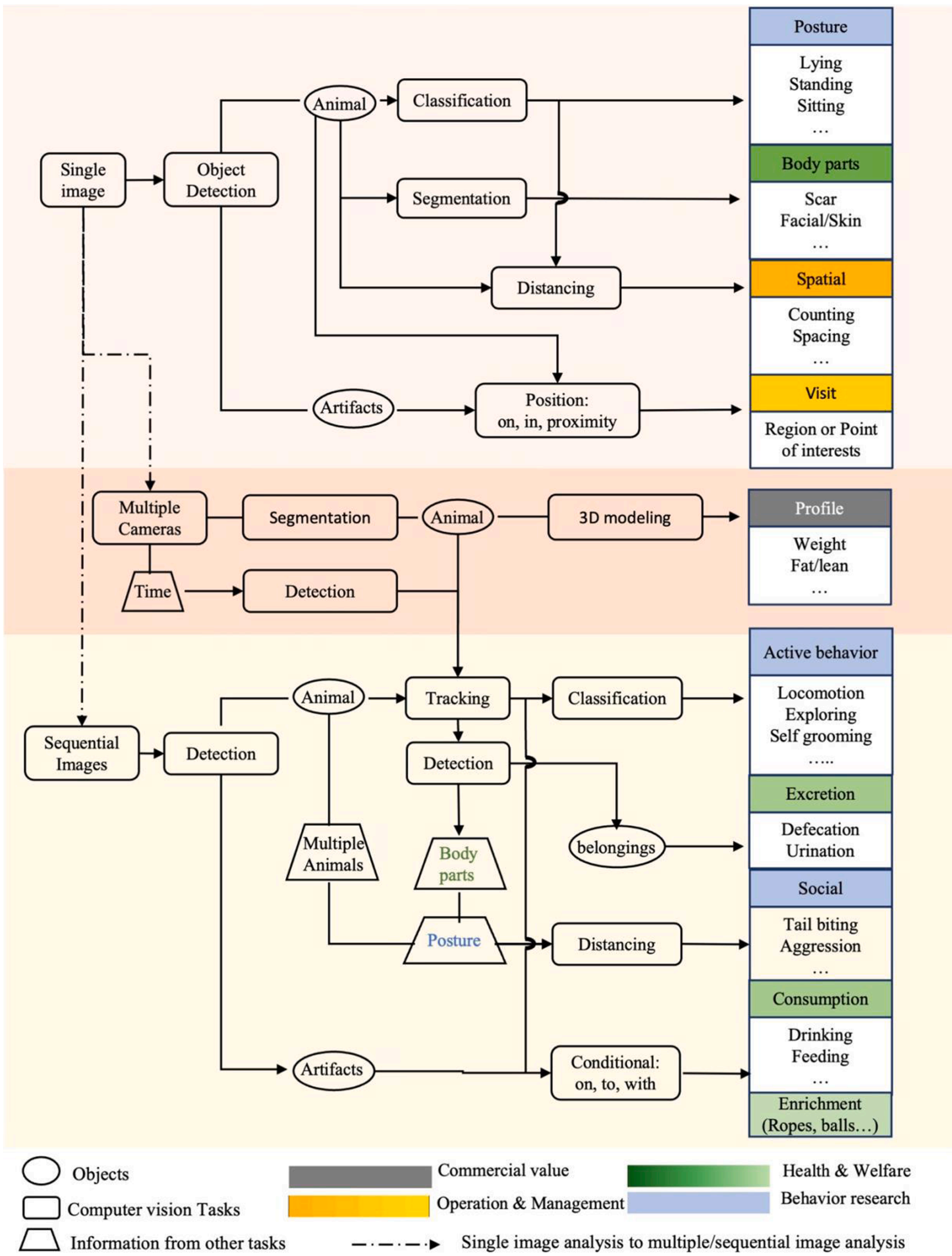

Fig. 3. Relationship of existing computer vision tasks with standard cameras to precision pig farming (Artifacts-feeder, drinker, etc.).

successfully buit on mobile devices to remove reflection, obstruction, raindrop, etc for recoverying clean images (Xue et al., 2015; Liu et al., 2020b). Furthermore, a standard procedure in animal experiments may lead to additional problems in computer vision tasks. For example, if the computer vision research does not involve optical character recognition, pigs should not be marked with colored letters and numbers on their body. The marks can help annotators track animals visually, but they also serve as animal features to computer vision algorithms (Jover et al., 2009; Kashiha et al., 2013b; Zhang et al., 2019). Without sufficient description and discussion, it is hard to justify the impact of the marks on algorithms.

4. An overview of computer vision algorithms in pig management tasks

4.1. Computer vision applications in commercial farms

Scientists around the world have been studying the compter vision in livestock industry for several decades and some technologies have successfully transitioned into commercial products. The underlying concept for computer vision in pig production systems offers assistance to daily farming operations by allowing better utilization of farm staff and specialized animal caretakers (Benjamin and Yik, 2019; Tian et al., 2019). The information from image analysis or computer vision tasks can directly inform some operational and strategic decisions related to farm management (Fernandes et al., 2020). As shown in Fig. 3, certain simple animal management tasks can be replaced by surveillance cameras with computer vision algorithms, such as animal counting, routine inspections, and event detection. Some of these tasks are successfully implemented into commercial products, such as *ScoutMonitoring (USA), RO-MAIN (Canada), FANCOM (Netherlands),* etc.

In general, multiple pieces of information need to connect in order to generate a valid message which could include the identification information, subject-object, time-related messages, and task-specific content (e.g., behaviors, distance, body measures). For example, to get the “time of visit to the feeder” for a particular pig, artificial intelligence needs to detect pig and feeder, recognize the pig, calculate the relationship (on, in, proximity) between the pig and feeder, then register the information to the proper identification records. Object detection, pigs’ spatial relationship, and temporal correspondence of the pigs can advise producers as to the optimal number of pigs per pen, indicate temperature problems, identify animals, and inform pig’s preference to a region or point of interest (Kashiha et al., 2013b; Haladjian et al., 2017; Sun et al., 2020; Chen et al., 2020c; García et al., 2020). Similarly, measuring a pig’s body shape can provide information to estimate body weight and score carcass traits. Further, the changes in weights over time can indicate the health and growth state of the pigs (Jun et al., 2018; Fernandes et al., 2020).

Complex animal management tasks that require simple judgment could be trained by supervised learning with the labels provided by animal specialists that indicate postures, stationary behaviors, lameness, and wounds (Chijioke Ojukwu et al., 2020; Liu et al., 2020a; Yang et al., 2021). As shown in Fig. 3, a number of active behaviors and social interactions need more than one type of detection and classification to distinguish from each other. For example, a head-to-head knocking event is recognized as “two pigs in a frame simultaneously meet at a certain acceleration (motion feature) and with a certain distance (position feature)” (Norton et al., 2019). Sometimes, indirect evidence is used to indicate a complex event or behavior (e.g., detection of blood to indicate tail biting) (Matthews et al., 2017). It is worth noting that the information used for decision support is not only the event itself but also all the relevant notes that can reveal what happened. Even if the indirect evidence (e.g., blood) could indicate the event (injury), producers still need to know which animal was injured and the reason behind it.

Apart from standard cameras, there exist other imaging technologies that provide useful complementary information. Thermal cameras can measure abnormal body surface temperature caused by stress, fever, inflammation, and ischemia (McManus et al., 2016); stereo cameras, structured light, or time-of-flight cameras can be used for 3D imaging of pigs (Zanuttigh et al., 2016; Condotta et al., 2020); and hyperspectral imaging for evaluating the meat attributes and chemical characteristics (Tao and Ngadi, 2018). In addition, diverse medical imaging technologies such as ultrasound, computed tomography, and magnetic resonance imaging have also been employed in farm applications such as evaluating muscle and fat composition and bone mineralization in live animals (Scholz et al., 2015). Computer vision algorithms also play a pivotal role in the above modalities.

Once a surveillance camera is deployed on a pig farm, producers will encounter another challenge to manage and use the raw data coming from the cameras. Instead of storing all the recorded data and analyzing each frame, a “smart camera” should be able to implement on-device detection algorithms that decide when and what should be recorded for further analysis. Wurtz et al. (2019) summarized research papers that focused on feature extraction algorithms published before 2019. Since 2019, the state-of-the-art algorithms for the keyframe selection in a commercial swine operation have tried to learn the probability of a pig’s need to be recorded that can be revealed from activity levels, abnormal spatial–temporal patterns, and aggressive events, as shown in Table 1. Other real-time computer vision tasks such as animal detection and tracking identify animals and link with other computer vision tasks with less computation (Seo et al., 2020). The sampling rate needed for behavior analysis is often lower than standard video frame rates. Therefore, the frame rates and image quality should dynamically change

Table 1
Recently applied algorithms described in the reviewed literature.

Algorithms	Description	Reference
Frame selection		
Structural similarity measure (SSIM)	Select high-quality frames from video	(Marsot et al., 2020)
Convolutional neural network (CNN)	Detect anomaly activity	(Wutke et al., 2020)
CNN - long short-term memory (LSTM)	Recognize aggressive episodes, Engagement episodes	(Chen et al., 2020b, 2020a)
Detection		
Faster R-CNN	Detect pigs (group-housed), lying behavior	(Riekert et al., 2020)
Adapted Tiny-You Only Look Once (YOLO)	Real-time detection of pigs (group-housed)	(Lee et al., 2019; Seo et al., 2020, 2019)
Single shot detector (SSD)	Detect pigs (group-housed)	(Deng and Yu, 2020)
CClusnet	Piglet counting under occlusion	(Huang et al., 2021)
Animal segmentation		
YOLO	Detect pigs, separation of touching-pigs (group-housed)	(Seo et al., 2019; Shao et al., 2021; van der Zande et al., 2021)
DeepLabv3	Semantic segmentation	(Sa et al., 2019; Shao et al., 2021)
Attention guided CNN	Instance segmentation	(Hu et al., 2021)
Tracking		
Simple Online Real-time Tracking (SORT)	Individual tracking pigs (group-housed)	(van der Zande et al., 2021)
Color feature fusion	Correlation filtering (group-housed)	(Sun et al., 2020)
Classification		
Support vector machines (SVMs)	lateral and sternal lying posture (group housed pigs); social behavior	(Gan et al., 2021; Nasirahmadi et al., 2019)
DenseNet	Behavior pattern (individual gestation sows); Pig skeleton extraction (group housed pigs)	(Kasani et al., 2021; Khan et al., 2020)
CNN + LSTM	Tail-biting interaction	(Khan et al., 2020; Liu et al., 2020a)

to optimize the usage of available computation and storage resources.

The filtered videos and images should be further analyzed by edge computing devices that can execute algorithms closer to the data, connect the data with dependencies, and package the decision-support messages before being transferred to the cloud for further advanced analysis. The algorithm-embedded cameras are typically not able to achieve complex computer vision tasks. Edge computation has higher computational power and higher tolerance to data transfer speed than a "smart camera." Since edge computing allows data to be closer to the computing nodes, data can be accessed and processed in real-time with little transmission time. This allows remote farms without efficient network infrastructures to be equipped quickly. The computer vision tasks that require more resources, data bandwidth, and execution time can be completed with edge computing such as feature extraction, segmentation, behavior recognition, etc. Since 2019, many scientists have tackled pig segmentation tasks since the pig contour can assist both body parts identification and behavior recognition tasks. Various convolutional neural network (CNN)-based detectors, such as Faster R-CNN, single-shot detection (SSD), and You Only Look Once (YOLO), received significant attention in many fields and achieved a high accuracy concerning pig segmentation.

4.2. Application of computer vision on pig behavior research

Computer vision has been successfully applied to various animal behavior tracking and modeling studies, such as birds, horses, and wild animals (Li et al., 2021; Miñano and Taylor, 2021; Mounir et al., 2021). Computer vision tasks such as object recognition, event detection, and motion analysis can directly leverage manual animal behavioral labeling. Keyframe selection (event detection, video summarization, etc.) can help reduce the redundant video content and the workload of animal behavior analysis. Object detection (tracking and identification) also has the potential to "shrink" the operational procedures involved. Commercially available vision systems can track the postures and behaviors of small animals, such as mice, in a relatively simple experimental environment (Tscharke and Banhazi, 2016). However, there is currently no tool that can be used to study domestic animals either in a lab or commercial setting.

Advanced computer vision approaches might redefine the pig behavior research methods and reform the approach to livestock farming. As shown in Table 1, the classic behavior recognition tasks use classification algorithms to select the most-like behaviors, similar to how humans categorize postures and behaviors. Most recently, certain emerging computer vision methods, such as pose estimation, or joint detection, can be used to estimate pigs' motion and may directly indicate behaviors and abnormal actions (Chen et al., 2020a; Psota et al., 2020; Yik et al., 2020). Many research endeavors need more than one camera to record an entire pen of animals and require different view angles to identify behaviors. Image registration can transform objects from different views into one coordinate system that could supplement the details of indistinguishable behaviors and significantly reduce the workload of behavior analysis by constructing the connection of animals in different views (Chang et al., 2000; Zitova and Flusser, 2003). 3D reconstruction has been successfully applied to build realistic models of humans and certain live animals capable of demonstrating abundant details related to an animal's posture and activities (Holte et al., 2012; Zuffi et al., 2017). In the future, if postures and behaviors can be digitalized and quantized with 3D reconstruction models, many research topics in animal applications may become accessible in the field of metrology.

4.3. Common issues in algorithm development

Over the years, we have witnessed machine vision algorithm improvements concerning computing speed and accuracy. These algorithms have received a lot of attention from several industries, such as automatic driving and precision livestock farming (Aly, 2008; Mendes et al., 2016; Zhang et al., 2019). While it is essential to prove that these algorithms apply to commercial settings, these discussions should not stop at the level of a feasibility analysis. For example, computing efficiency or execution speed is an important performance parameter that is not reported consistently. The algorithms that use fewer computational resources with fast execution speed can be used as real-time applications in embedded devices. The algorithms with high prediction accuracy requiring high-performance computation can be used on edge-computing devices or cloud computing applications. Studies that describe computation resources, report execution speed, and demonstrate application scenarios are particularly helpful and advance the research in this area (Sa et al., 2019; Seo et al., 2020). Even if the prediction for certain scenes is inaccurate, the results can still be valuable to developers. For example, studies that have tested the algorithms using different datasets (Riekert et al., 2020; Hu et al., 2021), reported drawbacks, and discussed the reason of false predictions are very helpful to researchers working at the intersection of computer science and animal science (Chen, 2020; Liu et al., 2020a).

There is a critical need to establish a benchmark methodology for reporting results in the future. A benchmark methodology for reporting results should be speficially designed for animal behavior recognition tasks. The accuracy of behavior recognition would rely on the objectivity and credibility of the dataset. The computer vision datasets originating from pig farms are typically characterized by uncertainty in annotation due to occlusion, behavioral labeling, etc. The prediction errors may not reflect the true performance of machine learning but might contain the error of "true prediction to false annotation." For example, transitions between postures and behavior changes can be ambiguous to labelers. One solution for this problem is to include the confidence level for transition moments in the dataset. Alternatively, the accuracy calculation for computer vision algorithm in livestock feeding scenes can consider the probability of labels during transition periods. Several studies have used special indicators to evaluate algorithm performances considering the nature of tasks in pig farms, such as the time length of successfully tracking an animal (Ahrendt et al., 2011; Riekert et al., 2020).

4.4. Inspiration from other computer vision applications

Computer vision techniques have been successfully applied in many real-life human scenarios. Technology advancement in the computer vision field is very rapid. If one technology has been successfully applied in a particular scenario, it is likely that it can be applied to a livestock production scenario. We provide here a few examples. The traditional 3D reconstruction relied on the 3D sensors or multiple view geometry reconstruction from 2D images for animal body scoring and weight estimation studies (Qiao et al., 2021; Wang et al., 2021a). This approach has limitations in commercial farm settings due to expensive sensors or the spacing requirement to deploy cameras. Monocular video-based 3D reconstruction received much attention in human animation. The geometry of people was represented as a Skinned Multi-Person Linear (SMPL) model, and the parameters were optimized with the motion of humans in videos (Alldieck et al., 2018; Loper et al., 2015). This technology fits the requirement of the livestock production scenarios of less expensive and more affordable cameras to recognize the different levels of activities and body conditions. Moreover, image quality improvement algorithms have been successfully commercialized in the smartphone and film industries. The techniques, such as occlusion removal, may improve the data quality by removing the mud marks on pigs and reducing the fencing occlusion effects (McCloskey, 2014; Dong et al., 2020). Yet another computer vision application is crowd counting to monitor crowds in rallies or games (Oh et al., 2020). This application translated to pigs finds potential in detecting and managing congestion in pens. In recent years, camera-based measurement of vital signs such as heart rate and variability, breathing rate, temperature, etc. - referred to as photoplethysmography - has reached sufficient accuracy to have potential in practical deployment (Nowara et al., 2020). These methods can be extended to identify fatigue or unobtrusive early heart failure detection in pig farms.

5. Dataset construction for computer vision in pig behavior studies

Constructing a reliable dataset that serves different vision challenges is a prerequisite for practical use of computer vision. Currently, most studies in precision pig farming are based on small, custom-built datasets that prevent further development of computer vision. Firstly, the performance of algorithms, such as accuracy, efficiency, and errors, are evaluated with different datasets (Yang and Xiao, 2020). As a result, researchers cannot directly compare the advantages and disadvantages of different algorithms (Sa et al., 2019). Secondly, current public-available animal datasets are not only too task-specific, but data collected comes from different farms and has a different distribution, making it difficult to merge two or more models when constructing a pipeline for a single application. Although there are many published works that utilized pig datasets, only a few dataset is publicly available for use (Bergamini et al., 2021). Lastly, the description of most datasets does not contain sufficient detail to help the users understand the content of the data, such as environment diversity, animal variation, and unique marks on animals. Unlike other machine vision applications, high proximity objects and high occlusion visual conditions are typical in pig farm scenes (Riekert et al., 2020; Yang et al., 2021).

5.1. Data collection and data reporting

A benchmarking methodology and dataset should be established to objectively evaluate the performance and robustness of different algorithms applied to different scenes. As Fig. 4 indicates, pigs in the nursery and grow-finishing stages are housed in a group setting, making it difficult for observers to isolate complete individual pigs from a single view. Gestation or farrowing sows could be kept alone, but the camera view can be occluded because of the fences, pipelines, etc. Visual conditions can be improved by optimizing the camera position and the view angle, but cameras at lower heights are problematic due to disturbance that can occur from interactions with and between animals. In general, image quality in pig feeding environments is typically not ideal for behavior analysis and computer vision tasks. On the other hand, although a dataset that shows complete, non-occluded animals would improve the algorithm's accuracy, it would not represent realistic conditions on the farm, which is misleading. Huang et al. (2021) highlighted the occlusion in farrowing pens and suggested the approach to annotate pigs and count pigs under two types of occlusion (body-separated occlusion, part-missing occlusion). The visual conditions for most pig farms are challenging, which inevitably limits the application of computer vision.

Annotating videos or images for computer vision tasks must consider the complexity of the actual scene. Table 2 summarizes the research groups that explained image characteristics and data variation when constructing datasets for developing computer vision algorithms. Among all mentioned challenges, illumination, occlusion, and

Table 2
Variation of the published applications (utilizing pig datasets) for developing computer vision algorithms.

Categories	Impact factors	Reference
Environment		
Background-Floor	Bedding, slot, material	(van der Zande et al., 2021)
Illumination	Diurnal & nocturnal change, lighting, shadow	(Guo et al., 2014; Marsot et al., 2020; Sa et al., 2019; Seo et al., 2020; Sun et al., 2020; Yang, 2018)
Reflection	Surface water, stain, metal materials.	(Guo et al., 2015, 2014)
Animal		
Occupation	Age, size, group size	(Sun et al., 2020; van der Zande et al., 2021; Yang, 2018)
Internal factors	Genetics, sex, individual	(Yang, 2018; Bergamini et al., 2021)
Vision		
occlusion	Overlapping, obstacle, pen bar	(Guo et al., 2014; Huang et al., 2021; Nasirahmadi et al., 2019; Riekert et al., 2020; Yang, 2018)
Viewpoint	Center view, side view	(Hu et al., 2021; Küster et al., 2020; Yang and Xiao, 2020)
Augmentation	Shift, rotation, distortions, scale-up/down	(Chen, 2020; Liu et al., 2020a; Sun et al., 2020; Tian et al., 2019)*

**Datasets with public access for downloading: (Tian et al., 2019; Bergamini et al., 2021).*

Fig. 4. Common scenes in pig feeding operations.

overlapping are widely recognized challenges in pig farms that affect computer vision detection but also create manual errors (Tian et al., 2019). Every published dataset has a unique type of housing environment or a specific group of animals, making it hard for the readers to compare the robustness of the models. Meanwhile, the manual behavioral labeling contains some uncertainty due to underreporting of counting, identification and false reporting of postures and behaviors. To create a "ground-truth" label, labelers may need to verify the labels from more than one view-angle. A well-trained expert might predict a pig's postures and behaviors from one view. However, certain categories may not be distinguishable in particular views. If only one expert labels animal behavior, the algorithm will not learn from "objective" labels but subjective ones.

5.2. Data annotation

Creating a benchmark dataset with sufficient variation is necessary to achieve the goal of recognizing any individual animal under various visual conditions within any environment. The benchmark dataset can be used for supervised learning and for evaluating and comparing the performance of both supervised learning and unsupervised learning algorithms. However, dataset construction and annotation are time-consuming and expensive. Due to limited resources, the dataset preparation may be divided into several stages to achieve balance and diversity. Fig. 5 shows a theoretical construction of a reliable dataset that would prioritize dataset content over computer vision algorithms that focus on a specific application scenario (various vision augmentation and different animals). The robustness of computer vision algorithms, such as detection, tracking, and identification, is essential; these algorithms build the foundation for precision livestock farming. Making sure that different pigs (growth stage, size, sex) can be detected in various vision augmentation (rotation, shift, distortion, etc.) will enable linking results from behavior analysis and computer vision research through identification information. This correlation allows the dataset to continue growing by adding various animal behaviors from different cameras and housing environments.

The dataset should contain both image data (graphic annotation of the image) and corresponding information to supplement the annotations of interest, such as pig identification, location, body shape, postures, and behaviors (i.e., different labels associated with graphic annotations). However, it is worth noting that the annotation process could introduce additional uncertainty that might affect algorithm performance evaluation. As shown in Fig. 6, the annotation approach is not identical and deterministic for different annotators. If the annotation rules are not predefined and the annotators are not well trained, the "ground-truth" annotations used for machine learning development are unreliable and inconsistent. Including more than one annotator and

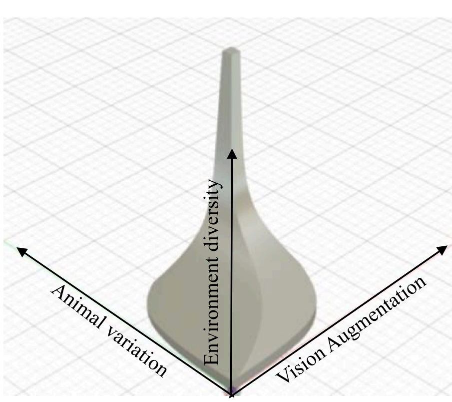

Fig. 5. A theoretical construction of a reliable dataset to develop robust computer vision models in precision livestock farming (Vision Augmentation × Environment Diversity × Animal Variation).

sufficiently evaluating the dataset can improve the reliability of the graphic annotation. An alternative way is to modify the calculation of prediction accuracy in the algorithm development stage. The successful detection of a pig is more reliable than the pixel-level accuracy (detection of pig contour) for most computer vision tasks. The most-used accuracy reporting (e.g., intersection over union) may not indicate the true performance of the algorithms.

In addition to graphical annotations, behavior analysis results might be useful for animal behavioral labeling used in computer vision tasks. Animal postures and behaviors are currently manually scored by animal specialists that follow widely recognized rules to reduce the uncertainty from humans, such as blind design, ethogram, and cross-evaluation of the results from different labelers. The cooperation between animal scientists and computer scientists will accelerate animal behavior studies and broaden the application scope of computer vision in precision livestock farming. However, there are still information gaps that prevent direct use of the results from behavior analysis in the computer vision field. There are significant differences between image annotation and traditional behavioral labeling that may complicate this approach. For example, the resolution of labels (e.g., label/minute) from animal specialists in animal science studies is relatively coarser than the resolution of computer vision labels (e.g., frames/second). Certain action behaviors are undistinguished in a single image but could be recognized by a human from a series of consecutive frames. Animal specialists may label the transition moment of a pig or may label the primary postures and behaviors of a pig throughout a period of time. There is a need to study how to transform records from animal behavior studies into labels of animals in computer vision tasks.

We conclude that it is necessary to establish a benchmark approach to document dataset. As shown in Fig. 7, the person making judgments often needs an additional view (e.g., front view, side view) or uses higher-level abilities (induction, deduction, and prediction) to differentiate behaviors. The difficulties of recognizing the behaviors are not split in the annotation process. Although the label accurately describes pig's postures and behaviors, they are mixed with other explicit cases with the same label and lead to extra prediction errors that algorithm developers do not see. The credibility of the behavioral labeler needs to be noted explicitly to obtain a more objective and general dataset. Here we summarized three levels of observation that we developed to indicate the common behavioral labeling scenarios. As shown in Fig. 7. The public available dataset should have sufficient description accompany with the release of the dataset. Users should be able to know the provenance of the dataset, how it originated, how the data was collected, who was responsible for data collection, are there any errors in the dataset and what are the sources of error, who is responsible for maintaining the dataset, what is the recommended use of the dataset, etc. A datasheet could serve as a template for livestock data creators to start preparing the dataset documentation (Gebru et al., 2021). The benchmark approach is being developed and promoted in academia to improve dataset transparency and communication between creators and users (https://www.microsoft.com/en-us/research/project/datasheets-for-datasets/).

- Ground-truth labeling: The body shape of animals can be clearly observed by labelers. Body parts, locations, postures, and behaviors can be determined unambiguously by labelers.
- Reliable labeling: The body shape of animals is distinguishable to labelers. Only visible parts, locations, postures, and behaviors are determined or estimated with confidence by labelers.
- Predictable labeling: The body shape of animals is distinguishable to labelers. Body parts, locations, postures, and behaviors can be predicted and confirmed from the secondary data source, such as other cameras, sensors, etcs.

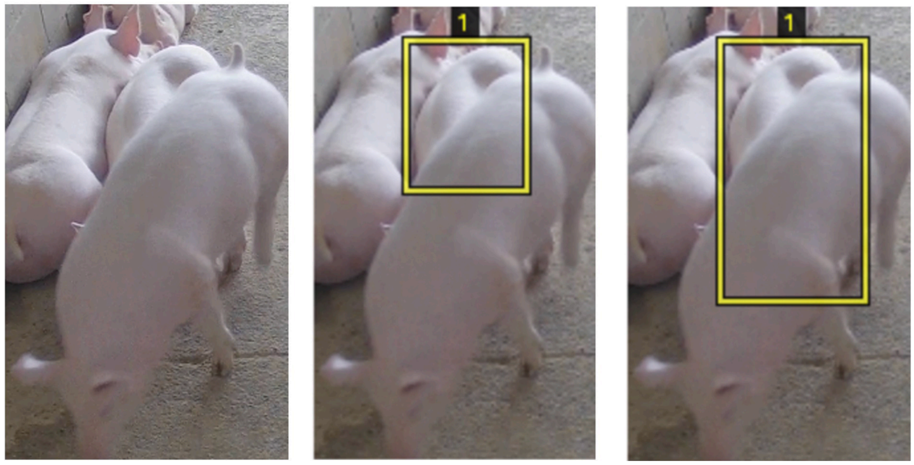

Fig. 6. Pig image annotation of the occluded pig based on different rules.

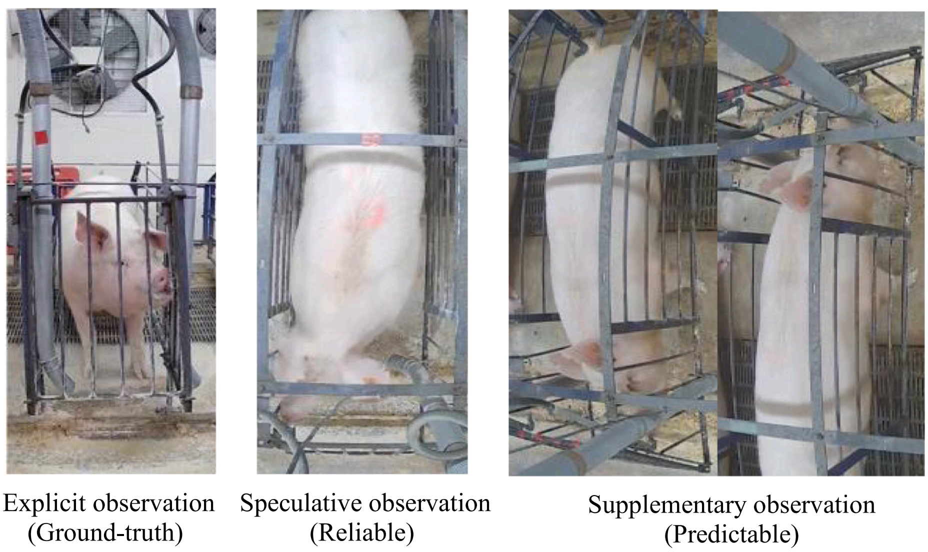

Fig. 7. Example of labeling drinking behavior from different views.

5.3. Annotation workflow

We highlight several critical research gaps between computer-based annotations and traditional behavioral labeling methods. Through human observation, animal posture and behavior are observed by one specialist and summarized into the natural-language definition for other labelers to follow, as indicated in Fig. 8. This process is not only prone to lead to misunderstandings between specialists and labelers, but the learning and correction of the ethogram is a very time-consuming task. Many widely recognized datasets have traditionally relayed the annotation tasks to multiple users with candidate images and decided the labels by the number of agreements of the same categories (Deng et al., 2009; Lin et al., 2015). Such a process could be applied to postures and behaviors labeling that intends to convert the subjective behavior labeling process to an objective behavior annotation process and reduce the time spent on the learning and validation.

However, the label that diverges from the "agreement" of labelers could also be correct. For example, the labels to all three images included in Fig. 8 below are "feeding behavior," according to the definition, but only "003.img" is officially identified as "feeding behavior" in the ethogram. Labelers may interpret the same image differently, leading to incongruences, including missing details, overlapped definitions, composite behaviors, etc (Minnen et al., 2006). The voting system and the rule of "majority win" from semantic annotations may not be suitable for posture labeling and behavior labeling. Sometimes, the behavioral label with disagreement indicates an important but non-explicit label to animals (e.g., irregular breathing in resting), which is shown as "minority win" instead. To create an unbiased label for animals, we may involve a supervision process or find ways to converge on the following: 1) how can an "objective ethogram" be created, 2) how can spatial and temporal features (movement and duration) be labeled in a numerical way, 3) how can annotation tasks be split and recombined (identification, graphic annotation, postures, and behaviors), and 4) how can multi-dimension labels for the same identification originating from different annotators be verified?

6. Conclusions

Although many scientists forecast a bright future for pig farming operations strengthened with computer vision embedded technologies in the background, a lot more work remains to be done with respect to the creation and release of publicly available datasets and methods that are well established and utilized by a large number of research and industry communities. Several bottlenecks need to be overcome to promote the actual realization of commercial applications. Among others, this paper has identified the following bottlenecks: 1) the lack of

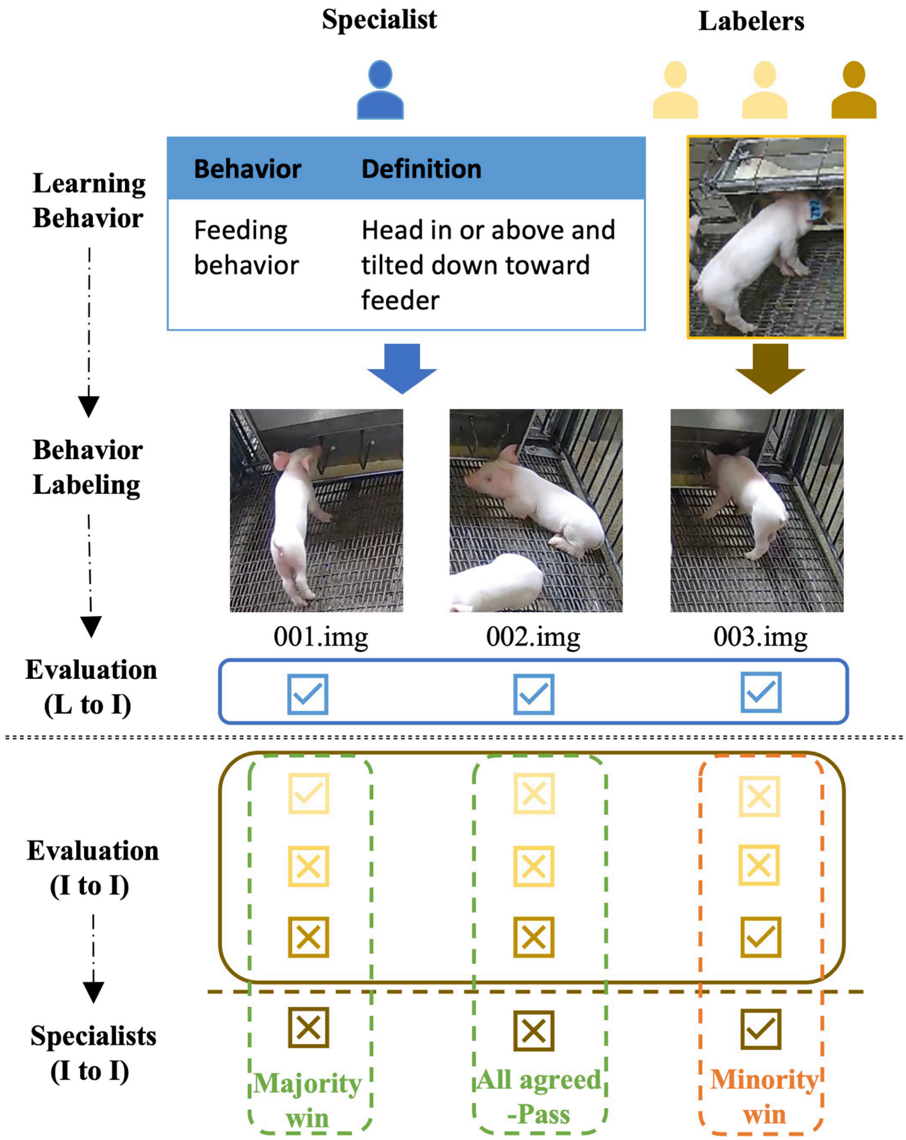

Fig. 8. Example of language-based (Color in blue; L to I) behavioral labeling process by one specialist and image-based (Color in yellow; I to I) behavioral labeling process by group labelers (results are displayed by different levels of yellow color). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

benchmark dataset to demonstrate the pig production scenes, 2) the lack of standard annotation and evaluation procedures to label animals in pig production environments, and 3) inconsistent and non-realistic discussion of the computer vision algorithm performance and result measures.

Recent studies have demonstrated that certain pig management tasks can be replaced by cameras loaded with computer vision algorithms, such as counting, routine inspections, and event detection. However, health status and well-being examination through behavior recognition represent more challenging tasks for computer vision algorithms. The reasons why the health and well-being status are harder to automate include 1) subjective scoring of animal behaviors, 2) the behavior analysis learning and correction process is both labor-intensive and time-consuming, 3) the lack of efficient tools and methods to label and analyze either predictable or unpredictable animal postures and behaviors.

Computer vision methods can accelerate the progress of animal behavior research, whereas animal behavior analysis can provide a reliable dataset, extend the research score, and increment the commercial value of computer vision applications on the precision pig farming. We need to strengthen the collaboration between animal-based scientists and computer-based scientists.

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.

Acknowledgments

This work is supported by Agriculture and Food Research Initiative (AFRI) grant no. 2020-67021-32799/project accession no.1024178 from the USDA National Institute of Food and Agriculture.

References

Ahrendt, P., Gregersen, T., Karstoft, H., 2011. Development of a real-time computer vision system for tracking loose-housed pigs. Comput. Electron. Agric. 76, 169–174. https://doi.org/10.1016/j.compag.2011.01.011.

Albernaz-Gonçalves, R., Olmos, G., Hötzel, M.J., 2021. My pigs are ok, why change? – animal welfare accounts of pig farmers. Animal 15, 100154. https://doi.org/10.1016/j.animal.2020.100154.

Alldieck, T., Magnor, M., Xu, W., Theobalt, C., Pons-Moll, G., 2018. Video based reconstruction of 3D people models. In: 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition. Presented at the 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, Salt Lake City, UT, pp. 8387–8397. doi: 10.1109/CVPR.2018.00875.

Alonso, M.E., González-Montaña, J.R., Lomillos, J.M., 2020. Consumers' concerns and perceptions of farm animal welfare. Animals 10, 385. https://doi.org/10.3390/ani10030385.

Aly, M., 2008. Real time detection of lane markers in urban streets. In: 2008 IEEE Intelligent Vehicles Symposium. IEEE, pp. 7–12.

Benjamin, M., Yik, S., 2019. Precision livestock farming in swine welfare: a review for swine practitioners. Animals 9, 133. https://doi.org/10.3390/ani9040133.

Berckmans, D., 2017. General introduction to precision livestock farming. Animal Frontiers 7, 6–11. https://doi.org/10.2527/af.2017.0102.

Bergamini, L., Pini, S., Simoni, A., Vezzani, R., Calderara, S., D'Eath, R., Fisher, R., 2021. Extracting accurate long-term behavior changes from a large pig dataset. In: Proceedings of the 16th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications. Presented at the 16th International Conference on Computer Vision Theory and Applications, SCITEPRESS - Science and Technology Publications, Online Streaming, — Select a Country —, pp. 524–533. doi: 10.5220/0010288405240533.

Brandl, N., Jørgensen, E., 1996. Determination of live weight of pigs from dimensions measured using image analysis. Comput. Electron. Agric. 15, 57–72. https://doi.org/10.1016/0168-1699(96)00003-8.

Byrd, C., Anderson, N., Lugar, D., Safranski, T., Lucy, M., Johnson, J., 2019. Evaluating the effects of in utero heat stress on piglet physiology and behavior following weaning and transport. Animals 9, 191. https://doi.org/10.3390/ani9040191.

Cadenas-Fernández, E., Sánchez-Vizcaíno, J.M., Pintore, A., Denurra, D., Cherchi, M., Jurado, C., Vicente, J., Barasona, J.A., 2019. Free-ranging pig and wild boar interactions in an endemic area of African Swine Fever. Front. Vet. Sci. 6, 376. https://doi.org/10.3389/fvets.2019.00376.

Chang, T.-H., Gong, S., Ong, E.-J., 2000. Tracking multiple people under occlusion using multiple cameras. In: BMVC. Citeseer, pp. 1–10.

Chen, G., Shen, S., Wen, L., Luo, S., Bo, L., 2020. Efficient pig counting in crowds with keypoints tracking and spatial-aware temporal response filtering. In: 2020 IEEE International Conference on Robotics and Automation (ICRA). Presented at the 2020 IEEE International Conference on Robotics and Automation (ICRA), pp. 10052–10058. doi: 10.1109/ICRA40945.2020.9197211.

Chen, C., Zhu, W., Oczak, M., Maschat, K., Baumgartner, J., Larsen, M.L.V., Norton, T., 2020a. A computer vision approach for recognition of the engagement of pigs with different enrichment objects. Comput. Electron. Agric. 175, 105580 https://doi.org/10.1016/j.compag.2020.105580.

Chen, C., Zhu, W., Steibel, J., Siegford, J., Wurtz, K., Han, J., Norton, T., 2020b. Recognition of aggressive episodes of pigs based on convolutional neural network and long short-term memory. Comput. Electron. Agric. 169, 105166 https://doi.org/10.1016/j.compag.2019.105166.

Chen, C., 2020. Recognition of feeding behaviour of pigs and determination of feeding time of each pig by a video-based deep learning method. Comput. Electronics Agric. 11.

Chijioke Ojukwu, C., Feng, Y., Jia, G., Zhao, H., Ta, H., 1. College of Engineering, Huazhong Agricultural University, Wuhan 430070, China, 2. Key Laboratory of Agricultural Equipment in Mid-lower Yangtze River, Ministry of Agriculture and Rural Affairs, Wuhan 430070, China, 2020. Development of a computer vision system to detect inactivity in group-housed pigs. International Journal of Agricultural and Biological Engineering 13, 42–46. doi: 10.25165/j.ijabe.20201301.5030.

Condotta, I.C.F.S., Brown-Brandl, T.M., Silva-Miranda, K.O., Stinn, J.P., 2018a. Evaluation of a depth sensor for mass estimation of growing and finishing pigs. Biosyst. Eng. 173, 11–18. https://doi.org/10.1016/j.biosystemseng.2018.03.002.

Condotta, I.C.F.S., Brown-Brandl, T.M., Stinn, J.P., Rohrer, G.A., Davis, J.D., Silva-Miranda, K.O., 2018b. Dimensions of the modern pig. Trans. ASABE 61, 1729–1739. https://doi.org/10.13031/trans.12826.

Condotta, I.C.F.S., Brown-Brandl, T.M., Pitla, S.K., Stinn, J.P., Silva-Miranda, K.O., 2020. Evaluation of low-cost depth cameras for agricultural applications. Comput. Electron. Agric. 173, 105394 https://doi.org/10.1016/j.compag.2020.105394.

Dan, S., Mukherjee, K., Roy, S., Nath Mandal, S., Kumar Hajra, D., Banik, S., 2021. Individual pig recognition based on ear images. In: Bhattacharjee, D., Kole, D.K., Dey, N., Basu, S., Plewczynski, D. (Eds.), Proceedings of International Conference on Frontiers in Computing and Systems, Advances in Intelligent Systems and Computing. Springer Singapore, Singapore, pp. 587–599. 10.1007/978-981-15-7834-2_55.

Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., Fei-Fei, L., 2009. Imagenet: A large-scale hierarchical image database. In: 2009 IEEE Conference on Computer Vision and Pattern Recognition. Ieee, pp. 248–255.

Deng, M., Yu, R., 2020. Pig target detection method based on SSD convolution network. J. Phys.: Conf. Ser. 1486, 022031 https://doi.org/10.1088/1742-6596/1486/2/022031.

Dong, J., Zhang, L., Zhang, H., Liu, W., 2020. Occlusion-aware GAN for face de-occlusion in the wild. In: 2020 IEEE International Conference on Multimedia and Expo (ICME). Presented at the 2020 IEEE International Conference on Multimedia and Expo (ICME), pp. 1–6. doi: 10.1109/ICME46284.2020.9102788.

Elmore, M.R.P., Garner, J.P., Johnson, A.K., Richert, B.T., Pajor, E.A., 2010. A flooring comparison: The impact of rubber mats on the health, behavior, and welfare of group-housed sows at breeding. Applied Animal Behaviour Science 123, 7–15. https://doi.org/10.1016/j.applanim.2009.11.012.

Fernandes, A.F.A., Dórea, J.R.R., Rosa, G.J. de M., 2020. Image analysis and computer vision applications in animal sciences: an overview. Front. Vet. Sci. 7, 551269 https://doi.org/10.3389/fvets.2020.551269.

Fernández-Carrión, E., Barasona, J.Á., Sánchez, Á., Jurado, C., Cadenas-Fernández, E., Sánchez-Vizcaíno, J.M., 2020. Computer vision applied to detect lethargy through animal motion monitoring: a trial on African swine fever in wild boar. Animals 10 (12), 2241.

Fleming, S.A., Monaikul, S., Patsavas, A.J., Waworuntu, R.V., Berg, B.M., Dilger, R.N., 2019. Dietary polydextrose and galactooligosaccharide increase exploratory behavior, improve recognition memory, and alter neurochemistry in the young pig. Nutr. Neurosci. 22, 499–512. https://doi.org/10.1080/1028415X.2017.1415280.

Gan, H., Ou, M., Huang, E., Xu, C., Li, S., Li, J., Liu, K., Xue, Y., 2021. Automated detection and analysis of social behaviors among preweaning piglets using key point-based spatial and temporal features. Comput. Electron. Agric. 188, 106357 https://doi.org/10.1016/j.compag.2021.106357.

García, R., Aguilar, J., Toro, M., Pinto, A., Rodríguez, P., 2020. A systematic literature review on the use of machine learning in precision livestock farming. Comput. Electron. Agric. 179, 105826 https://doi.org/10.1016/j.compag.2020.105826.

Gebru, T., Morgenstern, J., Vecchione, B., Vaughan, J.W., Wallach, H., Daumé III, H., Crawford, K., 2021. Datasheets for Datasets. arXiv:1803.09010 [cs].

Gronskyte, R., Clemmensen, L.H., Hviid, M.S., Kulahci, M., 2015. Pig herd monitoring and undesirable tripping and stepping prevention. Comput. Electron. Agric. 119, 51–60. https://doi.org/10.1016/j.compag.2015.09.021.

Gronskyte, R., Clemmensen, L.H., Hviid, M.S., Kulahci, M., 2016. Monitoring pig movement at the slaughterhouse using optical flow and modified angular histograms. Biosyst. Eng. 141, 19–30. https://doi.org/10.1016/j.biosystemseng.2015.10.002.

Guo, Y., Zhu, W., Jiao, P., Chen, J., 2014. Foreground detection of group-housed pigs based on the combination of Mixture of Gaussians using prediction mechanism and threshold segmentation. Biosyst. Eng. 125, 98–104. https://doi.org/10.1016/j.biosystemseng.2014.07.002.

Guo, Y., Zhu, W., Jiao, P., Ma, C., Yang, J., 2015. Multi-object extraction from topview group-housed pig images based on adaptive partitioning and multilevel thresholding segmentation. Biosyst. Eng. 135, 54–60. https://doi.org/10.1016/j.biosystemseng.2015.05.001.

Haladjian, J., Ermis, A., Hodaie, Z., Brügge, B., 2017. iPig: towards tracking the behavior of free-roaming pigs. In: Proceedings of the Fourth International Conference on Animal-Computer Interaction. Presented at the ACI2017: Fourth International Conference on Animal-Computer Interaction, ACM, Milton Keynes United Kingdom, pp. 1–5. doi: 10.1145/3152130.3152145.

Holte, M.B., Tran, C., Trivedi, M.M., Moeslund, T.B., 2012. Human pose estimation and activity recognition from multi-view videos: comparative explorations of recent developments. IEEE J. Sel. Top. Signal Process. 6, 538–552. https://doi.org/10.1109/JSTSP.2012.2196975.

Hu, Z., Yang, H., Lou, T., 2021. Dual attention-guided feature pyramid network for instance segmentation of group pigs. Comput. Electron. Agric. 186, 106140 https://doi.org/10.1016/j.compag.2021.106140.

Huang, E., Mao, A., Gan, H., Camila Ceballos, M., Parsons, T.D., Xue, Y., Liu, K., 2021. Center clustering network improves piglet counting under occlusion. Comput. Electron. Agric. 189, 106417 https://doi.org/10.1016/j.compag.2021.106417.

Joosen, P., Norton, T., Marchant-Ford, J., Berckmans, D., 2019. Animal welfare monitoring by real-time physiological signals 8.

Jover, J.N., Alcaniz-Raya, M., Gomez, V., Balasch, S., Moreno, J.R., Colomer, V.G., Torres, A., 2009. An automatic colour-based computer vision algorithm for tracking the position of piglets. Spanish J. Agric. Res. 7, 535–549.

Jun, K., Kim, S.J., Ji, H.W., 2018. Estimating pig weights from images without constraint on posture and illumination. Comput. Electron. Agric. 153, 169–176. https://doi.org/10.1016/j.compag.2018.08.006.

Kasani, P.H., Oh, S.M., Choi, Y.H., Ha, S.H., Jun, H., Park, K.H., Ko, H.S., Kim, J.E., Choi, J.W., Cho, E.S., Kim, J.S., 2021. A computer vision-based approach for behavior recognition of gestating sows fed different fiber levels during high ambient temperature. J Anim Sci Technol 63, 367–379. https://doi.org/10.5187/jast.2021.e35.

Kashiha, M., Bahr, C., Haredasht, S.A., Ott, S., Moons, C.P.H., Niewold, T.A., Ödberg, F.O., Berckmans, D., 2013a. The automatic monitoring of pigs water use by cameras. Comput. Electron. Agric. 90, 164–169. https://doi.org/10.1016/j.compag.2012.09.015.

Kashiha, M., Bahr, C., Ott, S., Moons, C.P.H., Niewold, T.A., Ödberg, F.O., Berckmans, D., 2013b. Automatic identification of marked pigs in a pen using image pattern recognition. Comput. Electron. Agric. 93, 111–120. https://doi.org/10.1016/j.compag.2013.01.013.

Kashiha, M., Pluk, A., Bahr, C., Vranken, E., Berckmans, D., 2013c. Development of an early warning system for a broiler house using computer vision. Biosyst. Eng. 116, 36–45. https://doi.org/10.1016/j.biosystemseng.2013.06.004.

Khan, M.H., McDonagh, J., Khan, S., Shahabuddin, M., Arora, A., Khan, F.S., Shao, L., Tzimiropoulos, G., 2020. Animalweb: A large-scale hierarchical dataset of annotated animal faces. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 6939–6948.

Kongsro, J., 2014. Estimation of pig weight using a Microsoft Kinect prototype imaging system. Comput. Electron. Agric. 109, 32–35. https://doi.org/10.1016/j.compag.2014.08.008.

Kulikov, V.A., Khotskin, N.V., Nikitin, S.V., Lankin, V.S., Kulikov, A.V., Trapezov, O.V., 2014. Application of 3-D imaging sensor for tracking minipigs in the open field test. J. Neurosci. Methods 235, 219–225. https://doi.org/10.1016/j.jneumeth.2014.07.012.

Küster, S., Kardel, M., Ammer, S., Brünger, J., Koch, R., Traulsen, I., 2020. Usage of computer vision analysis for automatic detection of activity changes in sows during final gestation. Comput. Electron. Agric. 169, 105177 https://doi.org/10.1016/j.compag.2019.105177.
Lao, F., Brown-Brandl, T., Stinn, J.P., Liu, K., Teng, G., Xin, H., 2016. Automatic recognition of lactating sow behaviors through depth image processing. Comput. Electron. Agric. 125, 56–62. https://doi.org/10.1016/j.compag.2016.04.026.
Larue, B., 2022. On the economics of meat processing, livestock queuing, and worker safety. Canadian J. Agric. Econ./Revue canadienne d'agroeconomie 70, 63–72.
Lee, S., Ahn, H., Seo, J., Chung, Y., Park, D., Pan, S., 2019. Practical monitoring of undergrown pigs for IoT-based large-scale smart farm. IEEE Access 7, 173796–173810. https://doi.org/10.1109/ACCESS.2019.2955761.
Li, C., Ghorbani, N., Broomé, S., Rashid, M., Black, M.J., Hernlund, E., Kjellström, H., Zuffi, S., 2021. hSMAL: Detailed Horse Shape and Pose Reconstruction for Motion Pattern Recognition. arXiv:2106.10102 [cs].
Lin, T.-Y., Maire, M., Belongie, S., Bourdev, L., Girshick, R., Hays, J., Perona, P., Ramanan, D., Zitnick, C.L., Dollár, P., 2015. Microsoft COCO: Common Objects in Context. arXiv:1405.0312 [cs].
Liu, Y.-L., Lai, W.-S., Yang, M.-H., Chuang, Y.-Y., Huang, J.-B., 2020. Learning to see through obstructions. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 14215–14224.
Liu, D., Oczak, M., Maschat, K., Baumgartner, J., Pletzer, B., He, D., Norton, T., 2020a. A computer vision-based method for spatial-temporal action recognition of tail-biting behaviour in group-housed pigs. Biosyst. Eng. 195, 27–41. https://doi.org/10.1016/j.biosystemseng.2020.04.007.
Loper, M., Mahmood, N., Romero, J., Pons-Moll, G., Black, M.J., 2015. SMPL: a skinned multi-person linear model. ACM Trans. Graph. 34, 1–16. https://doi.org/10.1145/2816795.2818013.
Marsot, M., Mei, J., Shan, X., Ye, L., Feng, P., Yan, X., Li, C., Zhao, Y., 2020. An adaptive pig face recognition approach using Convolutional Neural Networks. Comput. Electron. Agric. 173, 105386 https://doi.org/10.1016/j.compag.2020.105386.
Matthews, S.G., Miller, A.L., Clapp, J., Plötz, T., Kyriazakis, I., 2016. Early detection of health and welfare compromises through automated detection of behavioural changes in pigs. Vet. J. 217, 43–51. https://doi.org/10.1016/j.tvjl.2016.09.005.
Matthews, S.G., Miller, A.L., PlÖtz, T., Kyriazakis, I., 2017. Automated tracking to measure behavioural changes in pigs for health and welfare monitoring. Sci Rep 7, 17582. https://doi.org/10.1038/s41598-017-17451-6.
McBride, W.D., Key, N., 2013. U.S. Hog Production From 1992 to 2009: Technology, Restructuring, and Productivity Growth, err158 48.
McCloskey, S., 2014. Masking Light Fields to Remove Partial Occlusion. In: 2014 22nd International Conference on Pattern Recognition. Presented at the 2014 22nd International Conference on Pattern Recognition (ICPR), IEEE, Stockholm, Sweden, pp. 2053–2058. doi: 10.1109/ICPR.2014.358.
McManus, C., Tanure, C.B., Peripolli, V., Seixas, L., Fischer, V., Gabbi, A.M., Menegassi, S.R.O., Stumpf, M.T., Kolling, G.J., Dias, E., Costa, J.B.G., 2016. Infrared thermography in animal production: An overview. Comput. Electron. Agric. 123, 10–16. https://doi.org/10.1016/j.compag.2016.01.027.
Meizhi, W., Lu, Y., Jijun, L., Wanying, Z., Zhonghong, W., 2017. Water consumption and wastage of nursery pig with different drinkers at different water pressures in summer 6.
Mendes, C.C.T., Frémont, V., Wolf, D.F., 2016. Exploiting fully convolutional neural networks for fast road detection. In: 2016 IEEE International Conference on Robotics and Automation (ICRA). IEEE, pp. 3174–3179.
Miller, A.L., Dalton, H.A., Kanellos, T., Kyriazakis, I., 2019. How many pigs within a group need to be sick to lead to a diagnostic change in the group's behavior?1. J. Anim. Sci. 97, 1956–1966. https://doi.org/10.1093/jas/skz083.
Miñano, S., Taylor, G.K., 2021. Through hawks' eyes: reconstructing a bird's visual field in flight to study gaze strategy and attention during perching and obstacle avoidance (preprint). Animal Behavior and Cognition. https://doi.org/10.1101/2021.06.16.446415.
Minnen, D., Westeyn, T., Starner, T., Ward, J.A., Lukowicz, P., 2006. Performance Metrics and Evaluation Issues for Continuous Activity Recognition 9.
Miranda-de la Lama, G.C., Estévez-Moreno, L.X., Villarroel, M., Rayas-Amor, A.A., María, G.A., Sepúlveda, W.S., 2019. Consumer attitudes toward animal welfare-friendly products and willingness to pay: Exploration of Mexican market segments. J. Appl. Anim. Welfare Sci. 22, 13–25.
Mounir, R., Gula, R., Theuerkauf, J., Sarkar, S., 2021. Spatio-Temporal Event Segmentation and Localization for Wildlife Extended Videos. arXiv:2005.02463 [cs, eess].
Nasirahmadi, A., Hensel, O., Edwards, S.A., Sturm, B., 2016. Automatic detection of mounting behaviours among pigs using image analysis. Comput. Electron. Agric. 124, 295–302. https://doi.org/10.1016/j.compag.2016.04.022.
Nasirahmadi, A., Sturm, B., Olsson, A.-C., Jeppsson, K.-H., Müller, S., Edwards, S., Hensel, O., 2019. Automatic scoring of lateral and sternal lying posture in grouped pigs using image processing and Support Vector Machine. Comput. Electron. Agric. 156, 475–481. https://doi.org/10.1016/j.compag.2018.12.009.
Neethirajan, S., Kemp, B., 2021. Digital livestock farming. Sens. Bio-Sens. Res. 32, 100408 https://doi.org/10.1016/j.sbsr.2021.100408.
Norton, T., Berckmans, D., 2018. Engineering advances in Precision Livestock Farming. Biosyst. Eng. 173, 1–3. https://doi.org/10.1016/j.biosystemseng.2018.09.008.
Norton, T., Chen, C., Larsen, M.L.V., Berckmans, D., 2019. Review: Precision livestock farming: building 'digital representations' to bring the animals closer to the farmer. Animal 13, 3009–3017. https://doi.org/10.1017/S175173111900199X.
Nowara, E.M., Marks, T.K., Mansour, H., Veeraraghavan, A., 2020. Near-infrared imaging photoplethysmography during driving. IEEE Trans. Intell. Transp. Syst. 1–12 https://doi.org/10.1109/TITS.2020.3038317.
Oczak, M., Maschat, K., Berckmans, D., Vranken, E., Baumgartner, J., 2016. Automatic estimation of number of piglets in a pen during farrowing, using image analysis. Biosyst. Eng. 151, 81–89. https://doi.org/10.1016/j.biosystemseng.2016.08.018.
Oh, M., Olsen, P., Ramamurthy, K.N., 2020. Crowd counting with decomposed uncertainty. AAAI 34, 11799–11806. https://doi.org/10.1609/aaai.v34i07.6852.
Pedersen, L.J., 2018. Overview of commercial pig production systems and their main welfare challenges. In: Advances in Pig Welfare. Elsevier, pp. 3–25. doi: 10.1016/B978-0-08-101012-9.00001-0.
Pezzuolo, A., Guarino, M., Sartori, L., González, L.A., Marinello, F., 2018. On-barn pig weight estimation based on body measurements by a Kinect v1 depth camera. Comput. Electron. Agric. 148, 29–36. https://doi.org/10.1016/j.compag.2018.03.003.
T. Psota, E., Schmidt, T., Mote, B., C. Pérez, L., 2020. Long-term tracking of group-housed livestock using keypoint detection and MAP estimation for individual animal identification. Sensors 20, 3670. doi: 10.3390/s20133670.
Qiao, Y., Kong, H., Clark, C., Lomax, S., Su, D., Eiffert, S., Sukkarieh, S., 2021. Intelligent perception for cattle monitoring: a review for cattle identification, body condition score evaluation, and weight estimation. Comput. Electron. Agric. 185, 106143 https://doi.org/10.1016/j.compag.2021.106143.
Ramaekers, P.J.L., Verstegen, M.W.A., Hartog, L.A. den, Swinkels, J.W.G.M., 1996. Control of individual daily growth in group-housed pigs using feeding stations.
Rauw, W.M., Rydhmer, L., Kyriazakis, I., Øverland, M., Gilbert, H., Dekkers, J.C., Hermesch, S., Bouquet, A., Gómez Izquierdo, E., Louveau, I., Gomez-Raya, L., 2020. Prospects for sustainability of pig production in relation to climate change and novel feed resources. J. Sci. Food Agric. 100, 3575–3586. https://doi.org/10.1002/jsfa.10338.
Riekert, M., Klein, A., Adrion, F., Hoffmann, C., Gallmann, E., 2020. Automatically detecting pig position and posture by 2D camera imaging and deep learning. Comput. Electron. Agric. 174, 105391 https://doi.org/10.1016/j.compag.2020.105391.
Robbins, L.A., Green-Miller, A.R., Johnson, J.S., Gaskill, B.N., 2020. Early life thermal stress: impacts on future temperature preference in weaned pigs (3 to 15 kg). J. Anim. Sci. 98, skaa327.
Sa, J., Choi, Y., Lee, H., Chung, Y., Park, D., Cho, J., 2019. Fast pig detection with a top-view camera under various illumination conditions. Symmetry 11, 266. https://doi.org/10.3390/sym11020266.
Salau, J., Haas, J.H., Junge, W., Thaller, G., 2016. Extrinsic calibration of a multi-Kinect camera scanning passage for measuring functional traits in dairy cows. Biosyst. Eng. 151, 409–424. https://doi.org/10.1016/j.biosystemseng.2016.10.008.
Schofield, C.P., 1990. Evaluation of image analysis as a means of estimating the weight of pigs. J. Agric. Eng. Res. 47, 287–296. https://doi.org/10.1016/0021-8634(90)80048-Y.
Schofield, C.P., Marchant, J.A., White, R.P., Brandl, N., Wilson, M., 1999. Monitoring pig growth using a prototype imaging system. J. Agric. Eng. Res. 72, 205–210. https://doi.org/10.1006/jaer.1998.0365.
Scholz, A.M., Bünger, L., Kongsro, J., Baulain, U., Mitchell, A.D., 2015. Non-invasive methods for the determination of body and carcass composition in livestock: dual-energy X-ray absorptiometry, computed tomography, magnetic resonance imaging and ultrasound: invited review. Animal 9, 1250–1264. https://doi.org/10.1017/S1751731115000336.
Seo, J., Ahn, H., Kim, D., Lee, S., Chung, Y., Park, D., 2020. EmbeddedPigDet—fast and accurate pig detection for embedded board implementations. Appl. Sci. 10, 2878. https://doi.org/10.3390/app10082878.
Seo, J., Sa, J., Choi, Y., Chung, Y., Park, D., Kim, H., 2019. A YOLO-based separation of touching-pigs for smart pig farm applications. In: 2019 21st International Conference on Advanced Communication Technology (ICACT). Presented at the 2019 21st International Conference on Advanced Communication Technology (ICACT), pp. 395–401. doi: 10.23919/ICACT.2019.8701968.
Shao, H., Pu, J., Mu, J., 2021. Pig-posture recognition based on computer vision: dataset and exploration. Animals 11, 1295. https://doi.org/10.3390/ani11051295.
Shao, B., Xin, H., 2008. A real-time computer vision assessment and control of thermal comfort for group-housed pigs. Comput. Electron. Agric. 62, 15–21. https://doi.org/10.1016/j.compag.2007.09.006.
Sharma, A., Jain, A., Gupta, P., Chowdary, V., 2021. Machine learning applications for precision agriculture: a comprehensive review. IEEE Access 9, 4843–4873. https://doi.org/10.1109/ACCESS.2020.3048415.
Shi, C., Teng, G., Li, Z., 2016. An approach of pig weight estimation using binocular stereo system based on LabVIEW. Comput. Electron. Agric. 129, 37–43. https://doi.org/10.1016/j.compag.2016.08.012.
Shi, C., Zhang, J., Teng, G., 2020. Division of pig growth stages according to body component variation using computer vision. PJZ 52. https://doi.org/10.17582/journal.pjz/20191108061105.
Stajnko, D., Brus, M., Hočevar, M., 2008. Estimation of bull live weight through thermographically measured body dimensions. Comput. Electron. Agric. 61, 233–240. https://doi.org/10.1016/j.compag.2007.12.002.
Stavrakakis, S., Li, W., Guy, J.H., Morgan, G., Ushaw, G., Johnson, G.R., Edwards, S.A., 2015. Validity of the Microsoft Kinect sensor for assessment of normal walking patterns in pigs. Comput. Electron. Agric. 117, 1–7. https://doi.org/10.1016/j.compag.2015.07.003.
Sun, L., Chen, S., Liu, T., Liu, C., Liu, Y., College of Information and Electrical Engineering, China Agricultural University, Beijing 100083, China, 2020. Pig target tracking algorithm based on multi-channel color feature fusion. Int. J. Agric. Biol. Eng. 13, 180–185. doi: 10.25165/j.ijabe.20201303.5346.
Tao, F., Ngadi, M., 2018. Recent advances in rapid and nondestructive determination of fat content and fatty acids composition of muscle foods. Crit. Rev. Food Sci. Nutr. 58, 1565–1593. https://doi.org/10.1080/10408398.2016.1261332.

Taylor, R.E., Field, T.G., 2007. Scientific Farm Animal Production: An Introduction to Animal Science. Pearson Prentice Hall.
Tian, M., Guo, H., Chen, H., Wang, Q., Long, C., Ma, Y., 2019. Automated pig counting using deep learning. Comput. Electron. Agric. 163, 104840 https://doi.org/10.1016/j.compag.2019.05.049.
Torrey, S., Widowski, T.M., 2004. Effect of drinker type and sound stimuli on early-weaned pig performance and behavior12. J. Anim. Sci. 82, 2105–2114. https://doi.org/10.2527/2004.8272105x.
Tscharke, M., Banhazi, T.M., 2016. A brief review of the application of machine vision in livestock behaviour analysis. Journal of Agricultural Informatics / Agrárinformatika Folyóirat 7, 23–42. doi: 10.17700/jai.2016.7.1.279.
Tzanidakis, C., Simitzis, P., Arvanitis, K., Panagakis, P., 2021. An overview of the current trends in precision pig farming technologies. Livestock Science 249, 104530. https://doi.org/10.1016/j.livsci.2021.104530.
van der Zande, Lisette.E., Guzhva, O., Rodenburg, T.B., 2021. Individual detection and tracking of group housed pigs in their home pen using computer vision. Front. Anim. Sci. 2, 669312. doi: 10.3389/fanim.2021.669312.
Viazzi, S., Ismayilova, G., Oczak, M., Sonoda, L.T., Fels, M., Guarino, M., Vranken, E., Hartung, J., Bahr, C., Berckmans, D., 2014. Image feature extraction for classification of aggressive interactions among pigs. Comput. Electron. Agric. 104, 57–62. https://doi.org/10.1016/j.compag.2014.03.010.
Wang, K., Guo, H., Ma, Q., Su, W., Chen, L., Zhu, D., 2018. A portable and automatic Xtion-based measurement system for pig body size. Comput. Electron. Agric. 148, 291–298. https://doi.org/10.1016/j.compag.2018.03.018.
Wang, Z., Shadpour, S., Chan, E., Rotondo, V., Wood, K.M., Tulpan, D., 2021a. ASAS-NANP SYMPOSIUM: Applications of machine learning for livestock body weight prediction from digital images. J. Anim. Sci. 99, skab022. https://doi.org/10.1093/jas/skab022.
Wang, Y., Yang, W., Winter, P., Walker, L., 2008. Walk-through weighing of pigs using machine vision and an artificial neural network. Biosyst. Eng. 100, 117–125. https://doi.org/10.1016/j.biosystemseng.2007.08.008.
Wang, M., Youssef, A., Larsen, M., Rault, J.-L., Berckmans, D., Marchant-Forde, J.N., Hartung, J., Bleich, A., Lu, M., Norton, T., 2021b. Contactless video-based heart rate monitoring of a resting and an anesthetized pig. Animals 11, 442. https://doi.org/10.3390/ani11020442.
Wongsriworaphon, A., Arnonkijpanich, B., Pathumnakul, S., 2015. An approach based on digital image analysis to estimate the live weights of pigs in farm environments. Comput. Electron. Agric. 115, 26–33. https://doi.org/10.1016/j.compag.2015.05.004.
Woonwong, Y., Do Tien, D., Thanawongnuwech, R., 2020. The future of the pig industry after the introduction of African swine fever into Asia. Animal Front. 10, 30–37. https://doi.org/10.1093/af/vfaa037.
Wu, J., Tillett, R., McFarlane, N., Ju, X., Siebert, J.P., Schofield, P., 2004. Extracting the three-dimensional shape of live pigs using stereo photogrammetry. Comput. Electron. Agric. 44, 203–222. https://doi.org/10.1016/j.compag.2004.05.003.
Wurtz, K., Camerlink, I., D'Eath, R.B., Fernández, A.P., Norton, T., Steibel, J., Siegford, J., 2019. Recording behaviour of indoor-housed farm animals automatically using machine vision technology: a systematic review. PLoS ONE 14, e0226669. https://doi.org/10.1371/journal.pone.0226669.
Wutke, M., Schmitt, A.O., Traulsen, I., Gültas, M., 2020. Investigation of pig activity based on video data and semi-supervised neural networks. AgriEngineering 2, 581–595. https://doi.org/10.3390/agriengineering2040039.
Xue, T., Rubinstein, M., Liu, C., Freeman, W.T., 2015. A computational approach for obstruction-free photography. ACM Trans. Graph. 34, 1–11. https://doi.org/10.1145/2766940.
Yang, A., Huang, H., Zheng, B., Li, S., Gan, H., Chen, C., Yang, X., Xue, Y., 2020. An automatic recognition framework for sow daily behaviours based on motion and image analyses. Biosyst. Eng. 192, 56–71. https://doi.org/10.1016/j.biosystemseng.2020.01.016.
Yang, Q., Xiao, D., 2020. A review of video-based pig behavior recognition. Appl. Animal Behav. Sci. 233, 105146 https://doi.org/10.1016/j.applanim.2020.105146.
Yang, Q., Xiao, D., Cai, J., 2021. Pig mounting behaviour recognition based on video spatial–temporal features. Biosyst. Eng. 206, 55–66. https://doi.org/10.1016/j.biosystemseng.2021.03.011.
Yang, Q., 2018. Feeding behavior recognition for group-housed pigs with the Faster R-CNN. Comput. Electron. Agric. 8.
Yik, S., Benjamin, M., Lavagnino, M., Morris, D., 2020. DIAT (Depth-Infrared Image Annotation Transfer) for training a depth-based pig-pose detector. In: 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). Presented at the 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, Las Vegas, NV, USA, pp. 2459–2466. doi: 10.1109/IROS45743.2020.9340744.
Zanuttigh, P., Marin, G., Dal Mutto, C., Dominio, F., Minto, L., Cortelazzo, G.M., 2016. Time-of-Flight and Structured Light Depth Cameras. Springer International Publishing, Cham. doi: 10.1007/978-3-319-30973-6.
Zhang, Y., Cai, J., Xiao, D., Li, Z., Xiong, B., 2019. Real-time sow behavior detection based on deep learning. Comput. Electron. Agric. 163, 104884 https://doi.org/10.1016/j.compag.2019.104884.
Zhu, X., Chen, C., Zheng, B., Yang, X., Gan, H., Zheng, C., Yang, A., Mao, L., Xue, Y., 2020. Automatic recognition of lactating sow postures by refined two-stream RGB-D faster R-CNN. Biosyst. Eng. 189, 116–132. https://doi.org/10.1016/j.biosystemseng.2019.11.013.
Zhu, W., Guo, Y., Jiao, P., Ma, C., Chen, C., 2017. Recognition and drinking behaviour analysis of individual pigs based on machine vision. Livestock Science 205, 129–136. https://doi.org/10.1016/j.livsci.2017.09.003.
Zitova, B., Flusser, J., 2003. Image registration methods: a survey. Image Vis. Comput. 21, 977–1000.
Zuffi, S., Kanazawa, A., Jacobs, D.W., Black, M.J., 2017. 3D Menagerie: Modeling the 3D Shape and Pose of Animals. In: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Presented at the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, Honolulu, HI, pp. 5524–5532. doi: 10.1109/CVPR.2017.586.