Food Control 150 (2023) 109768

Contents lists available at ScienceDirect

Food Control

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

Applications of computer vision systems for meat safety assurance in abattoirs: A systematic review

Marianne Sandberg [a,**], Sergio Ghidini [b], Lis Alban [c,d], Andrea Capobianco Dondona [e], Bojan Blagojevic [f], Martijn Bouwknegt [g], Len Lipman [h], Jeppe Seidelin Dam [i], Ivan Nastasijevic [j], Dragan Antic [k,*]

[a] National Food Institute, Technical University of Denmark, 2800, Kgs. Lyngby, Denmark
[b] Department of Food and Drug, University of Parma, Via del Taglio 10, 43126, Parma, Italy
[c] Department for Food Safety, Veterinary Issues and Risk Analysis, Danish Agriculture & Food Council, Agrofood Park 13, DK-8200, Aarhus N, Denmark
[d] Department of Veterinary and Animal Sciences, University of Copenhagen, Grønnegårdsvej 8, DK-1870, Frederiksberg, Denmark
[e] Farm4Trade s.r.l., Via IV Novembre, 66041, Atessa, Italy
[f] Department of Veterinary Medicine, Faculty of Agriculture, University of Novi Sad, Trg D. Obradovica 8, 21000, Novi Sad, Serbia
[g] Vion Food Group, Boseind 15, 5281 RM, Boxtel, the Netherlands
[h] Department Population Health Sciences, Institute for Risk Assessment Sciences (IRAS), University of Utrecht, 3584, CM Utrecht, the Netherlands
[i] Danish Technological Institute, Grønnegårdsvej 1, 2630, Taastrup, Denmark
[j] Institute of Meat Hygiene and Technology, Kacanskog 13, 11000, Belgrade, Serbia
[k] Institute of Infection, Veterinary and Ecological Sciences, Faculty of Health and Life Sciences, University of Liverpool, Leahurst, Neston, CH64 7TE, United Kingdom

A R T I C L E I N F O

Keywords:
Computer vision
Imaging
Meat inspection
Meat safety assurance
Lesions
Carcass contamination

A B S T R A C T

Introduction in 2017–2019 of the new EU legislation on official controls in food production allowed use of computer vision systems (CVSs) as complementary tools in meat inspection of bovines, pigs and poultry. A systematic literature review was performed to identify and analyse relevant articles reporting on the performances of CVSs used in abattoirs for ante- and post-mortem veterinary inspection and meat safety assurance, including systems for detecting carcass/organ contamination and lesions. In this review, 62 articles were identified and analysed. There were 35 articles reporting on CVS performance in the detection of carcass/organ lesions and 27 in the detection of carcass contamination. CVSs for broiler chicken, pig and bovine meat safety assurance were reported in 53, 5 and 4 articles, respectively. Not all developed CVSs were validated, and only three articles reported results from real-time evaluation of CVS performance in an abattoir vs performance of the official veterinarian. Most of the reported CVS performance measures (i.e., sensitivity and specificity) were >80%. A high specificity in detecting lesions and carcass contamination (i.e., a low number of false positives) is of importance for the food business operator in order to minimise food waste, whereas a high sensitivity (i.e., a low number of false negatives) is required for production of wholesome and safe meat. At present, the existing CVSs developed for overall meat safety assurance of broiler chicken carcasses and organs demonstrate very high sensitivities but suboptimal specificities, indicating the need for further CVS development and optimisation.

1. Introduction

The European legislation on meat inspection has recently been revised and extended to cover the whole production chain, ideally from breeding of the animals to the kitchen of the consumer (farm-to-fork), including many aspects of potential risk prevention and control in a meat safety assurance system (MSAS) (Anon, 2017; 2019b). This new legislation enables implementation of different approaches to meat inspection, provided certain criteria are met and that the approach is based on risk assessment. The main components of official controls are ante-mortem (AM) inspection, which is the inspection of live animals, and post-mortem (PM) inspection, which is the inspection of carcasses and organs after slaughter. Both types of inspection aim to detect lesions/abnormalities related to zoonotic and non-zoonotic hazards, and

* Corresponding author.
** Corresponding author.
E-mail addresses: marsan@food.dtu.dk (M. Sandberg), Dragan.Antic@liverpool.ac.uk (D. Antic).

https://doi.org/10.1016/j.foodcont.2023.109768
Received 24 February 2023; Accepted 27 March 2023
Available online 30 March 2023

PM inspection additionally aims to detect carcass surface contamination. Inspection of carcasses regarding process-associated contamination with faeces, stomach or gut content (ingesta), bile, hair/feathers or blood is performed within the food business operator's (FBO's) food safety management system, and therefore, this inspection is the FBO's responsibility. The results of the FBO's own inspections should be verified by the competent authorities (CAs), i.e., official veterinarians (OVs). All these aspects have been suggested to be incorporated into a future overall comprehensive and integrated risk-based meat safety assurance system (RB-MSAS) (Blagojevic et al., 2021).

One of the most important components of the modern RB-MSAS is visual-only (i.e., hands-free) inspection of low-risk slaughter animals and detailed inspection of high-risk slaughter animals (Blagojevic et al., 2021). RB-MSAS is also characterised by its openness towards new technologies, including digital transformation of meat inspection that can improve the quality and the efficacy of the inspection as well as the feedback to the farmer. Therefore, computer vision systems (CVSs) are seen as a useful aid in risk-based meat inspection. Currently, CVSs are not widely used, and due to legislative restrictions, they will be used only as supporting tools for the meat inspection of bovines and pigs, whereas CVSs could, in principle, replace an inspector in poultry inspection. In a longer perspective, a CVS is supposed to reduce the inspectors' physical presence at the slaughterline while, at the same time, it increases the speed, consistency and overall effectiveness of meat inspection but with levels of sensitivity and specificity equal to those provided by human inspectors (Antunović et al., 2021; Blagojevic et al., 2021).

In the last decade, more information retrieved from the different steps in the meat chain, including at the abattoir, have become digitised, allowing better trace-back systems (Sandberg et al., 2015). This significantly facilitates investigation of foodborne disease outbreaks and recall of food batches as an action taken during an outbreak investigation. Digitisation of information also allows for more efficient reporting of findings from AM and PM inspection to the farmer, as demonstrated in the Danish Quality Assurance System in Chicken Production (KIK). Food chain information (FCI) is forwarded from the producer to the abattoir and backwards from the abattoir to the producer. This is performed digitally through the KIK database (Alfifi et al., 2020), as specified in Regulation (EC) No 853/2004 (Anon, 2004). Furthermore, CVSs offer a plethora of possibilities in relation to RB-MSAS, such as the capacity to monitor transportation of pigs to slaughter and to conduct AM and PM inspection remotely. For example, Almqvist et al. (2021) observed the good potential of remote PM inspection based on the usage of augmented-reality, live-stream video software intended for remotely situated small-scale abattoirs for pigs and wild game-handling establishments.

Meat inspection is the responsibility of OVs and their teams that are trained specifically to perform those tasks, such as official auxiliaries (OAs), meat hygiene inspectors and/or the abattoir's own staff, particularly in chicken abattoirs. Currently, meat inspection of poultry and wild game in the EU is conducted under legislation offering specific flexibilities, where the OA, under the responsibility of the OV, can conduct both AM and PM inspection, in situations when the PM inspection is carried out in low-capacity abattoirs (less than 1000 livestock units per year or less than 150,000 poultry, lagomorphs and small wild game per year) (Anon, 2017).

The criteria for condemnation of animals at slaughter and the respective carcasses and organs for human consumption are based on detection of clinical signs of diseases and characteristic lesions or abnormalities, using predefined lesion codes (Alban et al., 2022). Acute illness and active generalised infection lead to total condemnation, whilst in the case of localised conditions, only some tissues/organs are trimmed off (partial condemnation) (Vieira-Pinto et al., 2020). Implementation of a CVS would, therefore, serve for automation purposes in the identification of carcasses for partial and total condemnation. Today, in the case of poultry, the aim of the existing official controls is to evaluate the overall health status of the slaughtered flock, but not necessarily individual carcasses. Tracing of the individual broiler chicken carcasses for partial approval is often impossible given the line speed, and it requires a re-design of the current lines, to allow for channelling of affected carcasses to an area for trimming. Hence, implementation of a CVS for generating and handling big data, and technical solutions for tracing individual carcasses and for allowing routine handling of the different categories of meat, would also facilitate the partial condemnation of broiler chickens and contribute to a reduction of food waste.

The new European Union (EU) Regulation 2017/625 opens up the prospects for new technologies to be used to complement meat inspection when the documentation about their efficacy is accepted by the Member States, but for the time being, the new technologies are restricted to poultry only (Anon, 2017). For poultry, article 25 (point 2) in EU Regulation 2019/627 states that the CA can decide that only a representative sample of chickens from a flock needs to undergo PM inspection, if the poultry abattoir has a system that the OV assesses as appropriate to use for detecting poultry with abnormalities, contamination or defects (Anon, 2019b). During the high-speed processing, where more than 12,000 broiler chickens are slaughtered per hour, PM inspection is a challenge, since it is very labour intensive, time-consuming and tiring for inspectors. CVS, on the other hand, can handle broiler chicken meat inspection at any slaughter speed for any number of hours (Jørgensen, 2018; Yang et al., 2010). It can be argued that the meat inspection would be performed with greater accuracy and precision if CVS could contribute to the OV's judgement compared to not using this technology. The high intra-and inter-rater variation between human inspectors (Alban et al., 2022) could be minimised because the inspection could be conducted consistently at each abattoir. Better uniformity regarding detection of AM and PM inspection findings and a more harmonised way of using the associated condemnation criteria would benefit livestock producers, as they would not be economically penalised based on the abattoir to which the animals were sent.

In the United States, the application of CVSs (digital cameras, wide-angle imaging cameras, computer tomography, ultrasound scanners) intended for PM inspection in abattoirs has been extensively studied during recent decades, showing promising results. Currently, the United States Department of Agriculture Food Safety and Inspection Service (USDA FSIS) new technology information list includes only two non-intrusive imaging systems aimed at identifying organic contamination on meat and other surfaces. These are licensed as VerifEYE food safety technologies: Solo™ (eMerge Interactive, Inc., USA) and Carcass Inspection System (CIS) (eMerge Interactive, Inc., USA), the latter identifying organic contamination in real-time on full bovine carcass sides (Burfoot et al., 2011; USDA, 2022).

This systematic review investigates the status of the available CVSs for AM and PM inspection of bovines, pigs and broiler chickens regarding detection of lesions and carcass contamination, whereas meat quality conditions (sensory quality, chemical composition, quality assessment etc.) were left out of the scope of this paper. The performance of CVSs in future official controls and RB-MSAS is discussed while taking into account the legislative context related to CVSs.

2. Scope of the review

2.1. Systematic review approach, scope and research question

The review team included ten team members with expertise in development of CVSs, official controls, epidemiology and meat safety. A review protocol was developed using the Cochrane methodology for systematic reviews (www.cochrane.org), which was adopted and pretested in two previous systematic reviews in this research project (Antic et al., 2021; Zdolec et al., 2022). The review question was: *What is the effectiveness and detection performance of all available computer vision systems used in abattoirs to detect carcass contamination and pathological* *lesions?*

The review considered evidence on CVSs available in the public domain. Only primary research studies were used for data extraction and reporting. Key elements of the review question (PIT) were: Population (P), Index Test(s) (I) and Target condition (T). The population of interest included CVSs used for bovines, pigs and broiler chickens. All CVSs for detection of carcass contamination or lesions (Index test), developed on a lab scale for application in abattoirs, up to and inclusive of finished carcass chilling, were considered relevant for inclusion into the review. Relevant target conditions were: i) post-mortem visible contamination (faecal or other); ii) post-mortem gross pathology (lesions) and; iii) ante-mortem systems for animal health.

2.2. Search strategy and information sources

A comprehensive search algorithm was developed by extracting key words from a selection of known relevant review and primary articles on the topic. Key terms were combined using the Boolean operator "OR" into categories for study setting/process, Index Test (CVS), Target condition (contamination/gross pathology terms) and Population (bovines, pigs, chicken and organ terms), and the categories were combined using the "AND" operator. Algorithms were pre-tested in Scopus and CAB Direct to ensure that a known list of 20 relevant articles could be sufficiently identified, and the search was performed at the title, abstract and key word levels. Database searches were implemented in the bibliographic databases Scopus and CAB Direct searching for literature published from 1990 to 2021, with no language restrictions imposed. Database searches were conducted on April 20, 2020, and updated on September 10, 2021. Grey literature was also searched for citations not available in Scopus and CAB Direct, (Google Scholar and http://www.opengrey.eu). Search verification included reviewing the reference list of relevant review and primary articles. The search algorithm and results of searches can be found in Supplementary material.

2.3. Relevance screening, confirmation and eligibility criteria

All retrieved citations were de-duplicated in EndNote, imported into the Rayan platform (https://www.rayyan.ai/) and distributed equally within the review team, with each article reviewed by two team members. Each article was screened at the title and abstract levels using a pre-specified relevance screening form, and then its relevance was further confirmed using another checklist (Supplementary material). CVSs investigating organ segmentation, meat quality traits and describing only the initial stages of CVS development (without data on CVS performance) were excluded. All main research literature types were included: peer reviewed articles published in journals, conference articles, government and industry reports and theses. Language restrictions were then imposed so that only articles written in Dutch, English, French or German were included.

All articles passing the relevance screening and meeting the eligibility criteria were procured as full text documents for further relevance confirmation, and each article was reviewed by two team members. A pre-developed relevance confirmation form was used (Supplementary material) and disagreements were resolved through discussion.

2.4. Data extraction, analysis and reporting

After relevance confirmation and prioritisation of articles, short-listed articles were analysed for the type of data presented. It was agreed that a meta-analysis of the data was not possible due to the heterogeneity of the identified studies, differences between CVS technologies, and inconsistencies in data reporting. Hence, it was decided that risk-of-bias assessment of quantitative meta-analysis output was not needed, and so data extraction for descriptive analysis and narrative synthesis was performed, following a pre-developed protocol. Data on CVS effectiveness/performance were then presented in a narrative way. The data extraction tool contained targeted questions about population (bovines, pigs, broiler chickens), target condition (carcass/organ contamination or lesion), type of lesion(s) and/or contamination, purpose of CVS (animal welfare, food safety or animal health), type of CVS imaging, country of application, study setting (laboratory, research plant, commercial abattoir), number of samples (for CVS training/calibration and/or performance testing), method used for performance testing of CVS (based on evaluation of images (test of the machine learning model) or based on comparison of images from the CVS with the OVs'/raters' inspection results), and performance measures obtained. The sensitivity and specificity were chosen as the preferred performance measures to report, since these also provide measures of the false positives and false negatives. If sensitivity and specificity were not reported, other reported measures were extracted, or sensitivity and specificity were estimated by us when sufficient data were reported. Sensitivity and specificity are separate measures describing the ability to detect the true unwholesome and true wholesome carcasses, whereas accuracy, which was most often reported in the articles, is a combined measure for 1-sensitivity and 1-specificity (Thrusfield, 2018). Sensitivity is a measure of priority for the CAs, since the legislation states that meat originating from unwholesome animals (containing a zoonotic pathogen or being acutely ill due to any pathogen at the time of slaughter) is not fit for consumption. For the FBOs, the specificity is an important measure, as it is crucial to not categorise wholesome animals as unwholesome in the interests of ensuring a business case and acting sustainably. Data extraction was completed using Microsoft® Office Excel® 2016 (Microsoft Corporation). Two team members extracted data following a discussion, to ensure the correct data were captured.

3. Computer vision systems in meat safety assurance

3.1. Study characteristics

A flow chart of the review process and results is illustrated in Fig. 1. The review identified 62 articles describing CVSs to detect carcass contamination (27 articles corresponding to 44%) or carcass/organs lesions (35 articles corresponding to 56%). Almost 90% of the CVSs identified were developed for detection of broiler chicken carcass contamination or lesions. No studies of CVSs applicable in AM inspection were identified by this systematic review, but one article described a CVS developed for post-slaughter detection of lesions that indicate sub-optimal pre-slaughter animal welfare (Blömke et al., 2020). Also, only four studies investigated CVS for bovine carcass contamination. No articles were identified describing CVSs for bovine lesions, and only five articles were identified describing CVSs for lesions on pig carcasses and organs. Within the different CVSs, numerous novel imaging techniques, i.e., optical imaging (fluorescence and hyperspectral imaging), ultrasound imaging, tomographic imaging and thermal imaging, were identified during the systematic review, and these techniques show potential for use in meat inspection and future RB-MSAS.

3.2. Principles and fundamentals of CVSs used in meat safety assurance systems

PM inspection presents a challenge for the high-speed slaughter of poultry. Hence, it was recognised long ago that digitisation was the key to solve this problem. CVSs for meat quality assurance date back to the mid-nineties and the extensive work conducted by researchers from the USDA Agricultural Research Service. CVSs' rapid development was associated with development of information technologies, particularly image processing techniques. Research groups from the USDA embarked on more than two decades of research to develop CVSs for detection of carcass contamination and lesions particularly for the purpose of classification of wholesome and unwholesome carcasses (Yang et al., 2010).

Conventional CVSs aim to imitate the principle of human vision, using three bands of light (red, green, and blue) to acquire the

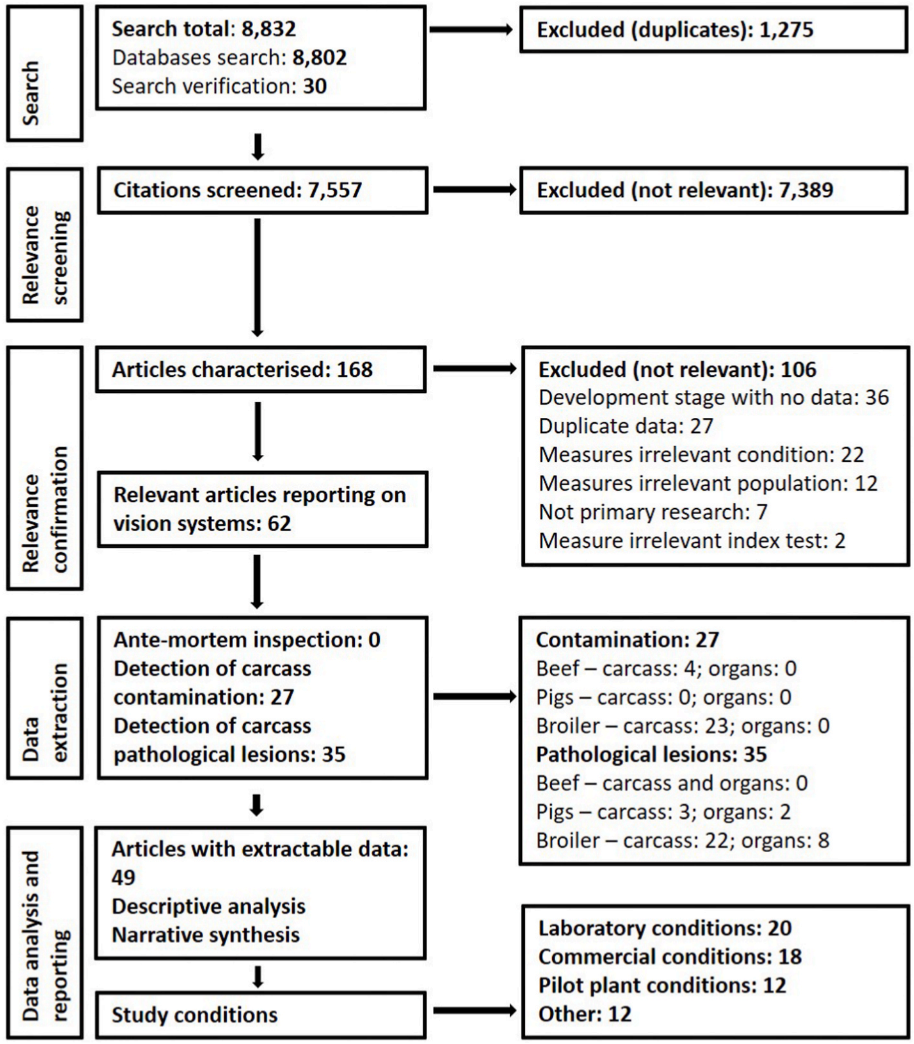

Fig. 1. Flow chart of the systematic review process.

characteristics of objects, and when working in the visible range of light, the features obtained by computer vision can include shape, colour, size and texture (Feng & Sun, 2012). For example, fluorescence imaging is superior for detecting animal faeces, and can be utilised with a laser-induced fluorescence imaging system (Burfoot et al., 2011; Cho et al., 2009), with final detection accuracy for faecal matter of 96.6% (Cho et al., 2009). The initial imaging methods used for meat quality and safety assessment were optical, i.e., fluorescence imaging and hyperspectral imaging. The principle of fluorescence imaging is to utilise the luminescence emitted by the tested objects to create an image (Xiong et al., 2017). A multispectral fluorescence imaging system was developed for detecting faecal matter on chicken carcasses (Cho et al., 2009; Park et al., 2004), and fluorescence imaging was also used to detect faecal contamination of bovine carcasses (Burfoot et al., 2011). However, conventional fluorescence imaging has limitations in meat safety assessment, because not all materials can be excited to fluoresce. Therefore, integration of fluorescence imaging with other imaging tools, such as microscopy imaging and hyperspectral imaging, was needed and achieved good results (Xiong et al., 2017). Hyperspectral imaging integrates computer vision and conventional spectroscopic techniques, so that both spectral and spatial information can be provided simultaneously (Xiong et al., 2017). The technology for hyperspectral imaging involves hardware to acquire the images and software to process the images so that useful information from them can be extracted for food analysis (Feng & Sun, 2012).

The initial CVS models were based on principle components analysis (Park, Lawrence, Windham, & Buhr, 2002), whereas the more recent models are based on fuzzy logic, random forest or neural networks (Chao et al., 2008; Yang et al., 2010). The principles and processes of training an artificial intelligence-system based on neural network modelling using machine learning is described in Fig. 2. This includes a test step in abattoir conditions to estimate the effect of the sub-optimal light conditions and humid air on the quality of the images. Before and during the training of the algorithms to accomplish the different tasks, there is a need for human input in the form of grading the image, e.g., with respect to the degree of severity for lesions caused by pneumonia (the size of affected area, aetiology, etc). The validation procedure is a testing process whereby the established and trained models are subjected to a new dataset containing images never used for the training but graded by humans (Fig. 2). Moreover, another very important step is testing the performance of a CVS (sensitivity and specificity) vs. the performance of the OV.

One very important characteristic of a CVS in chicken meat inspection is the ability to rapidly process the images, since the slaughter speed is between 8000–12,000 chickens/hour. Nakariyakul and Casasent (2009) investigated a dataset consisting of images of tumours on chickens and were successful in creating an algorithm that had the capacity to read at high speed lines. The authors also found that the ability of multispectral systems to record up to eight wavebands was sufficient to detect 32 of 40 chicken skin tumours. The hyperspectral reflectance

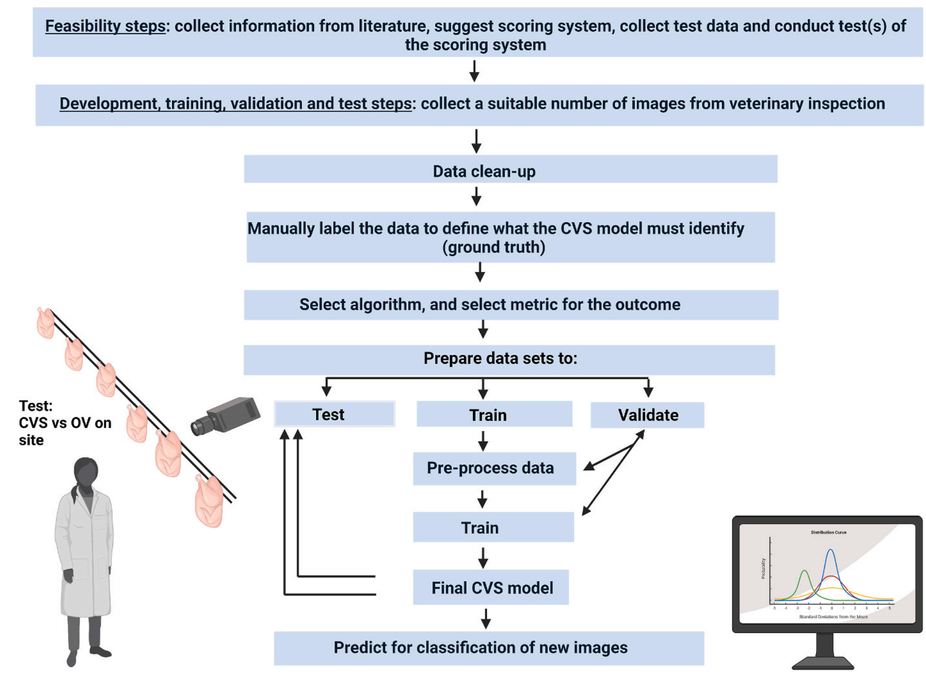

Fig. 2. Principles for development of computer vision systems that apply machine learning to the modelling.

imaging system was originally developed by Agricultural Research Service Instrumentalisation and Sensing Laboratory in Maryland, United States (Kim et al., 2001). In 2006 and 2007, the hyperspectral reflectance image systems were replaced with on-line multispectral inspection, indicating that cross validation between the camera system developed in the laboratory and the on-line multispectral inspection was not needed (Chao et al., 2007b; Yang et al., 2006). By acquiring only selected wavebands for every pixel instead of full-spectrum data, the volume of spectral data to be analysed is reduced, and on-line multispectral imaging can then be performed with high accuracy for objects moving at very high speeds (Yang et al., 2010).

In 2011–2014, similar work was initiated in Denmark, with an additional focus of developing a camera station to detect lesions/abnormalities on viscera, and which could work at high slaughter speeds. This work was performed by a co-operation between research institutions, a private company (IHFood), the poultry industry and the Danish food safety authorities (Jørgensen, 2018). The Danish group developed a CVS for chicken PM inspection, VetInspector, in which multispectral image analysis using neural network algorithms is utilised (Jørgensen, 2018; Jørgensen et al., 2017, 2018, 2019) (Fig. 3). VetInspector performs inspection of carcasses and viscera according to the list of lesions given by the official Danish lesion code list. This CVS consists of three camera stations placed on-line; one capturing images of the carcass (surface) and another one capturing images of the viscera (inside of the carcass). The third camera station inspects for contamination on the carcass surface (ongoing work) (Fig. 3).

Some other companies, such as Marel, Meyn, Foodmate and Baader Linco, have been developing different CVSs for quality grading of chicken carcasses, but the technical details are not published in the public domain. Typically, they involve use of a back or front camera, or both. Meyn have systems that can detect broken wings, red and blue bruises, faecal stains, remaining feathers, skin damage and footpad lesions (Jørgensen, 2018).

3.3. Performance of CVSs for detection of contamination and lesions on carcasses and organs

The CVSs for detection of lesions and contamination on bovine, pig and broiler chicken carcasses identified in the systematic review are listed in Tables 1 and 2. In total, 49 out of 62 articles identified in this

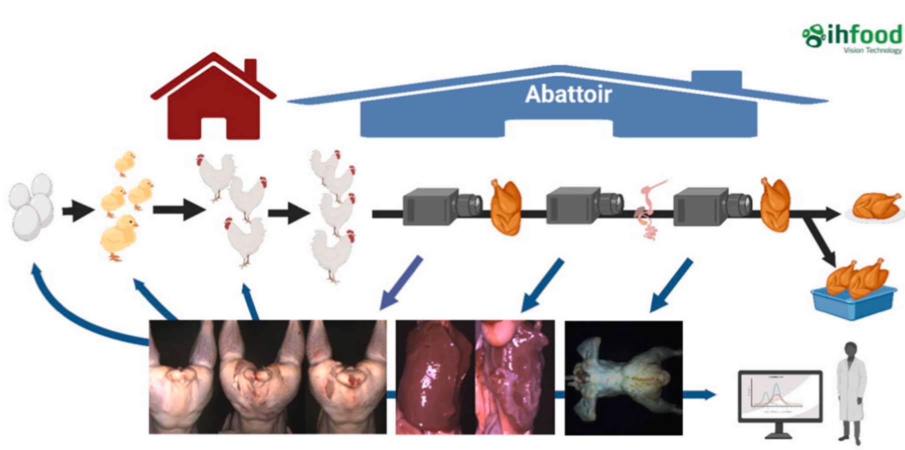

Fig. 3. VetInspector computer vision system for post-mortem inspection (two camera stations) and slaughter hygiene (one camera station) of chickens (IHFood.dk).

Table 1
Computer vision systems for detection of lesions in post-mortem inspection of broiler chickens and pigs identified in this systematic review.

REF. ID	REFERENCE	COUNTRY	SPECIES	PURPOSE OF CVS[A]	SPECIFIC LESIONS	N[B]	CVS PERFORMANCE TESTING METHOD[C]	CVS PERFORMANCE TESTING MEASURES[D]
9	Blömke et al. (2020)	Germany	Pig	AW	Ear and tail lesions (shape, colour, position)	NR	PTI vs OV	N: 5578, SE: 77%, SP: 96.5% (ear lesions) N: 5598, SE: 77.8%, SP: 99.7% (tail lesions)
75	McKenna et al. (2020)	UK	Pig	AH, FS	Liver (milk spots) and heart lesions (pericarditis)	NR	PTI	N: 450, SE: 77.3%, SP: 86.4% (milk spots) N: 382, SE: 92.6%, SP: 93.4% (pericarditis)
117	Trachtman et al. (2020)	Italy	Pig	AH	Pleurisy	5702	PTI	N: 200, SE: 92%, SP: 96%
169	Bonicelli et al. (2021)	Italy	Pig	AH	Enzootic pneumonia-like lesions	7154	PTI	N: 410, SE: 81.3–100% SP: 99.4% (EP images)
25	Chen et al. (1996)	USA	Chicken	AH, FS, AW	Unwholesome carcasses (septicaemia, cadaver)	NR	PTI	N: 286, SE: 96.8%, SP: 97.7%
88	Park et al. (1996)	USA	Chicken	AH	Unwholesome carcasses (tumour, bruises)	NR	PTI	N: 216, AC: 91.4%
87	Park et al. (1998)	USA	Chicken	AH, FS, AW	Unwholesome carcasses (airsacculitis, ascites, bruises, cadaver, leucosis, septicaemia, tumour)	61	PTI	N: 30, SE: 72.6–100%, SP: 28.6–85.7%
146	Chao et al. (2000)	USA	Chicken	AH, FS, AW	Unwholesome carcasses (airsacculitis, septicaemia, ascites and cadaver)	331	PTI	N:128, SE: 98%, SP: 91%
149	Chen et al. (2000)	USA	Chicken	AH, FS, AW	Unwholesome carcasses	NR	PTI	N: 1750, AC: 95%
16	Chao et al. (2002)	USA	Chicken	AH, FS, AW	Unwholesome carcasses (airsacculitis, septicaemia, ascites and cadaver)	1400	PTI	N: 13,191, SE: 82.2–87.3%, SP: 90.9–94%
94	Park, Lawrence, Windham, Chen, and Chao (2002)	USA	Chicken	AH, FS, AW	Unwholesome carcasses (septicaemia, cadaver)	NR	PTI	N: 176, AC: 91.4%
13	Chao et al. (2003)	USA	Chicken	AH, FS, AW	Unwholesome carcasses (septicaemia, cadaver)	NR	PTI	N: 120, SE: 93.8% SP: 100% (whole samples)
14	Chao et al. (2004)	USA	Chicken	AH, FS, AW	Unwholesome carcasses (septicaemia, airsacculitis, ascites, inflammation)	NR	PTI	N: 876, SE: 82–92%, SP: 78–95%
155	Kim et al. (2004)	USA	Chicken	AH	Skin tumour	13	PTI	N:13, SE: 76%, SP: 72%
167	Yang, Chao, Chen, et al. (2005)	USA	Chicken	AH, FS, AW	Unwholesome carcasses (systemic disease)	NR	PTI	N: 990, SE: 93.5–97.7%, SP: 95.7–99.7%
132	Yang, Chao, and Chen (2005)	USA	Chicken	AH, FS, AW	Unwholesome carcasses (inflammation, septicaemia)	245	PTI vs OV	N: 419, SP: 89.6% (wholesome carcasses), SE: 92.3% (inflammation), SE: 94.4% (septicaemia)
166	Yang et al. (2006)	USA	Chicken	AH, FS, AW	Unwholesome carcasses (systemic disease)	NR	PTI	N: 660, SE: 97.1–98.6%, SP: 96.3%
52	Kim et al. (2006)	USA	Chicken	AH, FS, AW	Unwholesome carcasses (septicaemia, airsacculitis, cadaver)	NR	PTI	N: 130, SE: 98.9%, SP: 97.1%
147	Chao et al. (2007a)	USA	Chicken	AH, FS, AW	Unwholesome carcasses	250	PTI	N: 104, SE: 93.2%, SP: 98.3%
21	Chao et al. (2007b)	USA	Chicken	AH, FS, AW	Unwholesome carcasses (systemic disease)	607	PTI vs OV	N: 481, SE: 91.4–96%, SP: 97.6%
23	Chao et al. (2008)	USA	Chicken	AH, FS, AW	Unwholesome carcasses	5642	PTI vs OV[e]	N: >100,000, SE: 96.2%, SP: 99.6%
134	Yang et al. (2010)	USA	Chicken	AH, FS, AW	Unwholesome carcasses (systemic disease)	5309	PTI vs OV[e]	N: 43,878, SE: 95.4–97.1%, SP: 99.3–99.8%
83	Nakariyakul and Casasent (2009)	USA	Chicken	AH	Skin tumour	NR	PTI	N: 40, SE: 80%, SP: NR
45	Hsieh et al. (2002)	USA	Chicken	AH, FS	Unwholesome livers (septicaemia)	200	PTI	N: 100, SE: 94%, SP: 98%
153	Ibarra et al. (2002)	USA	Chicken	AH, FS	Airsacculitis	161	PTI	N: 161, AC: 96.7%
48	Jørgensen et al. (2017)	Denmark	Chicken	AH, FS	Cobblestone liver, perihepatitis, necrotic hepatitis	NR	PTI	N: 1476, AC: 77.6%
49	Jørgensen et al. (2018)	Denmark	Chicken	AH, FS	"Unhealthy" viscera	NR	PTI	N: 2294, AC: 86%
151	De Jong (2013)	Netherlands	Chicken	AH, W	Footpad dermatitis	NR	PTI vs OV	N: 7157, SE, SP, AC, CORR: NR
164	Van Harn and de Jong (2017)	Netherlands	Chicken	AH, W	Footpad dermatitis	NR	PTI vs OV	N: 18 (flocks), AC: 96% (flocks)
165	Vanderhasselt et al. (2013)	Belgium	Chicken	AH, W	Footpad dermatitis	NR	PTI vs OV	N: 197, CORR: 0.9

[a] AH: animal health; AW: animal welfare; FS: food safety.
[b] n: number of samples used for training and calibration of the model (calibration dataset); NR: not reported.

[c] PTI: CVS performance testing based on evaluation of images (test of the machine learning model); PTI vs OV: CVS performance testing based on comparison of images from CVS with the OVs'/raters' inspection results of the same carcass.
[d] N: number of samples used for CVS testing (testing dataset); SE: sensitivity; SP: specificity; AC: accuracy; CORR: Spearman correlation coefficients.
[e] Study performed in real-time process on the slaughterline (line speed 140 chickens/min).

Table 2
Computer vision systems for detection of carcass surface contamination identified in this systematic review.

REF. ID	REFERENCE	COUNTRY	SPECIES	TYPE OF CONTAMINATION	TYPE OF CVS IMAGINGN	N[A]	CVS PERFORMANCE TESTING METHOD[B]	CVS PERFORMANCE TESTING MEASURES[C]
10	Burfoot et al. (2011)	UK	Bovine	Faecal and hair	Fluorescence	323	PTI vs OV	SE: NR, SP: NR, high number of false positives
93	Park, Lawrence, Windham, and Buhr (2002)	USA	Chicken	Faecal	Hyperspectral	16	PTI	SE: 97.3%, SP: NR
95	Park et al. (2004)	USA	Chicken	Faecal	Multispectral	72	PTI	SE: 92.4–98.8%, SP: 86.4%
97	Park et al. (2005)	USA	Chicken	Faecal	Hyperspectral	50	PTI	SE: 92.5–96.9%, SP: 36.9%
126	Windham, Heitschmidt, et al. (2005)	USA	Chicken	Crop/gizzard contents	Hyperspectral	24	PTI	SE: 53.3% (gizzard content), 72% (crop content), SP: NR
129	Windham, Smith, et al. (2005)	USA	Chicken	Faecal	Hyperspectral	72	PTI	SE: 100%, SP: 16.3% (threshold 1.00); SE: 100%, SP: 77.8% (threshold 1.05); SE: 94%, SP: 88.9% (threshold 1.10)
98	Park et al. (2006a)	USA	Chicken	Faecal	Hyperspectral	64	PTI	SE: 96.4%, SP: 85.7%
99	Park et al. (2006b)	USA	Chicken	Faecal	Hyperspectral	232	PTI	SE: 92.2–94.7%, SP: NR
67	Lawrence et al. (2006)	USA	Chicken	Faecal	Hyperspectral	72	PTI	SE: 98.2%, SP: >64.6%
105	Park et al. (2007)	USA	Chicken	Faecal	Hyperspectral	152	PTI	SE: 90.13%, SP: NR
125	Windham et al. (2007)	USA	Chicken	Faecal	Hyperspectral	72	PTI	SE: 88–100% SP: 83–88% (mixture tuned classifier); SE: 63–100%, SP: 62–67% (decision tree classifier)
44	Heitschmidt et al. (2007)	USA	Chicken	Faecal	Hyperspectral	56	PTI	SE: 98.7–99.4%, SP: 96.2–98.7%
30	Cho et al. (2009)	USA	Chicken	Faecal	Laser-induced fluorescence	15	PTI	SE: 96.6–100%, SP: NR
108	Park et al. (2009)	USA	Chicken	Faecal	Multispectral	48	PTI	SE: 91.6%, SP: 96.7%
141	Yoon et al. (2011)	USA	Chicken	Faecal	Hyperspectral	12	PTI	SE: 89–98%, SP: >99.6%
109	Park et al. (2011)	USA	Chicken	Faecal	Real-time multispectral	29,821	PTI vs OV[e]	SE: 91%, SP: 96.7%
51	Kang et al. (2016)	China	Chicken	Faecal, blood, bile	Multispectral	225	PTI	SE: 94.6%, SP: NR (faecal); SE: 88% SP: NR (blood); SE: 92%, SP: NR (bile)
131	Wu et al. (2017)	China	Chicken	Faecal, blood	Hyperspectral	20	PTI	SE: 100%, SP: 99.6% (SPA MLR classifier); SE: 69%, SP: 99% (SPA PLS classifier); SE: 100%, SP: 83.2% (SPA LS SVM classifier)
113	Seo et al. (2019)	USA	Chicken	Faecal	Multispectral fluorescence	30	PTI	SE: 97.6%, SP: NR

[a] n: number of samples used for validation and/or testing; NR: not reported.
[b] PTI: CVS performance testing based on evaluation of images (test of the machine learning model); PTI vs OV: CVS performance testing based on comparison of images from CVS with the OVs'/raters' inspection results of the same carcass.
[c] SE: sensitivity; SP: specificity.
[e] Study performed in real-time process on the slaughterline (line speed 150 chickens/min).

review reported extractable results on the performance of the CVS, while the remaining articles reported only on the development of the CVS with some preliminary data.

Tables 1 and 2 present values for sensitivities and specificities from the validation of the CVS or evaluation of its performance vs. the OV. The setup of the CVS model and the reported performance measures influence how the performance of the CVS in PM inspection is interpreted. For those CVSs detecting unwholesome carcasses, we found that many articles incorrectly reported accuracy as the value of sensitivity. Other articles only reported accuracies without any supporting data. Therefore, in the data extraction and analysis step, when the correct sensitivity and specificity data were reported in the article, these are presented in Tables 1 and 2 Otherwise, where possible, we calculated sensitivity and specificity to present in Tables 1 and 2 For CVSs designed to detect contamination, some articles reported figures for evaluating the limit of detection, since thresholds had been developed for different levels of, for instance the faecal or blood contamination. Only a few articles reported results of comparisons of the performance test of their final CVS against the performance of the OV. However, one could argue that evaluation of performance of the CVS vs. the OV is unnecessary if the initial optimisation and testing on new datasets in the algorithm was performed with the help of the OV. Hence, if the algorithm is fed with images of all possible lesions or contaminations, and the algorithm is capable of differentiating them, by definition, it should be able to work well and achieve its objectives. However, the effect of the slaughter speed on the performance of the OV has to be investigated independently, and therefore, studies reporting this aspect are of the utmost importance.

In just a few articles, agreement measures between a CVS and an OV or between OVs were also reported. Agreement studies can be conducted based on the images that are graded/annotated in the training and validation processes of the machine learning. However, some of the agreement studies found that the performance of the OV is also not perfect, because PM inspection is not an exact science or activity (Jørgensen, 2018). Hence, the performance required to approve and implement CVSs should be pragmatic and risk-based. The agreement measures capture the fact that there is considerable variation in how OVs classify lesions (Jørgensen, 2018).

Chao et al. (2008) and Yang et al. (2010) (both in the mentioned USDA research group) have developed and validated their CVS thoroughly over almost two decades, and they obtained high sensitivity and specificity values for their CVS in the real-time process on the slaughterline to detect unwholesome (systematically diseased) and wholesome chickens. Chao et al. (2008) described the development and validation/testing of a CVS able to be used at high slaughterline speeds, whereas Yang et al. (2010) reported the testing of the performance against the OV. According to Chao et al. (2008), the CVS's RGB (red/-green/blue) colour imaging of chicken spleens, hearts and livers was able to identify the chicken disease conditions of leucosis, septicaemia, airsacculitis and ascites under laboratory conditions. One problem with this CVS is that it required correct presentations of the visceral organs; this was often unachievable under real-life conditions on conventional broiler chicken slaughterlines.

Inspection and scoring of chicken footpad lesions are very often performed visually by trained abattoir staff in most European countries. The scores are used to indicate chicken welfare and suitability of the farm environment where chickens are reared. Footpad lesions are caused by wet litter, and so indicate suboptimal management and/or unsatisfactory ventilation of the house. One CVS to detect this welfare indicator is the Footpad Inspection System developed by Meyn, which is a video imaging system to score footpad lesions in broilers on the slaughterline (De Jong, 2013; Van Harn & de Jong, 2017; Vanderhasselt et al., 2013). Based on a limited dataset to compare footpad lesion inspection performance by the Meyn Footpad Inspection System vs. inspection by a trained OAs, the CVS's scores correlated well with those of the OAs at the flock level, but poorly at the individual chicken level (De Jong, 2013; Van Harn & de Jong, 2017). The reasons for the latter poor performance were sub-optimal images captured by the device and the fact that the person can cut into the footpad lesion to assess the depth/severity of the wound. Very often the lesions were scored as more severe by the CVS than they were by the OAs (Van Harn & de Jong, 2017). The main advantage of this CVS is that 99% of chicken feet in a flock were scored, compared to only 100 feet in a flock that are routinely scored by OAs, in accordance with the protocol, irrespective of the size of the flock (usually this amounts to only 0.33%–1.7% of the flock). Vanderhasselt et al. (2013) investigated the same CVS, and using Spearmans correlation coefficient, found unsatisfactory agreement between the CVS and the OAs at the individual chicken level but satisfactory agreement at the flock level. The authors concluded that the CVS should be improved considerably to produce a higher number of chickens with scores on both feet and provide better agreement with OAs' scores (Vanderhasselt et al., 2013).

In the systematic review process, we identified 23 articles describing development and/or validation and testing of CVSs for detection of contamination on chicken surfaces, most of them published by the USDA group. Park, Lawrence, Windham, and Buhr (2002) described a hyperspectral imaging system for detection of faeces and ingesta on chicken carcasses, with demonstrated potential application for on-line PM inspection and sensitivity of above 97%. Later, the same research group described a multispectral system, the performance of which was compared with the hyperspectral system (Park et al., 2004). The reported sensitivities for detection of faeces and ingesta ranged from 92.4% to 98.0%, while the specificity (86.4%), i.e., the proportion of false positives, was described as moderate. The only article reporting the study of a real-time CVS operating in an abattoir to detect faecal contamination on chicken carcasses and using hyperspectral imaging was published by Park et al. (2011). The authors reported that the CVS successfully identified spots of faecal contamination on a high-speed slaughterline (140 chickens per minute), with 91.0% sensitivity and 96.7% specificity.

Two different CVSs in pigs for detecting and scoring respiratory lesions caused by infectious agents, which often act together to cause the so-called "porcine respiratory disease complex" (PRDC), have been developed and tested (Figs. 4 and 5). The systems were developed to detect porcine pleuropneumonia (APP), caused by *Actinobacillus pleuropneumoniae* (Trachtman et al., 2020), and enzootic pneumonia (EP) that is caused by *Mycoplasma hyopneumoniae* (Bonicelli et al., 2021). Both CVSs were realised using thousands of images collected in different abattoirs, to guarantee the broadest possible variety of cases, situations, backgrounds and lighting conditions. In order to guarantee, as much as possible, a balance amongst the different types of lesions, all the images were labelled and scored by pig pathologists to be sure the different types of lesions were proportionally represented in the training and test datasets. This upstream work meant that the performances of the CVS compared to the evaluations done by pathologists could be accurately compared. The average specificity and sensitivity for APP were, respectively, 85.5% and 92.0% (Trachtman et al., 2020), while for EP they were, respectively, 95.31% and 99.38% (Bonicelli et al., 2021). Another CVS for pigs focusing on liver milk spots and heart pericarditis was described by McKenna et al. (2020), with somewhat lower reported sensitivity and specificity (Table 1).

Furthermore, Blömke et al. (2020) evaluated a CVS's performance for detecting ear and tail lesions as indicators of animal welfare (i.e., the so-called iceberg indicators, individual welfare parameters that can reliably be used as predictors of general welfare in a group of animals). In the development phase, the algorithm was taught to classify the ear and tail lesions based on a large number of images when the pilot version of the CVS was installed in the abattoir (specifications). Then, the evaluation of CVS performance was done in two steps. First, the assessment was image based and CVS performance was compared to findings by the OV. The second step was an agreement study where OV classified the lesions alongside the CVS in real-time. The observed agreement between CVS and OV was low, 0.62 and 0.55 for ear and tail lesions, respectively (Blömke et al., 2020).

Based on our systematic review, CVSs have not been widely considered for use in bovine meat safety assurance. We were able to identify only one CVS for detecting carcass faecal contamination, whilst no such systems have been reported for bovine carcass/organ lesions. Burfoot et al. (2011) used fluorescence imaging to monitor contamination trends and to characterise process hygiene in bovine abattoirs. They investigated the commercially developed VerifEYE Solo I, a hand-held fluorescence imaging device, to detect faecal contamination on bovine carcasses, although not in real-time during processing but in the chillers on the day after slaughter. The technology itself (VerifEYE) was developed in 2003, but was soon after withdrawn due to a high proportion of false negative and false positive results. Those findings were confirmed by Burfoot et al. (2011), and false positive results were mainly recorded in the interior cavity of the carcasses. The false negative readings were attributed to the system being based on the premise that faeces of grass-fed bovines contains the digestion products of chlorophyll and its precursors, which fluoresce; unfortunately, their levels can be highly variable depending on the actual animal diet. False positive readings were a consequence of the wide range of excitation wavelengths delivered by the VerifEYE, resulting in the fluorescence of non-faecal fluorophores naturally present in the carcass (carotene and haemoglobin porphyrins). In conclusion, this CVS is not practical for use for bovine carcass testing on the slaughterline, and so far, remains the only one developed for this purpose.

3.4. Regulatory aspects and approval

European Union (EU) Regulation 2017/625 addresses official

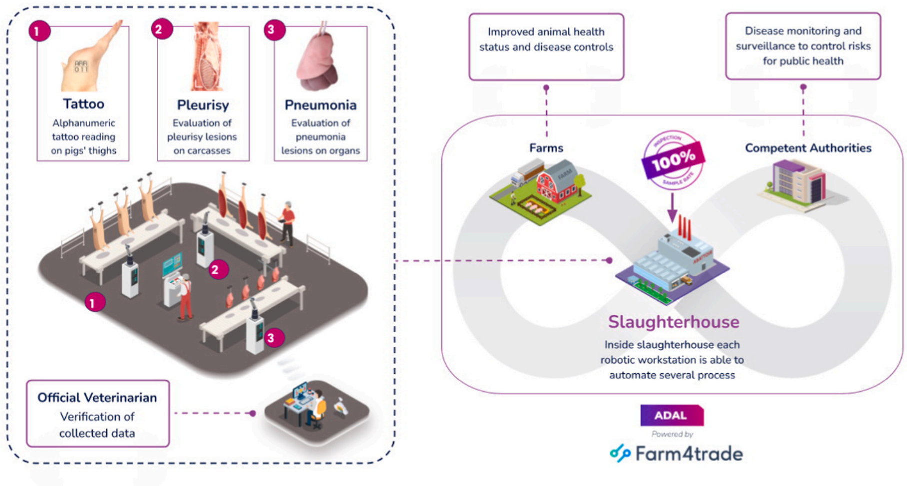

Fig. 4. Computer vision system stages and components.

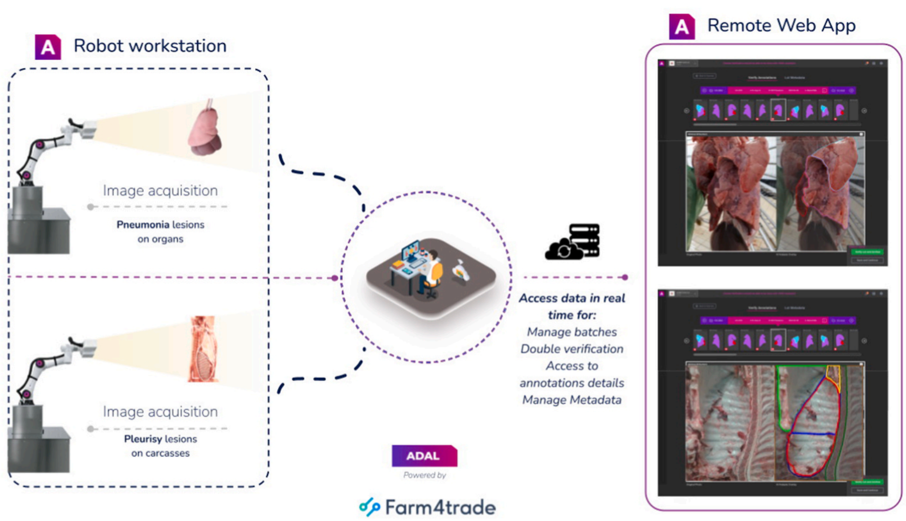

Fig. 5. Computer vision system for post-mortem inspection of pigs (Farm4Trade).

controls and other official activities performed to ensure the application of food and feed law, and rules on animal health and welfare, plant health and plant protection products (Anon, 2017). For meat inspection, amendments of Regulation 2017/625 are given in the delegated and implementing acts (EU 2019/624 and 2019/627) (Anon, 2019a, 2019b). Article 6 of Regulation 2019/627 specifies that "The Member States shall inform the Commission and other Member States on scientific and technological developments, as referred to in Article 16 (2) (b) of Regulation (EU) 2017/625 for consideration and further action as appropriate." The purpose of Article 6 is clearly to indicate openness to innovation and to encourage it (Anon, 2019b).

The EU Official Control Regulation EC 2019/627 contains a list of 21 non-compliances and reasons for declaring fresh meat as unfit for human consumption (Anon, 2019b). Two of these criteria specify that the meat produced: 1) should not pose a risk for humans and 2) should not originate from animals that suffer from diseases at the time of slaughter. This indicates that if there are signs indicating acute, generalised disease represented by abnormal behaviour, fever or septicaemia, the whole carcass should be condemned (Anon, 2019b). If, however, there are signs in the form of lesions indicating a previous infection, the meat from the carcass can be used for consumption after partial condemnation as explained by Alban et al. (2021). In some cases, additional processing in the form of freezing (for *Taenia saginata* cysticercus) or thermal treatment can be applied to quantitatively reduce the zoonotic agent present inside the muscle or on the surface of the meat (for *Campylobacter* spp.) (Anon, 2019b). These points constitute the risk-based principles for assessing which lesions/abnormalities are important to detect. Moreover, the partial condemnation could be automated.

In September 2021, the first two VetInspector stations in Europe were accepted for use as a support tool in poultry meat inspection in Denmark. Their implementation was possible due to the fact that Regulation EC 2019/627 had been amended with provisions for national food safety authorities (CAs) to decide that only a representative sample of chickens from a flock needs to undergo inspection, if the poultry abattoir has a system (such as CVS) to sort and discard carcasses of sub-optimal quality. On the other hand, the acceptance and use of CVSs in pig and bovine meat safety assurance require that previous training and performance studies be conducted. In Regulation (EU) 2017/625, article 18 (point 9) specifies the process for these new technologies to receive regulatory approval and be implemented in European red meat/poultry abattoirs, where "countries can implement pilot projects to evaluate new alternative technologies for meat inspection" (Anon, 2017). A similar amendment to the legislation, as stated above in the case of poultry, is needed, to incentivise CVS developers for future actions. This also means that the companies currently developing a CVS would be required to publish results about the development and validation of their CVS.

In the development and training of CVS models, as well as in the legislation process, the CAs have crucial roles. They make decisions as to which carcass/organ lesions qualify for condemnation, and they provide general criteria for the classifications of the lesions and condemnations. Some lesions are more important to detect with the CVS than others, and the decision-making process should be risk-based. Detected lesions could lead to partial condemnation of carcasses (e.g., for localised infection or lesions indicating prior infection) or total condemnation (e.g., for septicaemia at the time of slaughter). For some localised infections and other abnormalities like haemorrhages, the main reasons for detecting these conditions are to report them back to the farmer, or to improve animal welfare (e.g. bruises) or health (e.g. localised infections that qualify for partial condemnation). Hence, for these types of conditions, the sensitivity of detection may not need to be very high at the individual animal level, since if the condition is more prevalent, it would be reflected in detection at the flock/herd level.

3.5. Limitations and future work

In a RB-MSAS, a CVS should interact with a FCI database, which would allow for easy forward and backward flow of information. An advanced CVS would be capable of detecting and recording several lesions concurrently and, hence, provide a precise evaluation of abnormalities and generate accurate FCI. The data captured could, therefore, improve the studies of association between diseases and their management, biosecurity and overall heard health plans, which would lead to improved animal health. A digitised MSAS, of which CVS is a part, will increase traceability, which favours foodborne outbreak investigations, the monitoring of antibiotic usage/presence of antimicrobial resistance and assessment of animal health and welfare and productivity.

Most articles about CVS analysed in this review describe systems for inspection of broiler chicken carcasses or organs, lesions or surface contamination. The less than optimal performance of the CVSs, specifically the high numbers of false positives, presents a challenge, particularly in the case of a high number of animals slaughtered per hour (broiler chickens). Most of the identified CVSs for broiler chickens were reported to have a very high sensitivities but suboptimal specificities. Possible solutions to improve this problem are to train the models with more data, and to focus on the lesions (and their severity) of importance that will reduce risks for consumers. The challenge is not only the abundance of lesions and abnormalities to be detected, but also the lack of balanced datasets. In well-balanced datasets, all the classes of the different types of lesions are equally represented in order to allow the model to learn all the possible scenarios at the required level. Moreover, as mentioned above, the lesion code set and criteria for condemnation need to be re-assessed, with the purpose of harmonising the inspection between countries. Furthermore, the relevant legislation could be changed, allowing for abattoir staff to remove carcasses or meat cuts that for aesthetic reasons cannot be sold, which would allow the implementation of CVSs with low sensitivity to be used to detect these aesthetically unacceptable products that are of no food safety concern.

CVS-positive findings means carcasses could be diverted to a rejection line and subjected to re-inspection using a different type of CVS or a human inspector, which would lower the proportion of condemned carcasses. The other, perhaps economically infeasible, way of handling false positives could be to direct all carcasses with CVS-positive findings automatically to thermal treatment. The choice of approach would depend on the expected estimated percentage of false positives in the broiler chickens and the cost of abattoir staff sorting true positives from false positives. Hence, feasible ways to reduce the handling false positives must be identified to ensure regular utilisation of CVSs in broiler chickens abattoirs in the future as an efficient tool for standardisation of PM inspection. Moreover, the EU legislation should be modified to encourage both the public and private sectors to develop CVSs.

No studies describing CVSs for detection of AM conditions were identified in this systematic review. This could be because there is no provision in the related legislation for this, and hence, there is no research and no commercial interest in developing them. One could argue that developing CVSs for AM inspection is much more difficult than for PM inspection, since the farms differ to a greater extent than do the abattoirs. A way forward in the future could be changes in the legislation to follow a similar approach as for the CVS used in chicken PM inspection. A step-by-step approach could be conducted, first running AM CVS pilot projects, before regulatory authorisation of CVS use on a regular basis. The use would be permitted under the responsibility of, and subject to verification by, the OV, which implies that OV does not necessarily need to be present during the real-time operation of a well-performing CVS.

In regard to articles covering CVS for animal welfare, there were only three articles describing systems for the PM detection of footpad lesions in chickens. The existing system developed by Meyn is burdened with weaknesses on the individual chicken level, but is considered as good enough for use at the flock level. However, as this CVS detects only one condition, more general information on the chickens' health is lacking, and hence, this CVS is not sufficient for overall PM inspection.

Overall, a surprisingly low number of articles on CVS were identified in this systematic review. This is most likely because the knowledge about CVS development is kept confidential within the developing company before the results are validated, improvements are made and CVS implementation is finalised. The other reasons could be that there is limited research and development in this area because the investments needed are inadequate, and that the legislation still does not fully allow for CVS to be implemented.

CVSs offer many possibilities in relation to RB-MSAS. CVSs could be used in those situations where AM inspection is performed at the farm, during emergency slaughter, at the hunting site (for hunted wild game) or in very small abattoirs without the presence of an OV. When using a CVS in any of these situations, it is necessary to adopt a validated image acquisition protocol and to use high-quality images, as discussed by Almqvist et al. (2021). In Denmark, a CVS is in the pipeline for detection of surface contamination on finishing pig carcasses (personal communication Marchen Hviidt, Technological Institute, Denmark). In Italy, two CVSs have been developed and are currently being tested in Norway, to detect and score pleurisy and pneumonia in pigs at the abattoir; the approach used is promising for expansion to detect more lesion types (Bonicelli et al., 2021; Trachtman et al., 2020).

4. Conclusions

This paper investigates the status of available CVSs for meat safety assurance of bovines, pigs and broiler chickens, CVS performances in detecting carcass contamination and lesions and their future role in RB-MSAS in the European legislative context. The main problem associated with the identified CVSs is their underperformance, characterised by significant proportions of false positive and false negative findings. The future challenges are related to achieving CVSs' higher sensitivity for detection of the food safety and animal health/welfare related conditions and also higher specificity to minimise false positives, with the purpose of minimising food waste. Therefore, a CVS must be able to deliver on both test characteristics before it can be fully implemented in RB-MSAS. The underperformance is mainly a problem in the case of large numbers of slaughtered animals per hour, as in broiler chickens. The solution could be to divert carcasses with CVS-positive findings to a rejection line for re-inspection and then make a final decision of their destination (thermal treatment, pet food, etc.). In the cases of pig and bovine CVSs, the challenge lies in changing the legislation to allow CVSs to be used as a tool in meat safety assurance. However, CVS is an essential part of the future digitisation of meat production. The future digital systems will enable collection and handling of all data in a more efficient way, with overall aims of improving food safety and animal health and welfare.

Author contribution

M.S.: Conceptualisation, Investigation, Formal analysis, Writing - original draft preparation, review & editing; S.G.: Investigation, Formal analysis, Writing - review & editing; L.A.: Investigation, Formal analysis, Supervision, Writing - review & editing; A.C.D.: Investigation, Formal analysis, Writing - review & editing; B.B.: Investigation, Writing - review & editing; M.B.: Investigation, Writing - review & editing; L.L.: Investigation; J.S.D.: Investigation; I·N.: Investigation, Writing - review & editing; D.A.: Conceptualisation, Methodology, Investigation, Writing - review & editing, Supervision, Project administration.

Declarations of competing interest

MS participated as a researcher in the research projects that led to the development of VetInspector (IHFood.dk). LA is employed by the Danish Agriculture & Food Council that represents the farming and food industry of Denmark including companies, trade and farmers' associations. ACD is employed by Farm4Trade, the company that developed one CVS described in this paper. JSD is employed at the Danish Technological Institute and is currently participating in research projects to develop a CVS for pig lesions and for detection of faecal contamination on bovine carcasses.

Data availability

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

Acknowledgements

This publication is based upon work from COST Action 18105 (Risk-based Meat Inspection and Integrated Meat Safety Assurance; www.ribmins.com) supported by COST (European Cooperation in Science and Technology; www.cost.eu).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodcont.2023.109768.

References

Alban, L., Petersen, J. V., Bækbo, A. K., Pedersen, T.Ø., Kruse, A. B., Pacheco, G., & Larsen, M. H. (2021). Modernising meat inspection of pigs – a review of the Danish process from 2006-2020. *Food Control, 119*, Article 107450. https://doi.org/10.1016/j.foodcont.2020.107450. Article.

Alban, L., Vieira-Pinto, M., Meemken, D., Maurer, P., Ghidini, S., Santos, S., Laguna, J. G., Laukkanen-Ninios, R., Alvseike, O., & Langkabel, N. (2022). Differences in code terminology and frequency of findings in meat inspection of finishing pigs in seven European countries. *Food Control, 132*, Article 108394. https://doi.org/10.1016/j.foodcont.2021.108394. Article.

Alfifi, A., Dalsgaard, A., Christensen, J. P., Larsen, M. H., & Sandberg, M. (2020). The association between meat inspection codes, footpad lesions and thinning of broiler flocks in the Danish broiler production. *Preventive Veterinary Medicine, 185*, Article 105205. https://doi.org/10.1016/j.prevetmed.2020.105205. Article.

Almqvist, V., Berg, C., & Hultgren, J. (2021). Reliability of remote post-mortem veterinary meat inspections in pigs using augmented-reality live-stream video software. *Food Control, 125*, Article 107940. https://doi.org/10.1016/j.foodcont.2021.107940. Article.

Anon. (2004). Regulation (EC) No 853/2004 of the European Parliament and of the Council of 29 April 2004 laying down specific hygiene rules for food of animal origin. *Official Journal of the European Union, 139*, 1–55. http://data.europa.eu/eli/reg/2004/853/2021-10-28.

Anon. (2017). Regulation (EU) 2017/625 of the European Parliament and of the Council on official controls and other official activities performed to ensure the application of food and feed law, rules on animal health and welfare, plant health and plant protection products. *Official Journal of the European Union L, 95*, 1–142. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32017R0625&qid=1666108443788.

Anon. (2019a). *Commission Delegated Regulation (EU) 2019/624 of 8 February 2019 concerning specific rules for the performance of official controls on the production of meat and for production and relaying areas of live bivalve molluscs in accordance with Regulation (EU) 2017/625 of the European Parliament and of the Council, 131* pp. 1–17). Official Journal of The European Union. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32019R0624&qid=1666108809844.

Anon. (2019b). *Commission implementing regulation (EU) 2019/627 of 15 March 2019 laying down uniform practical arrangements for the performance of official controls on products of animal origin intended for human consumption in accordance with Regulation (EU) 2017/625 of the European Parliament and of the Council and amending Commission Regulation (EC) No 2074/2005 as regards official controls, 131* pp. 51–100). Official Journal of the European Union. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32019R0627&qid=1666108871450.

Antic, D., Houf, K., Michalopoulou, E., & Blagojevic, B. (2021). Beef abattoir interventions in a risk-based meat safety assurance system. *Meat Science, 182*, Article 108622. https://doi.org/10.1016/j.meatsci.2021.108622. Article.

Antunović, B., Blagojević, B., Johler, S., Guldimann, C., Vieira-Pinto, M., Vågsholm, I., Meemken, D., Alvseike, O., Georgiev, M., & Alban, L. (2021). Challenges and opportunities in the implementation of new meat inspection systems in Europe. *Trends in Food Science & Technology, 116*, 460–467. https://doi.org/10.1016/j.tifs.2021.08.002

Blagojevic, B., Nesbakken, T., Alvseike, O., Vågsholm, I., Antic, D., Johler, S., Houf, K., Meemken, D., Nastasijevic, I., Vieira-Pinto, M., Antunovic, B., Georgiev, M., & Alban, L. (2021). Drivers, opportunities, and challenges of the European risk-based meat safety assurance system. *Food Control, 124*, Article 107870. https://doi.org/10.1016/j.foodcont.2021.107870. Article.

Blömke, L., Volkmann, N., & Kemper, N. (2020). Evaluation of an automated assessment system for ear and tail lesions as animal welfare indicators in pigs at slaughter. *Meat Science, 159*. https://doi.org/10.1016/j.meatsci.2019.107934

Bonicelli, L., Trachtman, A. R., Rosamilia, A., Liuzzo, G., Hattab, J., Mira Alcaraz, E., Del Negro, E., Vincenzi, S., Capobianco Dondona, A., Calderara, S., & Marruchella, G. (2021). Training convolutional neural networks to score pneumonia in slaughtered pigs. *Animals, 11*, 3290. https://doi.org/10.3390/ani11113290

Burfoot, D., Tinker, D., Thorn, R., & Howell, M. (2011). Use of fluorescence imaging as a hygiene indicator for beef and lamb carcasses in UK slaughterhouses. *Biosystems Engineering, 109*, 175–185. https://doi.org/10.1016/j.biosystemseng.2011.03.002

Chao, K., Chen, Y. R., & Chan, D. E. (2003). Analysis of VIS/NIR spectral variations of wholesome, septicemia, and cadaver chicken samples. *Applied Engineering in Agriculture, 19*, 453–458. https://elibrary.asabe.org/abstract.asp?aid=14913.

Chao, K., Chen, Y. R., & Chan, D. E. (2004). A spectroscopic system for high-speed inspection of poultry carcasses. *Applied Engineering in Agriculture, 20*, 683–690. https://elibrary.asabe.org/abstract.asp?aid=17449.

Chao, K., Chen, Y. R., Hruschka, W. R., & Gwozdz, F. B. (2002). On-line inspection of poultry carcasses by a dual-camera system. *Journal of Food Engineering, 51*, 185–192. https://doi.org/10.1016/S0260-8774(01)00051-6

Chao, K., Park, B., Chen, Y., Hruschka, W., & Wheaton, F. (2000). Design of a dual-camera system for poultry carcasses inspection. *Applied Engineering in Agriculture, 16*, 581–587. https://elibrary.asabe.org/abstract.asp?aid=5291.

Chao, K., Yang, C.-C., Chen, Y.-R., Kim, M. S., & Chan, D. E. (2007a). Fast line-scan imaging system for broiler carcass inspection. *Sensing and Instrumentation for Food Quality and Safety, 1*, 62–71. https://doi.org/10.1007/s11694-007-9008-y

Chao, K., Yang, C. C., Chen, Y. R., Kim, M. S., & Chan, D. E. (2007b). Hyperspectral-multispectral line-scan imaging system for automated poultry carcass inspection applications for food safety. *Poultry Science, 86*, 2450–2460. https://doi.org/10.3382/ps.2006-00467

Chao, K., Yang, C. C., Kim, M. S., & Chan, D. E. (2008). High throughput spectral imaging system for wholesomeness inspection of chicken. *Applied Engineering in Agriculture, 24*, 475–485. https://www.ars.usda.gov/ARSUserFiles/953/2008ChaoEtAl24_4ApplEngrAgr475-485.pdf.

Chen, Y. R., Hruschka, W., & Early, H. (2000). A chicken carcass inspection system using visible/near–infrared reflectance: In plant trials. *Journal of Food Process Engineering, 23*, 89–99. https://doi.org/10.1111/j.1745-4530.2000.tb00505.x

Chen, Y. R., Huffman, R. W., Park, B., & Nguyen, M. (1996). Transportable spectrophotometer system for on-line classification of poultry carcasses. *Applied Spectroscopy, 50*, 910–916. https://opg.optica.org/as/abstract.cfm?URI=as-50-7-910.

Cho, B., Kim, M. S., Chao, K., Lawrence, K., Park, B., & Kim, K. (2009). Detection of fecal residue on poultry carcasses by laser-induced fluorescence imaging. *Journal of Food Science, 74*, E154–E159. https://doi.org/10.1111/j.1750-3841.2009.01103.x

De Jong, I. (2013). *Evaluatie Meyn footpad inspection system (evaluation Meyn footpad inspection system)*. Wageningen UR Livestock Research. https://edepot.wur.nl/275215.

Feng, Y. Z., & Sun, D. W. (2012). Application of hyperspectral imaging in food safety inspection and control: A review. *Critical Reviews in Food Science and Nutrition, 52*, 1039–1058. https://doi.org/10.1080/10408398.2011.651542

Heitschmidt, G. W., Park, B., Lawrence, K. C., Windham, W. R., & Smith, D. P. (2007). Improved hyperspectral imaging system for fecal detection on poultry carcasses. *Transactions of the ASABE, 50*, 1427–1432. https://elibrary.asabe.org/abstract.asp?aid=23615.

Hsieh, C., Chen, Y. R., Dey, B. P., & Chan, D. E. (2002). Separating septicemic and normal chicken livers by visible/near-infrared spectroscopy and back-propagation neural networks. *Transactions of the ASAE, 45*, 459–469. https://elibrary.asabe.org/abstract.asp?aid=8515.

Ibarra, J., Tao, Y., Newberry, L., & Chen, Y. (2002). Learning vector quantization for color classification of diseased air sacs in chicken carcasses. *Transactions of the ASAE, 45*, 1629–1635. https://elibrary.asabe.org/abstract.asp??JID=3&AID=11048&CID=t2002&v=45&i=5&T=1.

Jørgensen, A. (2018). *Computer vision analysis of broiler carcass and viscera*. Thesis, Aalborg University. https://vbn.aau.dk/ws/portalfiles/portal/289994360/PHD_Anders_Joergensen_E_pdf.pdf.

Jørgensen, A., Fagertun, J., & Moeslund, T. B. (2017). Diagnosis of broiler livers by classifying image patches. In P. Sharma, & F. Bianchi (Eds.), *Image analysis. SCIA 2017. Lecture notes in computer science, 10269*. Cham: Springer. https://doi.org/10.1007/978-3-319-59126-1_31.

Jørgensen, A., Fagertun, J., & Moeslund, T. B. (2018). Classify broiler viscera using an iterative approach on noisy labeled training data. In *G. Bebis et al., Advances in Visual Computing. ISVC 2018. Lecture Notes in Computer Science, 11241*Cham: Springer. https://doi.org/10.1007/978-3-030-03801-4_24.

Jørgensen, A., Pedersen, M., Gade, R., Fagertun, J., & Moeslund, T. B. (2019). Reaching behind specular highlights by registration of two images of broiler viscera. In G. Carneiro, & S. You (Eds.), *Computer vision – ACCV 2018 workshops. ACCV 2018. Lecture notes in computer science, 11367*. Cham: Springer. https://doi.org/10.1007/978-3-030-21074-8_30.

Kang, R., Yang, K., Zhang, X. X., Wu, W., & Chen, K. J. (2016). Development of online detection and processing system for contaminants on chicken carcass surface. *Applied Engineering in Agriculture, 32*, 133–139. https://elibrary.asabe.org/abstract.asp?aid=46623.

Kim, M. S., Chen, Y. R., Kang, S., Kim, I., Lefcourt, A. M., & Kim, M. (2006). Fluorescence characteristics of wholesome and unwholesome chicken carcasses. *Applied Spectroscopy, 60*, 1210–1216. https://doi.org/10.1366/000370206778664644

Kim, M. S., Chen, Y., & Mehl, P. (2001). Hyperspectral reflectance and fluorescence imaging system for food quality and safety. *Transactions of the ASAE, 44*, 721–729. https://elibrary.asabe.org/abstract.asp?aid=6099.

Kim, I., Kim, M., Chen, Y., & Kong, S. (2004). Detection of skin tumors on chicken carcasses using hyperspectral fluorescence imaging. *Transactions of the ASAE, 47*, 1785–1792. https://elibrary.asabe.org/abstract.asp?aid=17595.

Lawrence, K. C., Windham, W. R., Smith, D. P., Park, B., & Feldner, P. W. (2006). Effect of broiler carcass washing on fecal contaminant imaging. *Transactions of the ASABE, 49*, 133–140. https://elibrary.asabe.org/abstract.asp?aid=20216.

McKenna, S., Amaral, T., & Kyriazakis, I. (2020). Automated classification for visual-only postmortem inspection of porcine pathology. *IEEE Transactions on Automation Science and Engineering, 17*, 1005–1016. https://ieeexplore.ieee.org/document/8963870.

Nakariyakul, S., & Casasent, D. P. (2009). Fast feature selection algorithm for poultry skin tumor detection in hyperspectral data. *Journal of Food Engineering, 94*, 358–365. https://doi.org/10.1016/j.jfoodeng.2009.04.001

Park, B., Chen, Y. R., & Nguyen, M. (1998). Multi-spectral image analysis using neural network algorithm for inspection of poultry carcasses. *Journal of Agricultural Engineering Research, 69*, 351–363. https://doi.org/10.1006/jaer.1997.0258

Park, B., Chen, Y. R., Nguyen, M., & Hwang, H. (1996). Characterizing multispectral images of tumorous, bruised, skin-torn, and wholesome poultry carcasses. *Transactions of the ASAE, 39*, 1933–1941. https://elibrary.asabe.org/abstract.asp?aid=27672.

Park, B., Lawrence, K. C., Windham, W. R., & Buhr, R. J. (2002). Hyperspectral imaging for detecting fecal and ingesta contaminants on poultry carcasses. *Transactions of the ASAE, 45*, 2017–2026. https://elibrary.asabe.org/abstract.asp?aid=11413.

Park, B., Lawrence, K. C., Windham, W. R., Chen, Y. R., & Chao, K. (2002b). Discriminant analysis of dual-wavelength spectral images for classifying poultry carcasses. *Computers and Electronics in Agriculture, 33*, 219–231. https://doi.org/10.1016/S0168-1699(02)00010-8

Park, B., Lawrence, K. C., Windham, W. R., & Smith, D. P. (2004). Multispectral imaging system for fecal and ingesta detection on poultry carcasses. *Journal of Food Process Engineering, 27*, 311–327. https://doi.org/10.1111/j.1745-4530.2004.00464.x

Park, B., Lawrence, K. C., Windham, W. R., & Smith, D. P. (2005). Detection of cecal contaminants in visceral cavity of broiler carcasses using hyperspectral imaging. *Applied Engineering in Agriculture, 21*, 627–635. https://elibrary.asabe.org/abstract.asp?aid=18551.

Park, B., Lawrence, K. C., Windham, W. R., & Smith, D. P. (2006a). Performance of hyperspectral imaging system for poultry surface fecal contaminant detection. *Journal of Food Engineering, 75*, 340–348. https://doi.org/10.1016/j.jfoodeng.2005.03.060

Park, B., Lawrence, K. C., Windham, W. R., & Smith, D. P. (2006b). Performance of supervised classification algorithms of hyperspectral imagery for identifying fecal and ingesta contaminants. *Transactions of the ASABE, 49*, 2017–2024. https://elibrary.asabe.org/abstract.asp??JID=3&AID=22282&CID=t2006&v=49&i=6&T=1.

Park, B., Windham, W. R., Lawrence, K. C., & Smith, D. P. (2007). Contaminant classification of poultry hyperspectral imagery using a spectral angle mapper algorithm. *Biosystems Engineering, 96*, 323–333. https://doi.org/10.1016/j.biosystemseng.2006.11.012

Park, B., Yoon, S. C., Kise, M., Lawrence, K. C., & Windham, W. R. (2009). Adaptive image processing methods for improving contaminant detection accuracy on poultry carcasses. *Transactions of the ASABE, 52*, 999–1008. https://elibrary.asabe.org/abstract.asp?aid=27384.

Park, B., Yoon, S. C., Windham, W. R., & Lawrence, K. C. (2011). In-plant test of in-line multispectral imaging system for fecal detection during poultry processing. *Applied Engineering in Agriculture, 27*, 623–630. https://elibrary.asabe.org/abstract.asp?aid=38193.

Sandberg, M., Sørensen, L. L., Steenberg, B., Chowdhury, S., Ersbøll, A. K., & Alban, L. (2015). Risk factors for *Campylobacter* colonization in Danish broiler flocks, 2010 to 2011. *Poultry Science, 94*, 447–453. https://doi.org/10.3382/ps/peu065

Seo, Y. W., Lee, H., Mo, C., Kim, M. S., Baek, I., Lee, J., & Cho, B. K. (2019). Multispectral fluorescence imaging technique for on-line inspection of fecal residues on poultry carcasses. *Sensors, 19*, 3483. https://doi.org/10.3390/s19163483

Thrusfield, M. (2018). *Veterinary epidemiology*. John Wiley & Sons. https://onlinelibrary.wiley.com/doi/book/10.1002/9781118280249.

Trachtman, A. R., Bergamini, L., Palazzi, A., Porrello, A., Capobianco Dondona, A., Del Negro, E., Paolini, A., Vignola, G., Calderara, S., & Marruchella, G. (2020). Scoring pleurisy in slaughtered pigs using convolutional neural networks. *Veterinary Research, 51*, 51. https://doi.org/10.1186/s13567-020-00775-z

USDA. (2022). *Food safety and inspection Service new technology information*. https://www.fsis.usda.gov/sites/default/files/media_file/2021-09/complete-new-technology-table.pdf. (Accessed 3 February 2023).

Van Harn, J., & de Jong, I. (2017). *Validation of Meyn footpad inspection system*. Wageningen Livestock Research. Report 1044B https://library.wur.nl/WebQuery/wurpubs/fulltext/429581.

Vanderhasselt, R., Sprenger, M., Duchateau, L., & Tuyttens, F. (2013). Automated assessment of footpad dermatitis in broiler chickens at the slaughter-line: Evaluation and correspondence with human expert scores. *Poultry Science, 92*, 12–18. https://doi.org/10.3382/ps.2012-02153

Vieira-Pinto, M., Azevedo, J., Poeta, P., Pires, I., Ellebroek, L., Lopes, R., Veloso, M., & Alban, L. (2020). Classification of vertebral osteomyelitis and associated judgment applied during post-mortem inspection of swine carcasses in Portugal. *Foods, 9*, 1502. https://doi.org/10.3390/foods9101502

Windham, W. R., Heitschmidt, G. W., Lawrence, K. C., Park, B., & Smith, D. P. (2007). Effect of spectrally mixed hyperspectral image pixels on detection of cecal contaminated broiler carcasses. *International Journal of Poultry Science, 6*, 955–959. https://scialert.net/abstract/?doi=ijps.2007.955.959.

Windham, W. R., Heitschmidt, G. W., Smith, D. P., & Berrang, M. E. (2005a). Detection of ingesta on pre-chilled broiler carcasses by hyperspectral imaging. *International Journal of Poultry Science, 4*, 959–964. https://scialert.net/abstract/?doi=ijps.2005.959.964.

Windham, W. R., Smith, D. P., Berrang, M. E., Lawrence, K. C., & Feldner, P. W. (2005b). Effectiveness of hyperspectral imaging system for detecting cecal contaminated broiler carcasses. *International Journal of Poultry Science, 4*, 657–662. https://scialert.net/abstract/?doi=ijps.2005.657.662.

Wu, W., Chen, G. Y., Kang, R., Xia, J. C., Huang, Y. P., & Chen, K. J. (2017). Successive projections algorithm–multivariable linear regression classifier for the detection of contaminants on chicken carcasses in hyperspectral images. *Journal of Applied Spectroscopy, 84*, 535–541. https://doi.org/10.1007/s10812-017-0506-3

Xiong, Z., Sun, D. W., Pu, H., Gao, W., & Dai, Q. (2017). Applications of emerging imaging techniques for meat quality and safety detection and evaluation: A review. *Critical Reviews in Food Science and Nutrition, 57*, 755–768. https://doi.org/10.1080/10408398.2014.954282

Yang, C.-C., Chao, K., & Chen, Y. R. (2005b). Development of multispectral image processing algorithms for identification of wholesome, septicemic, and inflammatory process chickens. *Journal of Food Engineering, 69*, 225–234. https://doi.org/10.1016/j.jfoodeng.2004.07.021

Yang, C.-C., Chao, K., Chen, Y. R., & Early, H. L. (2005a). Systemically diseased chicken identification using multispectral images and region of interest analysis. *Computers and Electronics in Agriculture, 49*, 255–271. https://doi.org/10.1016/j.compag.2005.05.002

Yang, C.-C., Chao, K., Chen, Y., Kim, M., & Early, H. (2006). Simple multispectral image analysis for systemically diseased chicken identification. *Transactions of the ASABE, 49*, 245–257. https://elibrary.asabe.org/abstract.asp?aid=20223.

Yang, C.-C., Chao, K., Kim, M. S., Chan, D. E., Early, H. L., & Bell, M. (2010). Machine vision system for on-line wholesomeness inspection of poultry carcasses. *Poultry Science, 89*, 1252–1264. https://doi.org/10.3382/ps.2008-00561

Yoon, S. C., Park, B., Lawrence, K. C., Windham, W. R., & Heitschmidt, G. W. (2011). Line-scan hyperspectral imaging system for real-time inspection of poultry carcasses with fecal material and ingesta. *Computers and Electronics in Agriculture, 79*, 159–168. https://doi.org/10.1016/j.compag.2011.09.008

Zdolec, N., Kotsiri, A., Houf, K., Alvarez-Ordóñez, A., Blagojevic, B., Karabasil, N., Salines, M., & Antic, D. (2022). Systematic review and meta-analysis of the efficacy of interventions applied during primary processing to reduce microbial contamination on pig carcasses. *Foods, 11*, 2110. https://doi.org/10.3390/foods11142110