Beyond human vision – Use of Computer Vision Systems in Meat Inspection

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Meat inspection

Traditionally, meat inspection has relied on veterinary inspectors

- They are trained to identify disease, welfare issues, contamination, and defects in carcasses
- This human-based approach forms the cornerstone of food safety practices

However, inspector assessments are inherently subjective

- Influenced by factors such as experience, fatigue, and environmental conditions
- Resulting in variability in inspection performance

Introduction - 1

Computer vision systems (CVS) are being developed to detect findings at meat inspection

- Involving automated image analysis using advanced algorithms in the decision-making process
- This can potentially enhance the quality and scalability of meat inspection

However, the acceptance of using CVS as part of official meat inspection requires regulatory approval

- Implies generation of evidence demonstrating that CVS outputs meet or exceed the accuracy and reliability of the current meat inspection

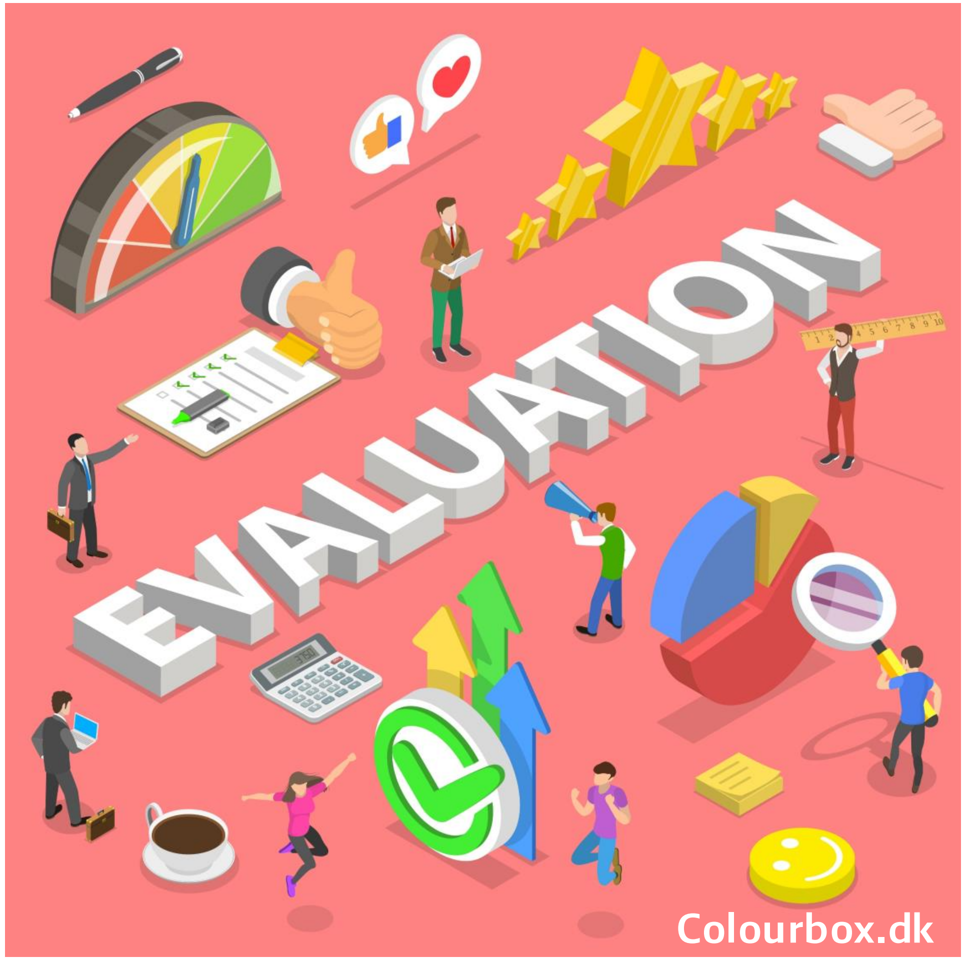
Introduction - 2

The question is how to evaluate the performance of such systems

- Textbooks would suggest a comparison with a gold standard

However, such validation is challenging in meat inspection

- Due to the absence of a definitive gold standard
- Because meat inspectors' judgement contains inherent uncertainties



Aim

We suggest making use of Bayesian latent class modelling, when assessing validity

- So, the CVS's performance is compared with that of the meat inspectors
- Without assuming that either test is perfect

We will show an example of this approach using real life data from a Danish pig abattoir

- Focus is on detection of faecal contamination of the carcass – a food safety issue

The CVS

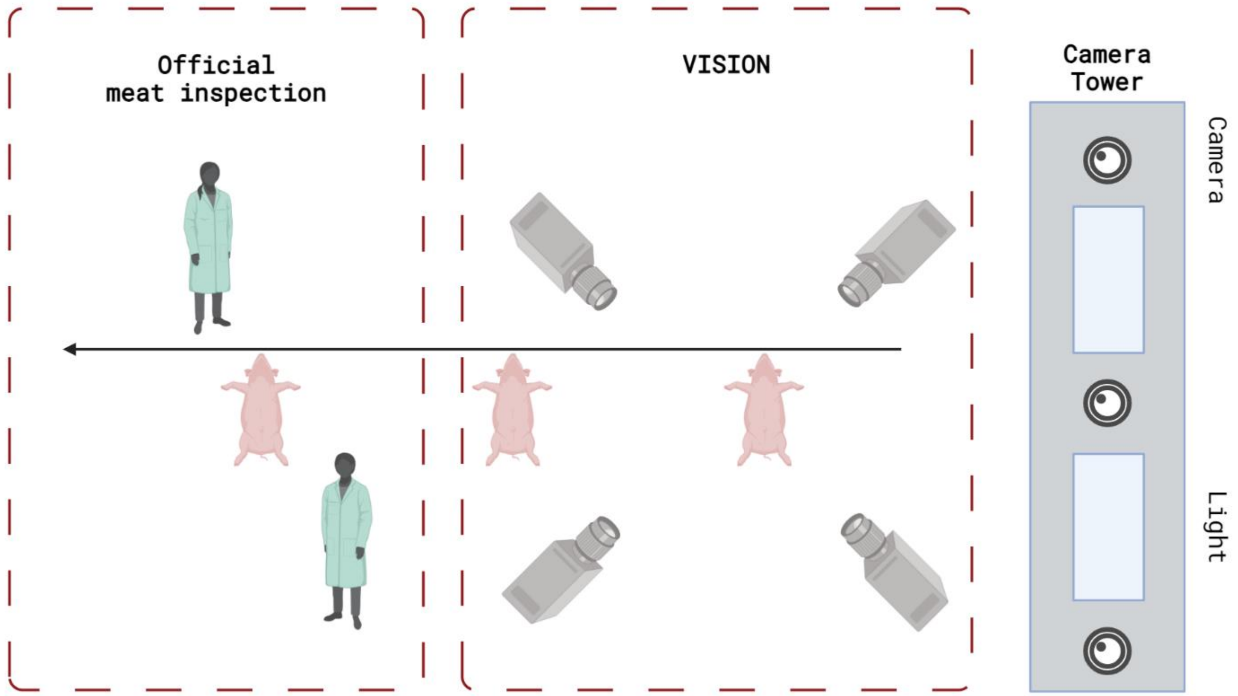
Developed by Danish Technological Institute

The 2024 version employed a combination of red-green-blue (RGB) and near-infrared (NIR) cameras

- 24 composite images generated per full carcass used for the subsequent processing

The 2025 version employed 18 RGB cameras

- Involving 36 composite images generated per full carcass



Materials

Data collected over 16 working days in 2024

- Encompassing 69,215 carcasses

For each carcass, the CVS results regarding faecal contamination were compared with those from the meat inspectors

The meat inspector data also included other findings than faecal contamination

- Not dealt with in this presentation – for more details please see Lund et al., 2025

Example of how faecal contamination might look – Photo kindly provided by Danish Technological Institute

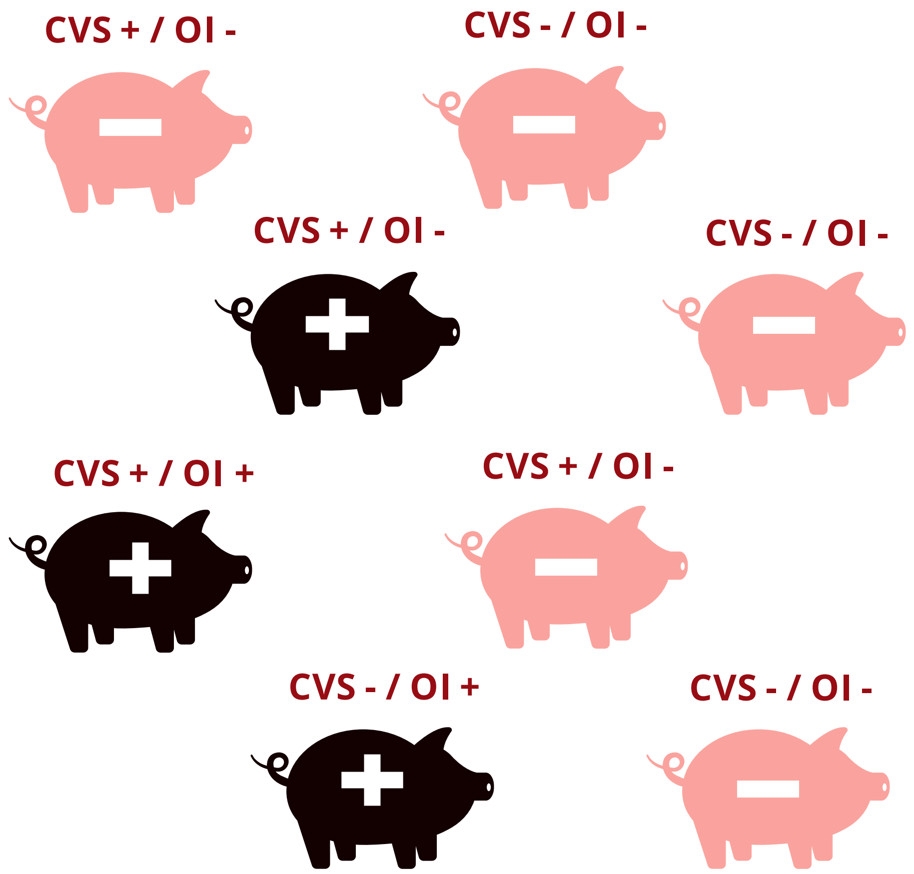
Methodology – Bayesian Latent Class Modelling

The model compares patterns in results from the use of CVS and the official meat inspectors (OI)

- Since neither method is perfect, and the true contamination status is unknown, the model treats the contamination status as a latent (unobserved) variable

The model examines where the two methods agree or disagree to estimate how good each is at correctly identifying contamination

- This includes estimating sensitivity and specificity



Technical details of the modeling

The model was run in R using JAGS (Just Another Gibbs Sampler) version 4.3.1 for Bayesian analysis together with

- The runjags package (Denwood, 2016), which interfaces with JAGS version 4.3.1, for Bayesian analysis, alongside the tidyverse package (Wickham et al., 2019)

The model ran for 500,000 iterations across two chains

- Discarding first 5,000 iterations as a burn-in period
- The remaining iterations were used for statistical inference

The efficiency of Markov Chain Monte Carlo sampling and model convergence was assessed through visual inspection of trace and autocorrelation plots

- As well as the Potential Scale Reduction Factor (PSRF), calculated using the Gelman-Rubin method
- Please see our paper for the details (Lund et al., 2025)

Results of the Bayesian latent class modelling

The median results showed that **the CVS** had:

- Sensitivity of **31.6% (95% C.I.: 27.6% - 39.1%)**
- Specificity of **97.9% (95% C.I.: 96.1% - 99.9%)**

Compared to **the meat inspectors**:

- Sensitivity of **22.0% (95% C.I.: 17.6% - 28.9%)**
- Specificity of **99.3% (95% C.I.: 98.2% - 100%)**

Sensitivity: how often contamination is correctly detected, when truly present

Specificity: how often a clean carcass is correctly identified

Discussion

Hence, CVS's strength lies in its ability to detect true contaminations

- Whereas meat inspectors can rule out false positives

Results are intuitively easy to understand for meat inspectors

- Such as sensitivity and specificity and relation to other findings at meat inspection

We find that Bayesian latent class modelling offers a robust and flexible framework for evaluating CVS

- Without the need for a gold standard

Also, for use in other species, such as **broilers**

- And for other issues like **animal health and welfare**

Colourbox.dk

Example: CVS for detection of chronic pleurisy

An animal health indicator finishing pigs

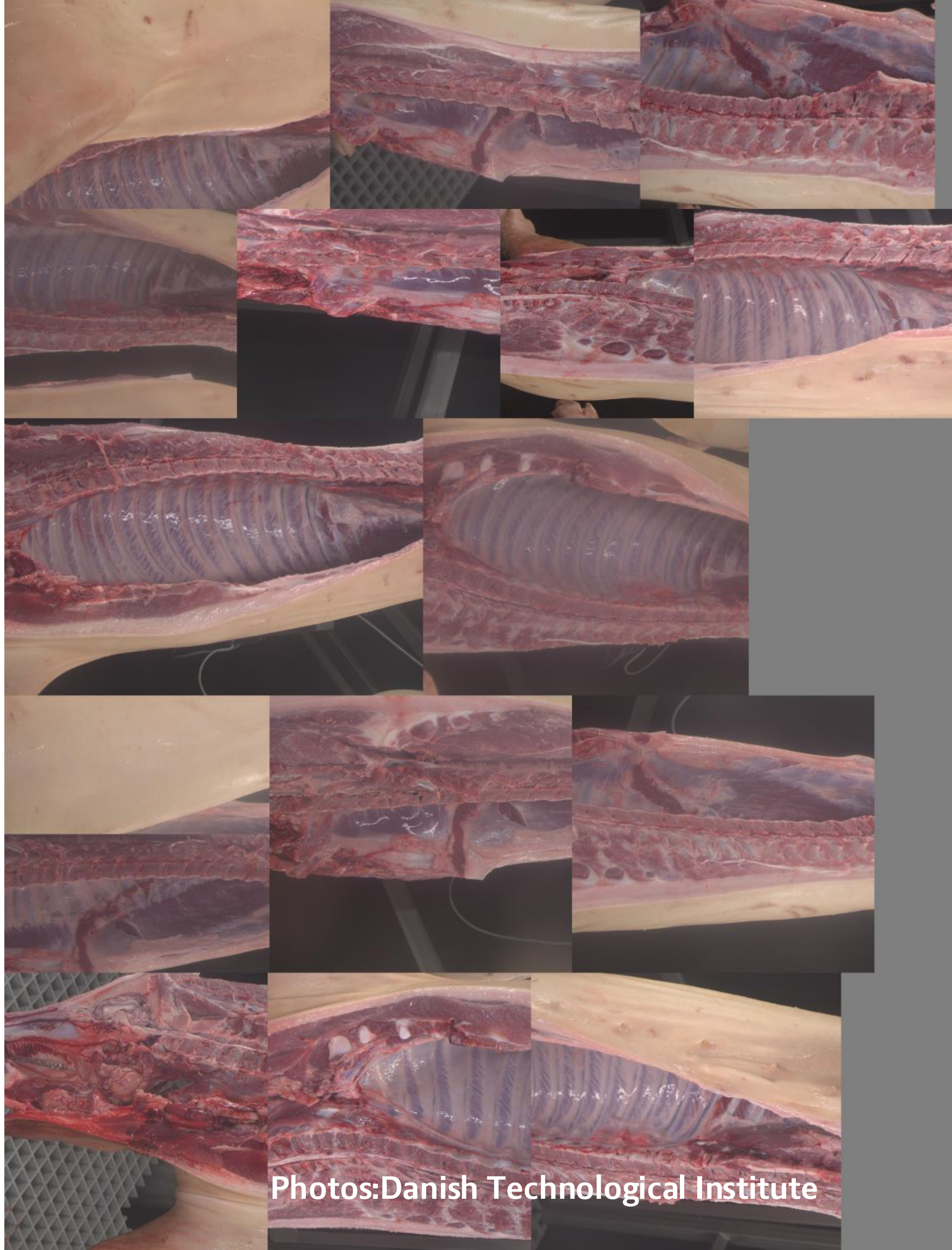
- Of interest to the pig producers (vaccination?)

Bayesian latent class modeling used to compare the performance of different CVS models

- 85,413 pig carcasses included, inspected across 15 slaughter days

Same result: CVS associated with a higher sensitivity than the meat inspectors but a sightly lower specificity

- Lund et al., Prev. Vet. Med. (2026)



Example: automatic detection of traumatic skin lesions in pigs after slaughter

An animal welfare indicator

- Enabling monitoring and control

Of interest to:

- Competent authorities (risk-based inspection)
- Abattoirs (customer requirement)
- Pig producers and their pigs

Pilot project, currently undertaken by Matteo Recchia, IZSLER, Italy

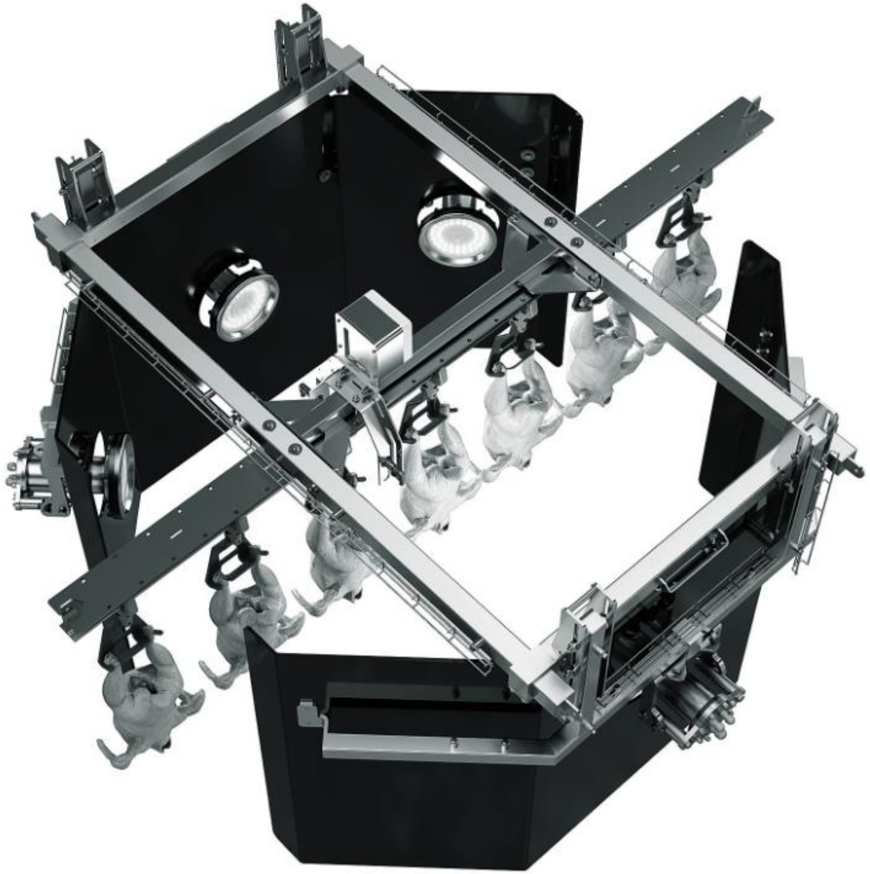
- In collaboration with Univ. of Copenhagen, Univ. of Milano, Univ. of Parma and DAFC

Photo by Matteo Recchia

CVS in broiler meat inspection

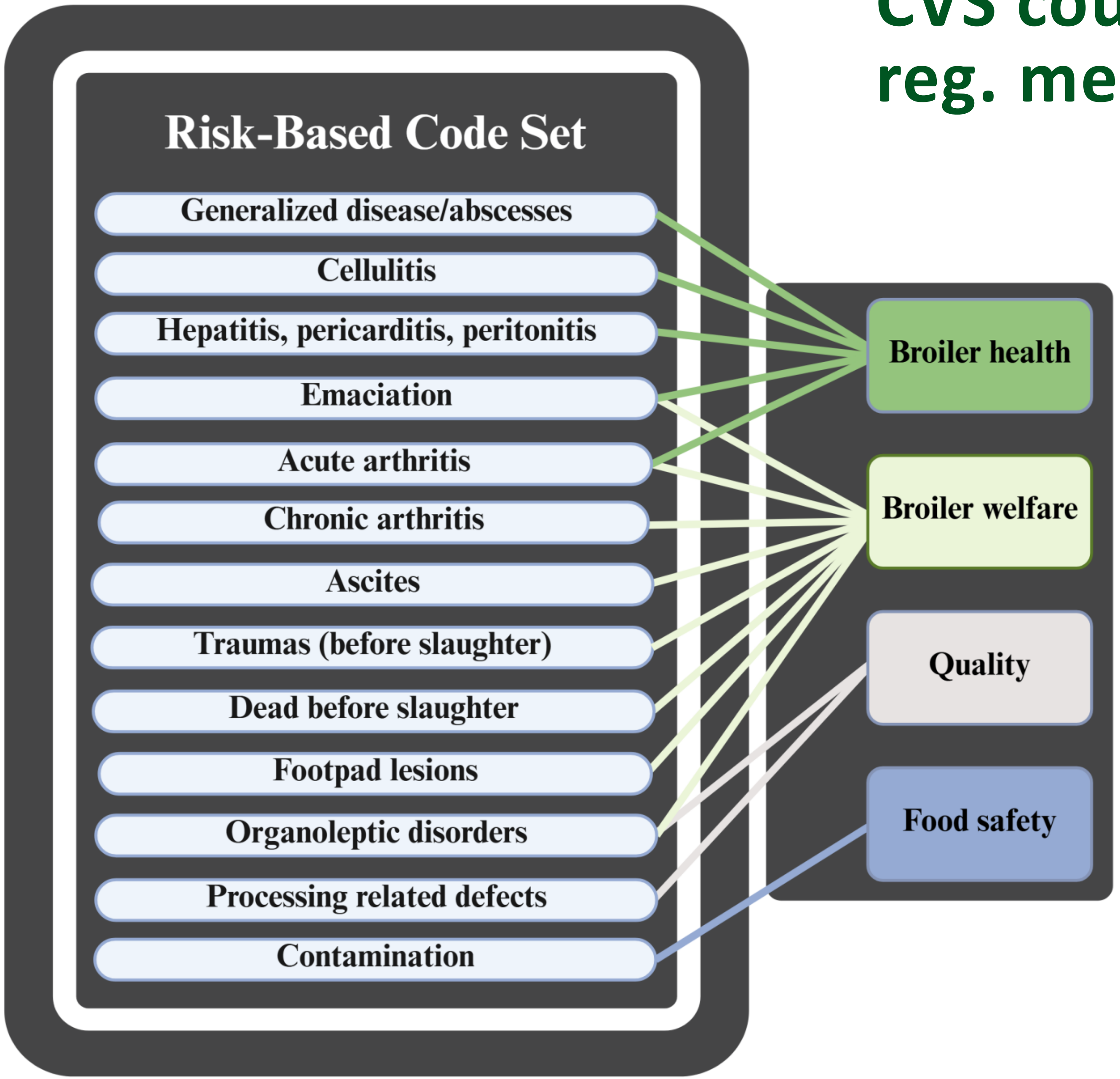
Slaughter speed is high in modern abattoirs

- 3-4 broilers inspected per second



Created with BioRender.com

CVS could constitute the solution reg. meat inspection



A harmonized list of codes to register would make sense

- For all abattoirs
- Across countries

Majewski et al. (2024) has developed a proposal

- Contains 13 codes
- With specification of main area of concern for each code

When to condemn?

Harmonised condemnation criteria required

- To be established for all 13 identified codes

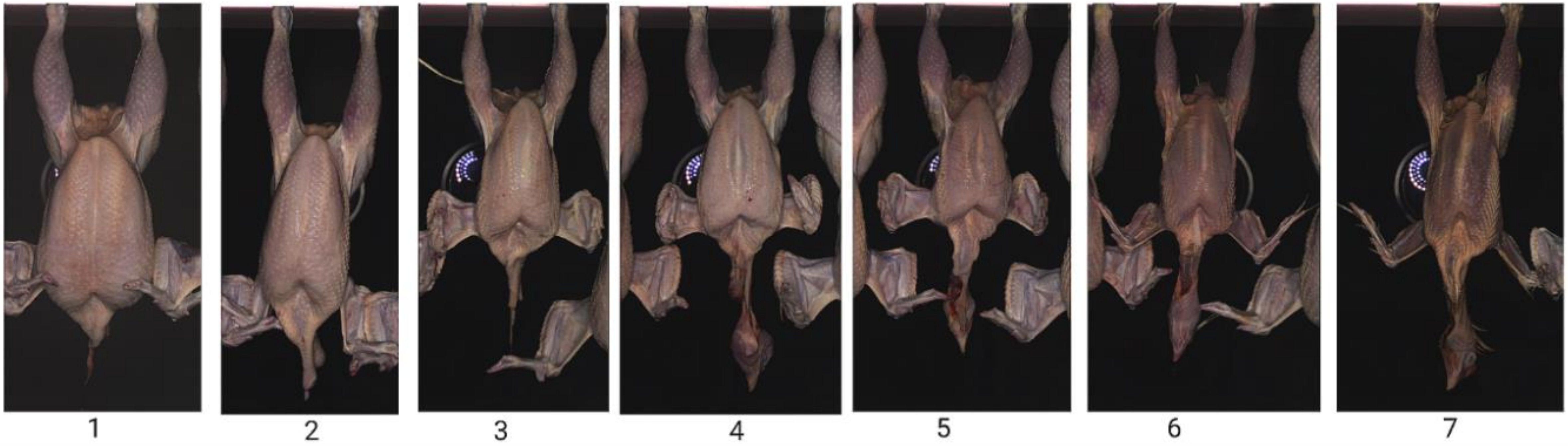
Survey has been undertaken among official veterinarians (OV) in Europe

- Input received from 155 OV regarding at which severity level the carcass should be condemned
- Definition of benchmark threshold was defined for each lesion, using 66.7%±1% as consensus criterion

For further interest, please contact Michal Majewski
micmaj@dtu.dk

Illustration: colourbox

Example: emaciation



	Camera view	Severity level (cumulative % of respondents)							
		NA	1	2	3	4	5	6	7
Emaciation/generalized disease	Front	0	3.2	9.0	21.3	45.2	79.4	94.8	100
	Front	0	10.5	50.0	66.4	80.9	87.5	97.4	100

Source: Majewski et al., submitted

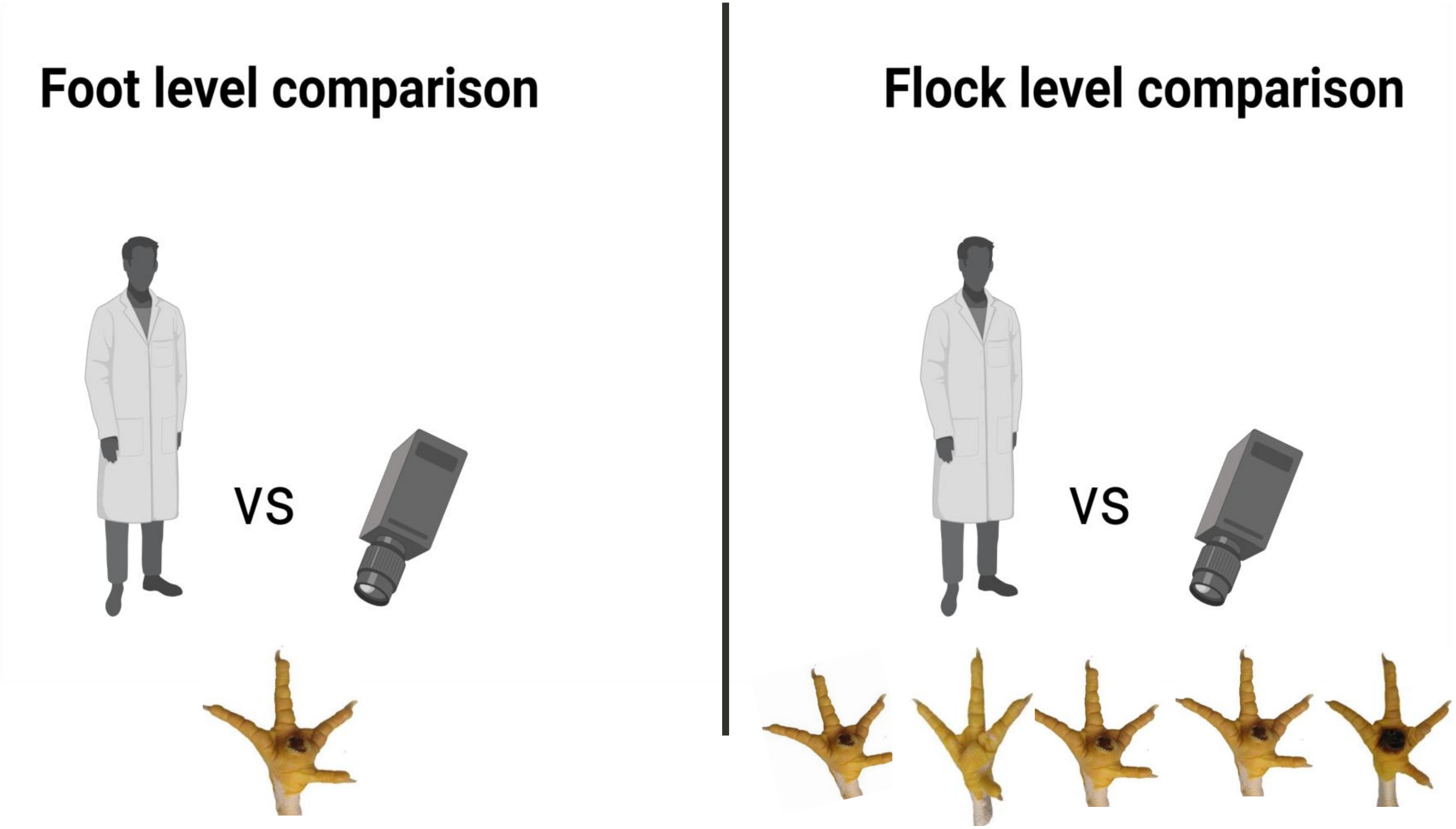
Animal welfare: Foot pad dermatitis in broilers

Today, first 50 and last 50 feet are being scored manually

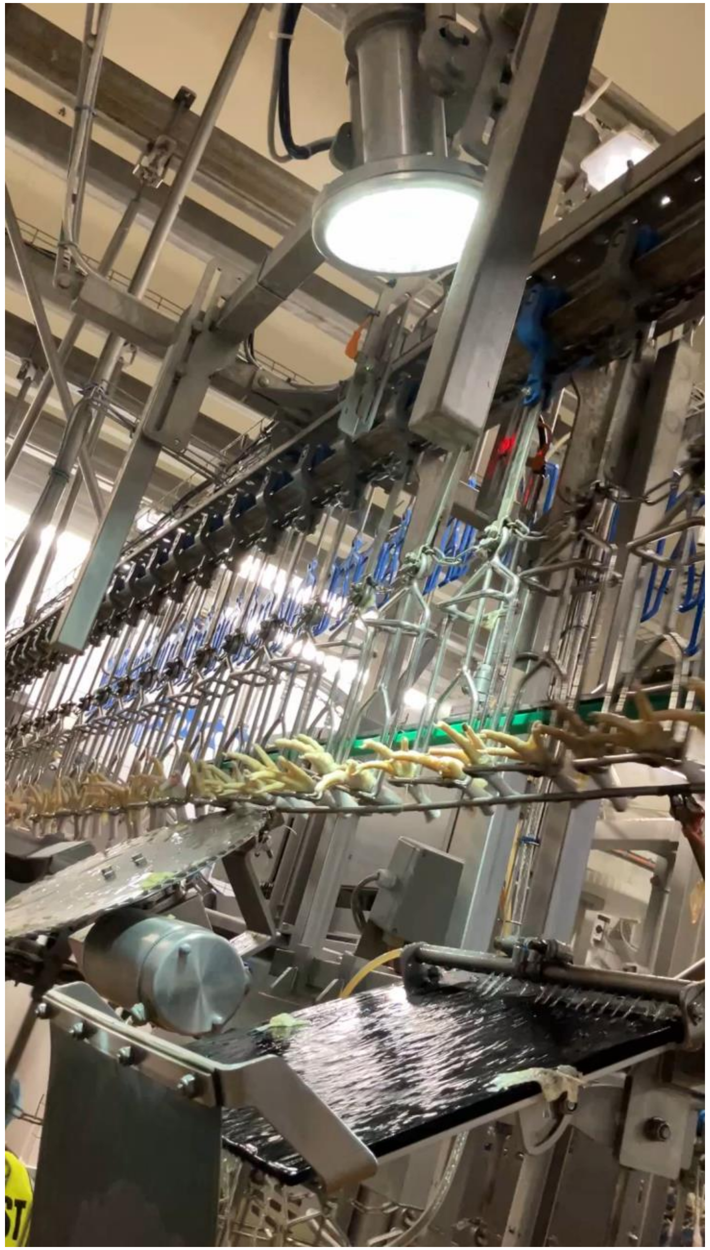
- = 100 feet per batch
- Allows scoring of depth of ulcer
- But only a limited number of feet

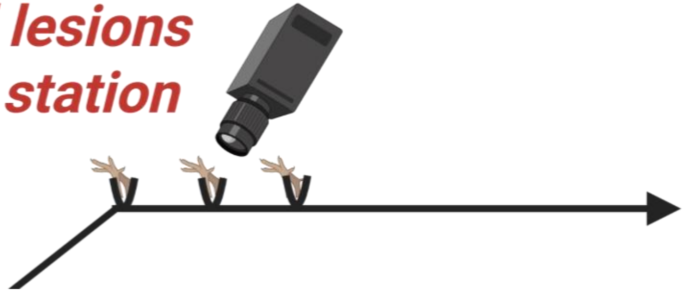
With CVS, all feet scored

- Comparison study currently undertaken to investigate impact



Footpad lesions scoring station

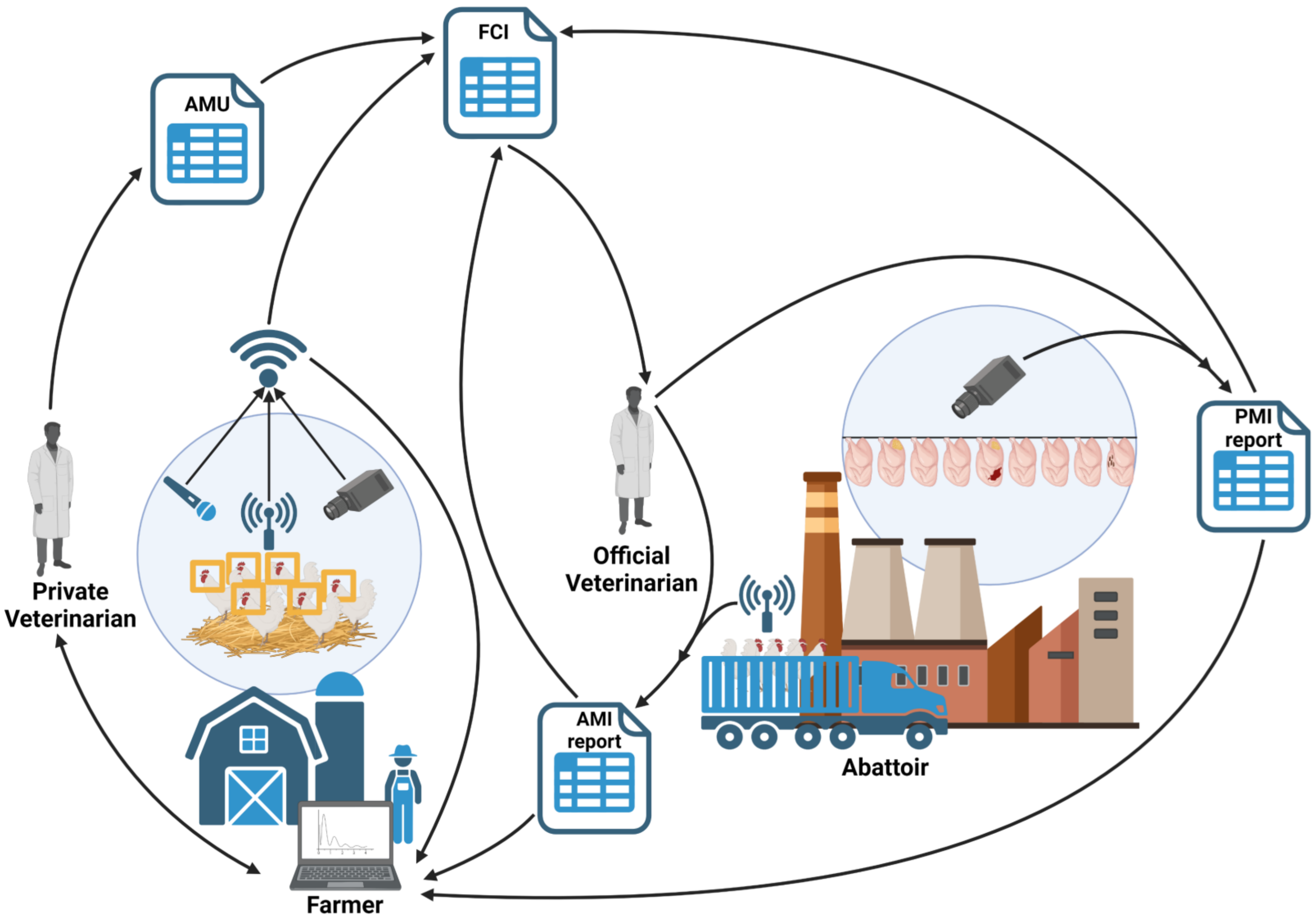




CVS are on their way

Potential requirements for CVS for use in meat inspection:

- They have been validated, e.g., using latent class modeling
- Validation should show acceptable results compared to the existing meat inspection
- Results should have been published in a peer-reviewed journal
- Next, pilot projects or national adoption projects can be undertaken



Majewski et al., 2026. Food Control.
https://doi.org/10.1016/j.foodcont.2026.112094

Epilogue

Pig validation work presented to EU Commission's Expert Group on Food Hygiene and Control of Food of Animal Origin on 23 May 2025

- Similar poultry work presented to the same Expert Group for the second time on 7 November 2025

Could be valuable to open legislation to allow a wider use of CVS in pigs and cattle inspection

- Because this is currently only allowed for poultry

Maybe the EU Commission will ask EFSA for their views?

Thanks for your attention

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Abbey Olsen

Marianne Sandberg

Michal Majewski

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Contents lists available at ScienceDirect

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

ELSEVIER

Using latent class modelling to evaluate the performance of a computer vision system for pig carcass contamination

Daniel Hjorth Lund [a,*], Lis Alban [b,c], Claus Hansen [a], Anders Dalsgaard [b], Matt Denwood [b], Abbey Olsen [b]

Preventive Veterinary Medicine 246 (2026) 106701

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ELSEVIER

Comparing computer vision models for detecting chronic pleurisy in pigs

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Food Control 165 (2024) 110665

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ELSEVIER

Development of a harmonized and risk-based code system for post-mortem inspection of broilers

Michał Majewski [a,b,*], Lis Alban [c,d], Désirée S. Jansson [e], Thomai Lazou [f], Nina Langkabel [g], Dragan Antic [j], Eija Kaukonen [h], Helena Wall [i], Madalena Vieira Pinto [k], Laila Østergaard [l], Ole Gyvelgaard Nielsen [l], Sergio Ghidini [m], Marianne Sandberg [a]

Tak.

More details about the two models that were used in combination to detect faecal contamination

Model 1 focused on the pelvic region and processing two images per carcass, and Model 2 processed the remaining 22 image angles of the carcass

Model 1 was trained on 3,037 images with faecal contaminations according to professional evaluation and annotation

- For each epoch, a random selection of 3,000 images from a superset of 27,330 images was added to the dataset
- A new random selection of non-contaminated images was performed for each epoch

Model 2 was trained on 1,626 professionally evaluated and annotated images.

- These images were combined with 800 randomly selected non-contaminated images for each epoch from a superset of 40,326 non-contaminated images

The images were mainly annotated by professionals at the Danish Technological Institute