# Validation of Computer Vision Systems for Detecting Meat Inspection Findings Using Latent Class Modelling

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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

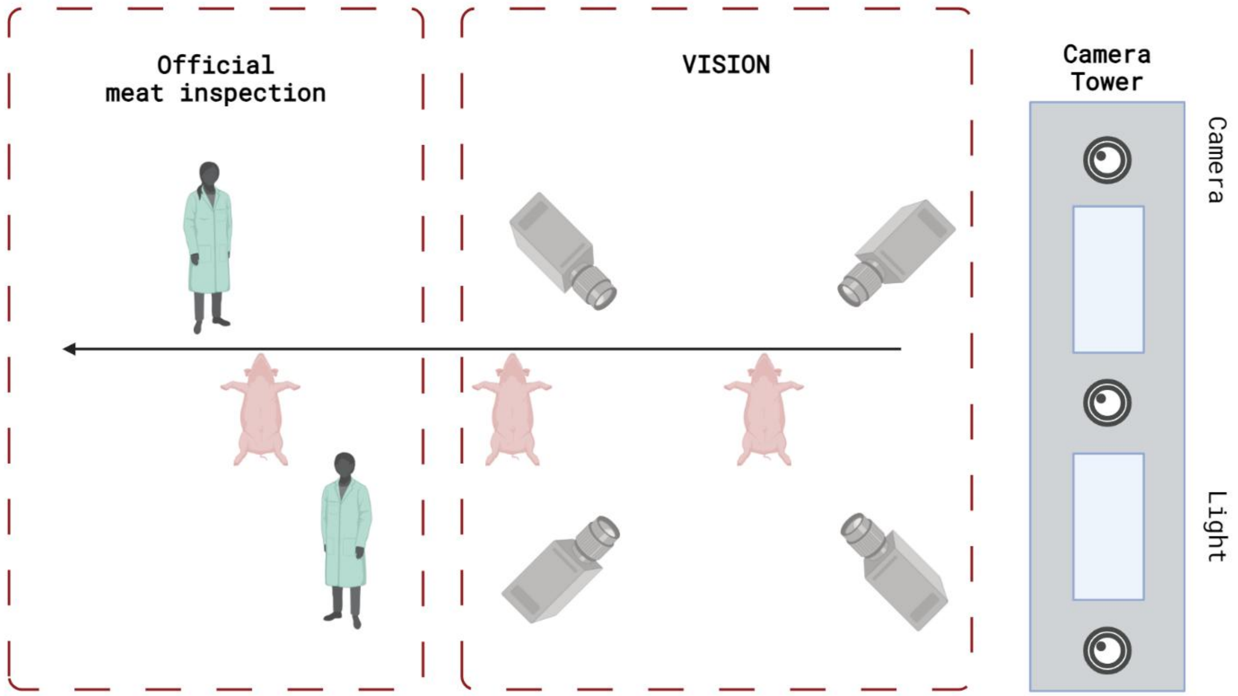
Developed by Danish Technological Institute

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 employs a total of 18 RGB cameras

- Involving 36 composite images generated per full carcass



# Materials

Data were 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

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

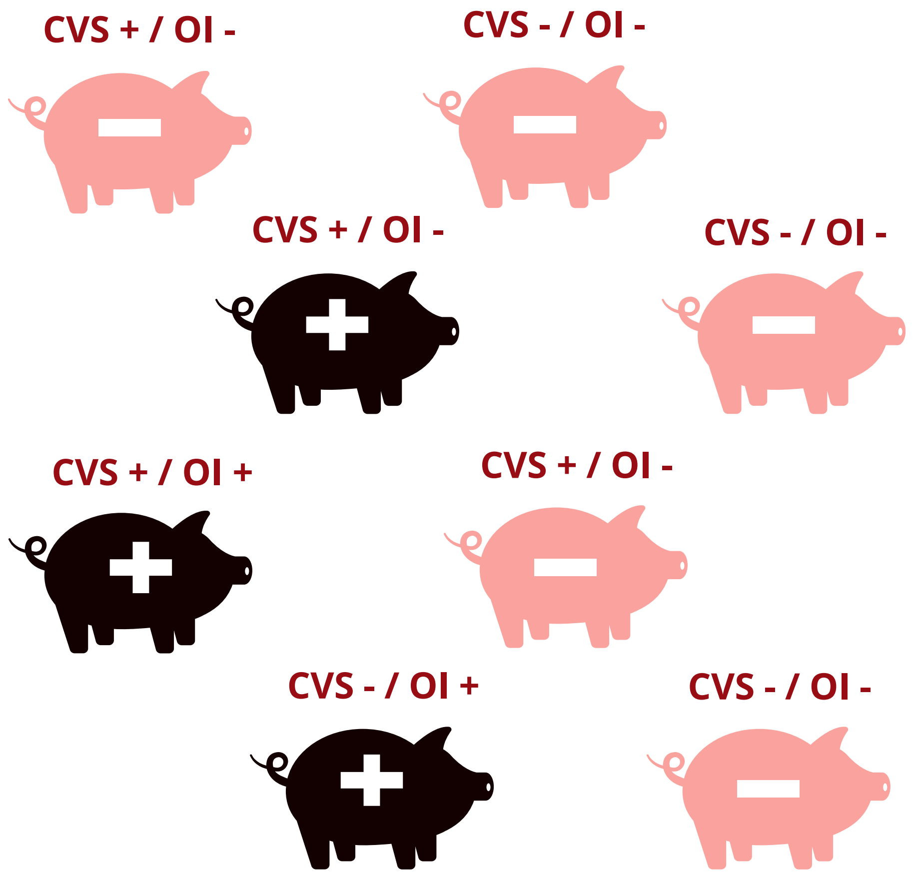
# Methodology – Bayesian Latent Class Modelling

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)

# Methodology – workflow

First, we investigated the potential effect of other meat inspection findings on CVS detection of faecal contamination

Next, sensitivity and specificity regarding detection of faecal contamination was assessed

- For both CVS and veterinary inspection

For positive and negative predictive probabilities, model validation and sensitivity analysis, please see our paper (Lund et al., 2025)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# Descriptive results

Four meat inspection findings were statistically associated with increased relative risk of a carcass being test positive

- 1) Abscess hind, 2) abscess toe, 3) minor slaughter defects and 4) oil contamination

Oil contamination showed high relative risk (RR=4.1)

- Among carcasses judged by meat inspectors to be devoid of faecal contamination

Shows that the CVS could not differentiate oil from faecal contamination

- Not a major problem, because both contaminations must be removed from carcass

| Meat inspector | CVS Row % (counts) | | Relative Risk | P-value |
|---|---|---|---|---|
| | Faecal + | Faecal - | | |
| Oil + | 29.6% (208) | 70.4% (494) | 4.1 | <0.001 |
| Oil - | 7.2% (4,773) | 92.8% (61,336) | 1.0 | |

# 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 latent class modelling offers a robust and flexible framework for evaluating CVS

- Without the need for a gold standard

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# Epilogue

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

- Today, CVS can be used only as an assisting tool in meat inspection of pigs and bovines
- Therefore, it could be valuable to open legislation to allow a wider use of CVS
- Because this is currently only allowed for poultry

We suggest that the requirement for such CVS should be that

- 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 can be undertaken

# Thanks for your attention

For more details, please see our paper (Lund at al., 2025), which has just been published (May 2025)

Preventive Veterinary Medicine 241 (2025) 106556

Contents lists available at ScienceDirect

Preventive Veterinary Medicine

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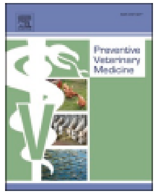

## Using latent class modelling to evaluate the performance of a computer vision system for pig carcass contamination

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# 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

# Tak.