Beyond human vision – validating camera vision systems in meat inspection

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Summary

Camera vision systems (CVS) are being developed and used in many areas of society. Lately, CVS are also being developed for use in meat inspection, but there has been – and is - concern about their validity. In this paper, we show how CVS can be validated against the existing meat inspection using Bayesian latent class modelling. Hereby, we compare meat inspection findings with those of the CVS, while assuming that both ways of detection are imperfect. We present two examples of this, where both deal with the use of CVS in post-mortem inspection of finishing pigs: 1) carcass contamination, which is a food safety issue, and 2) chronic pleurisy, which is an animal health issue. It is concluded that the CVS have a higher sensitivity than the meat inspectors, and that the meat inspectors have a slightly higher specificity than the CVS. We also briefly discuss the use of CVS and similar technologies in meat inspection of broilers and bovines.

Introduction

Slaughter animals arriving at the abattoir are first subjected to an ante-mortem (AM) inspection to check that the animals are fit for human consumption, implying that they appear normal and do not exhibit indications of animal welfare issues or disease. If the animals can be accepted at the AM inspection, they will be slaughtered. After slaughter, carcasses and organs are subjected to a post-mortem (PM) inspection, where the aim again is to check whether they are fit for human consumption. The inspection is done by either an official veterinarian or an official auxiliary working under the responsibility of the official veterinarian. These persons are trained to identify disease and welfare issues as well as contaminations and defects in carcasses. This human-based approach forms the cornerstone of food safety practices, although it is known that meat inspector assessments are inherently subjective and influenced by factors such as experience, fatigue, and environmental conditions. Another challenge is a shortage of personnel observed in many European countries, as many of the official veterinarians/auxiliaries are retiring, while recruitment is becoming more difficult (1).

Computer vision systems (CVS) are being used in several places in society, including when interpreting X-ray pictures in relation to cancer diagnoses and treatment. This involves cameras taking photos that are subjected to automated image analysis using advanced algorithms in the decision-making process. Computer vision systems are also already being used in multiple processes during slaughter. However, currently not directly in the PM inspection of pigs and bovines, even though this could potentially enhance the quality and scalability of inspection. The acceptance of using CVS directly in the official meat inspection of pigs and bovines requires regulatory approval. This would imply the generation of solid evidence demonstrating that CVS outputs meet or exceed the accuracy and reliability of the existing meat inspection.

Materials and methods

The question is, therefore, how to evaluate the performance of such systems, which one could say go beyond human vision. 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. The meat inspector's judgement contains inherent uncertainties, as described further up. Moreover, it would be impractical, unreasonable and potentially misguiding to compare the CVS results with a thorough pathological examination, as time constraints are an inherent part of the inspection. The solution, we suggest, is making use of Bayesian latent class modelling, a statistical approach, wherein the CVS's performance is compared with that of the meat inspectors under the assumption that both tests are imperfect. Our two recent scientific publications contain examples of this approach using real life data from a Danish pig abattoir. Our focus has been on detection of 1) faecal contamination of the carcass – a food safety issue and 2) chronic pleurisy – an animal health issue. For more details, please see Lund et al. (2,3).

The CVS used for both case studies was developed by the Danish Technological Institute. It has been in place for more than a decade in a large Danish pig abattoir, slaughtering finishing pigs only. The CVS is integrated directly into the slaughter line before the PM inspection, and it is called VISION. The early 2024 version employed a combination of red-green-blue (RGB) and near-infrared (NIR) cameras, generating 24 composite images per full carcass used for the subsequent processing (Fig. 1). In late 2024, the infrared cameras and lighting were replaced by broad-spectrum white LED lighting and additional cameras. The updated system uses 16 individual images (eight from each carcass half) to detect chronic pleurisy. The data for both case studies were collected from the abattoir. For the study of faecal contamination, 16 days of data were used from early 2024, encompassing 69,215 carcasses, whereas for chronic pleurisy, data from late 2024 were used, encompassing 89,613 carcasses slaughtered over 16 days. For each carcass, the VISION results regarding faecal contamination / chronic pleurisy were compared with those from the meat inspectors, where the meat inspector data also included other findings than faecal contamination and chronic pleurisy.

To validate the VISION, we used a Bayesian latent class statistical model that compares patterns in results from both VISION and the veterinary inspectors. Since neither method is perfect, and the true status is unknown, the model treats the status (faecally contaminated /chronic pleurisy) as a latent (unobserved) variable. Each slaughter day is treated as a separate population. The statistical model examines where the two methods agree or disagree to estimate how good each is at correctly identifying contamination. This includes estimating the sensitivity (how often contamination/chronic pleurisy is correctly detected when present) and specificity (how often a carcass without contamination/chronic pleurisy is correctly identified). The model runs hundreds of thousands of simulated scenarios based on the observed data and uses the most consistent patterns to estimate the true performance of VISION as well as the meat inspectors. For more details, please see Lund et al. (2,3).

Results

The descriptive analyses, done in the faecal contamination study, prior to the modelling, revealed that the meat inspection finding “oil contamination” was statistically associated with a 4-times higher probability of VISION detecting faecal contamination compared to carcasses, where the meat inspector did not find oil (RR = 4.1, $P < 0.001$). This showed that VISION could not differentiate oil from faecal contamination. Although faecal contamination is considered worse than oil from a food safety perspective, this is not considered a major problem, because both contaminations must be removed. The outputs from the Bayesian latent class model showed that VISION had a sensitivity of 31% and specificity of 98%, compared to 22% sensitivity and 99% specificity for the meat inspectors (Table 1). Similarly, the chronic pleurisy case study revealed that VISION had a sensitivity of 89.2% and a specificity of 98.8% compared to a sensitivity of 79.4% and a specificity of 99.4% for the meat inspectors. Please, see Lund et al. (2,3) regarding the positive and negative predictive probabilities, validation of the models and sensitivity analyses related to both case studies.

Discussion

Our two examples show that VISION’s strength lies in the ability to detect lesions and contaminations, whereas the meat inspectors can rule out false positives. We find that Bayesian latent class modelling is suitable for evaluating CVS against meat inspectors. Moreover, the results are intuitively easy to understand for meat inspectors, such as sensitivity and specificity and relation to other codes. In conclusion, Bayesian latent class modelling offers a robust and flexible framework for evaluating CVS, without requiring a gold standard.

However, CVS are not yet allowed for use in PM inspection of pigs and bovines in the European Union (EU), hence, there is a need for updating this legislation. The EU Hygiene Package legislation from 2004 is a cornerstone for public health and consumer confidence (Food hygiene - European Commission). Since this legislation came into force, only minor updates have been made, while e.g., the technological development within CVS has been ground-breaking. As described by Sandberg et al. (4), new technologies for use in meat inspection have either been developed or are in the pipeline. Similarly, citizens are getting acquainted with camera-equipped smart phones capable of recording high quality footages, and several cell phone applications require facial recognition through the camera when operating. So, why not use these technologies in meat inspections as effective means of ensuring food safety as well as animal health and welfare?

Therefore, we recommend a revision of the current meat inspection legislation to allow use of CVS not just as support for meat inspectors in their decision-making but also to replace the meat inspectors in parts of meat inspection, where this makes sense. Apart from our two examples, CVS detection of enlarged testicles on male pigs that are not surgically castrated would make sense because it makes little sense to insist on having an inspector to manually check all testicles (5). Instead, the CVS could act as the prolonged eyes of the meat inspector, only directing carcasses with faecal contamination, chronic pleurisy or enlarged testicles for individual inspection in the rework area. A third example is the use of video recordings using smartphones for remote

online AM inspection in case of emergency slaughter of a bovine that has had a hip dislocation or similar, disabling it from standing and walking, and hence, from being transported to the abattoir, as suggested by Poulsen et al. (6).

The use of CVS could potentially enhance the quality and scalability of meat inspection, among others, because the judgement could be harmonised, not just at an individual abattoir plant, but also between plants and between EU Member States. The latter would require harmonisation of the meat inspection code lists, because currently these differ substantially between the countries (7). Moreover, the condemnation criteria should be harmonised, implying deciding when a finding is so serious that it should be registered and result in condemnation, as suggested by Vieira-Pinto et al. (8). Inspiration for this can be found in the work done by Majewski et al. (9), who developed a harmonised code system for poultry, consisting of 13 codes. Poultry will likely be the first species for which CVS will be used in meat inspection, because the current speed of slaughter implies that the meat inspector is supposed to check around three broilers per second, which sounds like an impossible task. This challenge has already been recognised in the EU legislation. Therefore, the use of CVS is, in principle, already allowed for PM inspection of poultry in the EU. Outside PM inspection, CVS is also being developed and implemented, e.g., to measure tail lengths and detect tail lesions (10).

It would make sense to define criteria, for when CVS have acceptable performance, so the developer would know what work to undertake. For use of CVS in PMinspection, we recommend that the CVS is validated prior to their implementation. Moreover, we recommend that this includes a comparison with the existing way of undertaking meat inspection, e.g., using Bayesian latent class modeling, and that the validation shows acceptable results. Finally, to ensure transparency and acceptance, a requirement could be to have validation results published in a peer-reviewed scientific journal.

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. We would like to encourage more developers to present their work to this Committee, as it will show the plethora of tools that are in the pipeline. Next, it would be valuable to open legislation to allow wider use of CVS in the meat inspection of pigs and bovines, as it is in poultry today. Initially, the use of pilot projects at the abattoir should be allowed, while following the instructions given in Article 18.9 of the EU Regulation 2017/625. Hereby, meat inspectors and food business operators can gain experience in understanding how to make meat inspections better and more efficient and define exactly which criteria should be met to allow for replacing specific areas of physical inspection with CVS.

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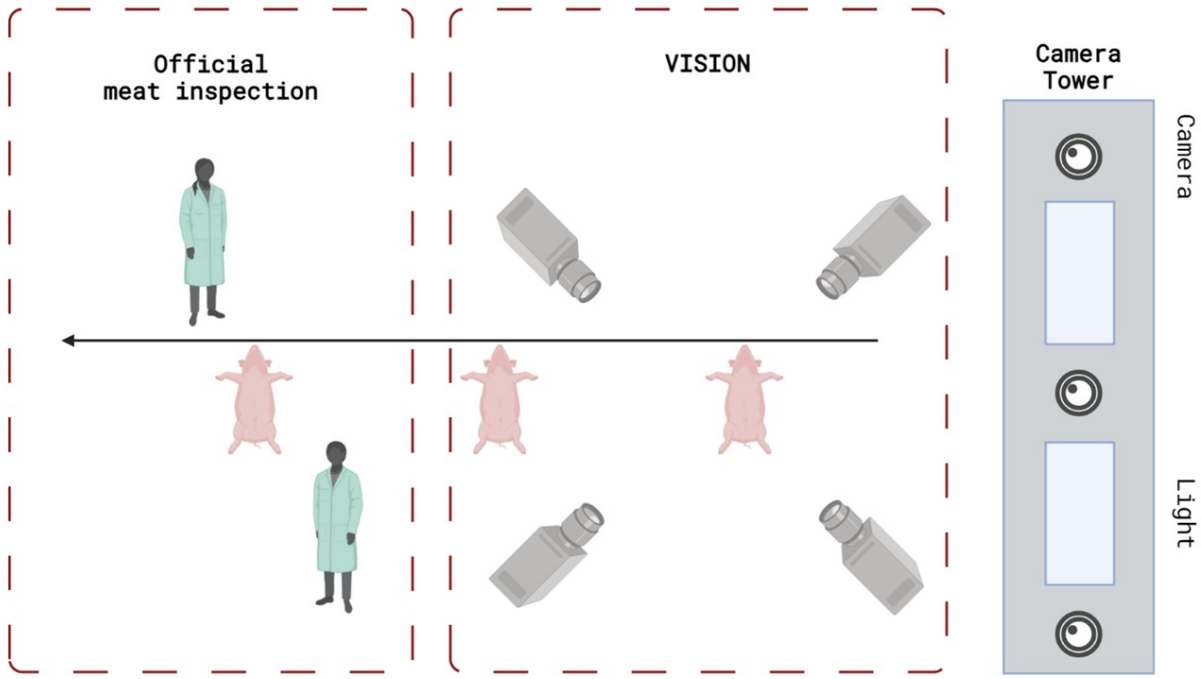


Figure 1. Graphical depiction of how the CVS called VISION works at the abattoir. Source: Lund et al. (2)

Keywords: Innovations, Artificial Intelligence, Data integration.

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