CAMERAS AND AI TO ENHANCE THE MEAT INSPECTION PROCESS

Daniel Lindegaard Hjorth Lund[1,2], Jeppe Seidelin Dam[2], Abbey Olsen[1], Ole Ryding[2*], Niels T. Madsen[2*]

[1] Copenhagen University, Department of Veterinary and Animal Sciences, Copenhagen, Denmark

[2] Danish Technological Institute, DMRI, 2630 Taastrup, Denmark

*Corresponding author email: ntm@dti.dk or olr@dti.dk

I. INTRODUCTION

The augmentation of visual meat inspection garners increasing attention due to its crucial role in ensuring food safety [1]. Currently, meat inspection is performed entirely by trained personnel. However, it can be argued that the inspection would be performed with greater accuracy and precision if computer vision systems (CVS) could contribute to the official meat inspection (OI) compared to not using this technology. The high intra- and inter-rater variation between human inspectors [2] could be minimized as OI may be conducted more consistently and be specifically targeted at detecting small contaminations on the large surfaces. Introduction of the new EU legislation on official controls in food production allows the use of CVSs as complementary tools in meat inspection. Therefore, in Denmark, an experimental equipment has been installed at one pig and two beef slaughter lines to augment the process of meat inspection, Figure 1. The CVS uses a trained Convolutional Neural Network (CNN) to detect plausible fecal contaminations of a size of approx. 0.5x0.5mm to 2x2mm depending on the camera set-up. This recent work evaluates the application of CVS in detecting fecal contamination on pig carcasses just before the post-mortem inspection phase at the slaughter line (Figure 1 left). The aim was to explore statistical techniques to evaluate the sensitivity (Se) and specificity (Sp) of CVS compared to OI in the absence of a true gold standard evaluation.

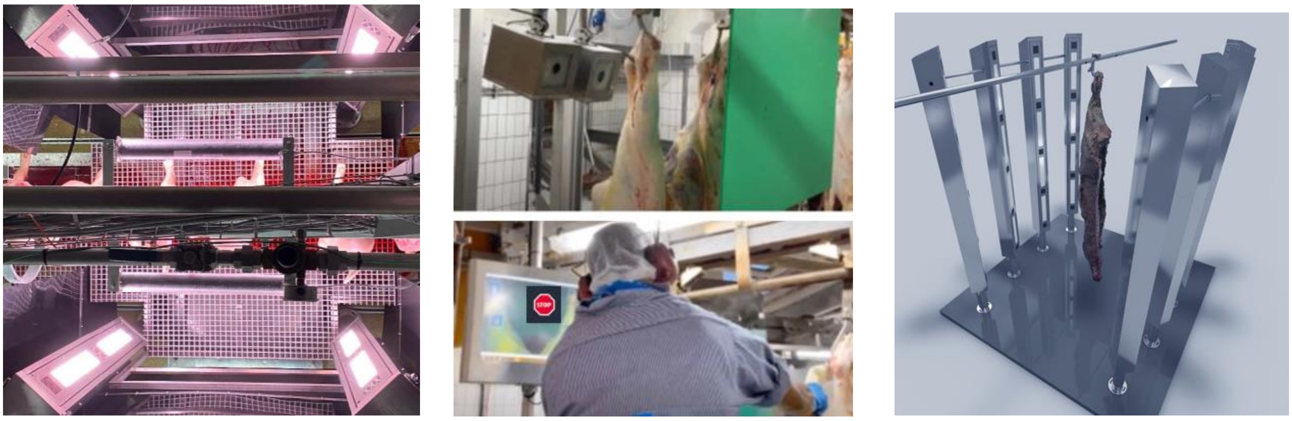

Figure 1. Pictures of the various computer vision systems (CVS)
Left: The CVS viewed from above the pig slaughter line, 4 towers each with 3 RGB+NIR cameras take 24 pictures of each half carcass side.
Middle: The 2-cam system imaging beef hind legs after dehiding points out contamination for operator steam vacuuming.
Right: The BCC-3™ [3] end-of-line equipped with 3 high resolution RGB cameras in each of the 4 corner towers imaging each half carcass.

II. MATERIALS AND METHODS

Data subsets originating from 15 representative normal production days of a slaughter line, processing at 428 carcasses/h, were collected for analysis and included a total of 71,298 pigs [4]. Carcasses with major slaughter defects were omitted as they were unsuitable, by definition, for inspection by either the OI or CVS [5].

The OI fecal findings were recorded on the main line inspection platform by three OI inspectors. OI observations were recorded by rotating inspectors according to internal guidelines, with inspectors being able to assign more than 35 different OI carcass remarks, albeit a maximum of 4 per carcass [5].
The analysis method used descriptive statistics, agreement calculations between CVS and OI and latent class modelling [6] to estimate the Se and Sp of both the methods.

III. RESULTS AND DISCUSSION

Through the application of latent class modelling, the Se and Sp of the CVS system were estimated at 31% and 97%, respectively, in contrast to the OI's 20% Se and 99% Sp (Table 1). CVS was better at detecting fecal contaminated carcasses with a Se of 31% versus 20% for the OI. Contrarily, the OI had, as expected, a near-perfect Sp of 99% versus 97% for CVS, demonstrating that both systems were adept at classifying carcasses devoid of fecal contamination, albeit with a slight edge to the official inspection. The results demonstrate the comparative strengths and limitations of the CVS and traditional OI. The CVS closely aligns with public health objectives by prioritizing the detection of contaminants to enhance food safety by ensuring contamination is identified, albeit at a risk of more false positives and higher operational cost due to the need for technology investment and its increased sensitivity. Conversely, the OI approach offers an efficient solution for food business operators, with high specificity effectively reducing false positives and associated costs, yet with a potential risk of missing some contaminated carcasses due to lower sensitivity. The combination of CVS and OI seems a way to increase the overall performance. The results highlight the possibility of using latent class modeling to estimate Se and Sp, though the specific values have not been validated and might be influenced by varying slaughter processes during the test.

Table 1 – The Se and Sp of both CVS and the OI as estimated by the latent class model. The latent class model's 95% confidence interval is shown in brackets. Also included are the results of using OI or CVS, respectively, as the gold standard.

Evaluation-group	CVS		Official Inspection (OI)	
	Sensitivity	Specificity	Sensitivity	Specificity
Latent class model	31% [27%-38%]	97% [95%-99%]	20% [14%-26%]	99% [99%-100%]
CVS-Gold standard/ Official inspection	29%	93%	-	-
OI-Gold standard / VISION	-	-	30%	97%

IV. CONCLUSION

The sensitivity and specificity of the CVS system were estimated at 31% and 97%, respectively, in contrast to the OI's 20% Se and 99% Sp. At present, the utilization of CVS technology as an aid to enhance detection of contaminations, subject to verification by OI, emerges as a feasible strategy. However, CVS CNN modelling is being iteratively improved with more data and better methods giving promising reductions in false positives, making the technology increasingly relevant.

ACKNOWLEDGEMENTS

The research has been supported by the Danish Pig Levy Fund and the Danish Cattle Levy Fund.

REFERENCES

1. Sandberg, M., Ghidini, S., Alban, L., Dondona, A. C., Bojan Blagojevic, B., Bouwknegt, M., Lipman, L., Dam, J.S., Nastasijevic, I.; Antic, D. (2023) Applications of computer vision systems for meat safety assurance in abattoirs: A systematic review. Food Control, 150: 109768
2. 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: 108394.
3. Online Beef Classification Center, BBC-3™
4. Lund, D. L. H. (2024) Determining the sensitivity and specificity of a camera-based technology to detect fecal contamination and evaluating its use in the Danish meat inspection. Master Thesis, 2 April, Copenhagen University.
5. Danish Ministry of Food Agriculture and Fisheries. (2022). Vejledning om udøvelse af kødkontrol, 10380.
6. Enøe, C., Christensen, G., Andersen, S., & Willeberg, P. (2003). The need for built-in validation of surveillance data so that changes in diagnostic performance of post-mortem meat inspection can be detected. Preventive Veterinary Medicine, 57(3): 117-125.