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Paper



Deep-learning-based classification of pig carcasses according to sex

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Abstract

Slaughterhouses provide an opportunity for the automated collection of data from large numbers of animals under standardised conditions. This study investigated the use of deep learning for automated classification of pig carcasses according to sex. A total of 4,219 images of female, entire male and surgically castrated male pigs slaughtered in Italy, Spain and the Netherlands were used. Images were acquired from different perspectives, and the vulva, scrotum or perianal region was annotated according to sex category. A YOLO11m object-detection model was trained and evaluated on an independent test set comprising 672 images from 224 carcasses. Classification performance was assessed both at the single-image level and at the animal level by combining predictions from three views of each carcass. Image-level accuracy was 97.5%, with macro-averaged precision, recall and F1-score of 97.7%, 97.5% and 97.6%, respectively. At the animal level, 219/224 carcasses were correctly classified, corresponding to an accuracy of 97.8%, with macro-averaged precision, recall and F1-score of 97.9%, 98.0% and 97.9%, respectively. All classification errors involved castrated males, particularly their distinction from females, whereas direct confusion between entire males and females did not occur. These results demonstrate the feasibility of deep learning-based sex classification of pig carcasses and support its potential integration into automated slaughterhouse data-collection systems.

Keywords

pig carcass, deep learning, sex categories

Introduction

Pig farming is a major component of the livestock sector worldwide, with pork representing approximately one third of global meat production in 2023 (FAO, 2025). It is particularly relevant in the European Union (EU), where about 132 million pigs were reared and 21 million tonnes of pig meat were produced in 2024 (Eurostat, 2025 a,b). The scale and economic relevance of pig farming generate huge amounts of valuable data throughout the supply chain, with potential benefits for farm profitability, consumer trust, meat quality and traceability. Slaughterhouses are well suited to the collection of such data, as large numbers of animals from different farms converge at a limited number of facilities, where they are processed under relatively standardised conditions. This offers a unique opportunity to gather information at both individual and herd levels, without additional manipulation of live animals (De Luca et al., 2021; Grandin, 2017).

Beyond routinely recorded traits (e.g., carcass weight and classification based on estimated lean meat percentage), post-mortem findings can provide retrospective information on pig health and welfare, thus helping to identify batches or farms which warrant further investigation. For example, lung and pleural lesions are widely used as indicators of respiratory disease; tail damage may reflect harmful behaviours on farm; skin injuries and bruises may reveal problems associated with animal management, transport, and lairage (Bottacini et al., 2018; De Luca et al., 2021; van Staaveren et al., 2017).

Modern slaughter plants operate at high line speeds, up to 800 pigs per hour, which allows only a few seconds for the examination of each carcass. Under these conditions, manual assessment of multiple traits is labour-intensive and susceptible to observer variability (Blömke et al., 2020; Huanca-Marca et al., 2025). Automated data acquisition may overcome these limitations yielding efficient, objective, and large-scale assessment without interference with routine operations. Computer vision is particularly well suited to this purpose, as digital images of carcasses and plucks can be processed to extract a wide range of phenotypic features. Accordingly, computer-vision and deep-learning approaches have been investigated to assess biting lesions (Blömke et al., 2020; D'Angelo et al., 2025), pneumonia (Bonicelli et al., 2021), pleurisy (Romano et al., 2025), and faecal contamination of carcasses (Tholen et al., 2026). Optical systems for the identification of carcass sex have also been patented (Schimitzek, 2019), and sex classification has been integrated into automated evisceration robots to guide the selection of the appropriate rectum-removal procedure (Kim et al., 2023). However, to the best of our knowledge, no peer-reviewed study has evaluated a deep-learning approach for automated sex classification of pig carcasses.

This study aimed to develop a deep-learning approach for the automated classification of pig carcasses according to sex category, a basic phenotypic feature that is nevertheless relevant for pig production and meat quality.

Materials and methods

Animals and photo acquisition

A random subset of carcasses from a previous investigation on tail docking and tail biting was studied herein (Romano et al., 2026). Briefly, the dataset comprised pigs slaughtered in three European countries, representing different production conditions: a) heavy pigs slaughtered in Italy at approximately 160–180 kg live weight and 9–10 months of age; b) pigs slaughtered in Spain at approximately 125–130 kg and 6–7 months of age; and c) pigs slaughtered in the Netherlands at approximately 90–100 kg and 5–6 months of age. These differences resulted in substantial variation in carcass size and conformation, increasing the overall heterogeneity of the dataset.

Digital images were acquired along the slaughter line, after carcass scalding and dehairing, using automated acquisition stations equipped with high-resolution RGB cameras and LED illumination. Image capture was triggered automatically upon detection of each carcass. In Italy and Spain, the cameras were mounted on a six-axis collaborative robot, whereas in the Netherlands three cameras were installed in fixed positions. In both configurations, each carcass was imaged from right, central, and left views, providing complementary perspectives of the tail and perineal region (Figure 1). Images belonging to the same carcass were identified by a common filename followed by the suffixes _0, _1, and _2 or _A, _B, and _C.

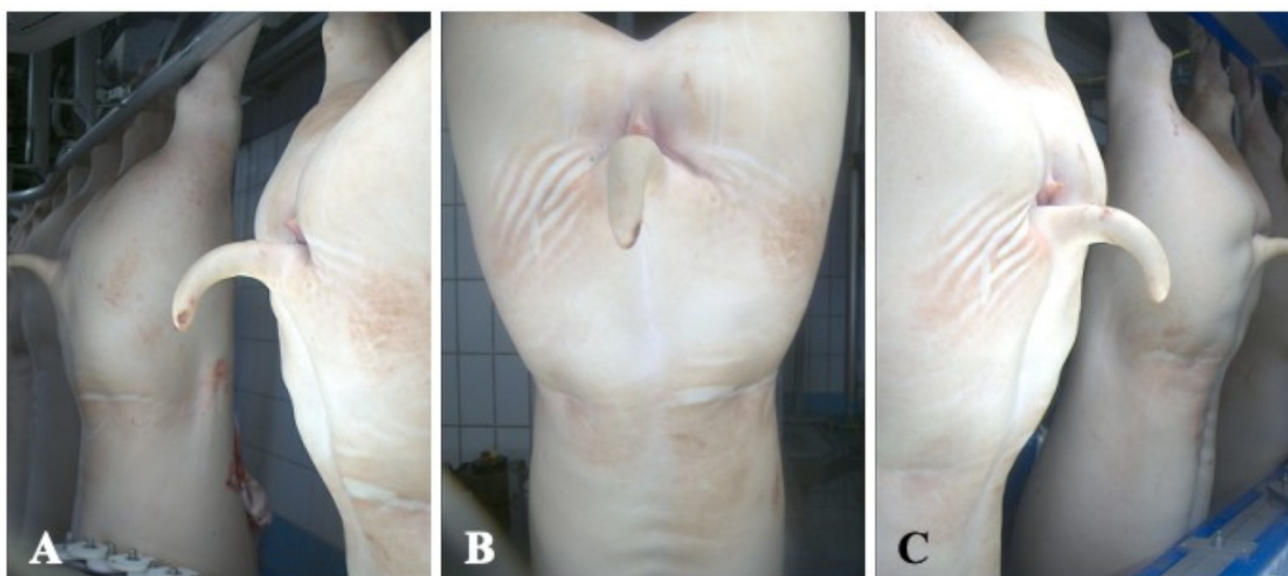


Figure 1. Pig carcass. Female. The same carcass is photographed from the right (A), central (B), and left (C) perspectives.

Image annotation and carcass classification

Pictures were annotated using LabelMe (Russell et al., 2008) and AnyLabeling (Nguyen, 2026) software. Three sex classes were considered: female, entire male, and castrated male. Ground-truth sex classes were assigned by consensus between two investigators, based on clearly visible external genital anatomy. For each class, the following anatomical features were manually delineated by the same investigators: the vulva in females, the scrotum in entire males, and the perianal area in castrated males (see Figure 2 A-C for details). Annotations were initially drawn as polygons and subsequently converted into rectangular bounding boxes for object-detection training. Images with insufficient visibility of the anatomical region of interest were excluded from the dataset (Figure 2 D).



Figure 2. Pig carcasses. Annotation using LabelMe software of a female (A), an entire male (B), and a castrated male (C). The carcass shown in D was not included in the study because its rotation prevented reliable annotation of the anatomical region of interest.

Dataset composition and features

A fully balanced dataset could not be obtained because no entire males were available in the Italian subset and only a limited number were available in the Spanish subset. Accordingly, the final dataset composition reflected the actual availability of each class across the three slaughterhouses. Overall, the dataset comprised 4,219 images, whose distribution by class and slaughterhouse is reported in Table I.

Slaughterhouse	Entire male, n (%)	Female, n (%)	Castrated male, n (%)	Total, n (%)*
Italy	0 (0.0)	185 (29.2)	448 (70.8)	633 (15.0)
Spain	121 (9.9)	667 (54.5)	436 (35.6)	1,224 (29.0)
Netherlands	1,266 (53.6)	623 (26.4)	473 (20.0)	2,362 (56.0)
Total, n (%)*	1,387 (32.9)	1,475 (35.0)	1,357 (32.2)	4,219 (100)

Table I. Dataset composition by slaughterhouse and sex class. Data are expressed as the number of images (n) and percentage (%). *Percentage refers to the overall dataset.

The final dataset was split into training, validation, and test sets (Table II). The training set and the validation set comprised 2,930 images and 617 images, respectively. The test set consisted of 672 pictures taken from 224 carcasses (i.e., each carcass was represented by three pictures corresponding to the right, central, and left views). All images from the same carcass were assigned to the same subset, thereby preventing data leakage between training, validation, and test sets.

Slaughterhouse	Class	Training set	Validation set	Test set	
		Images (n)	Images (n)	Images (n)	Carcasses (n)
Italy	Entire male	0	0	0	0
	Female	105	35	45	15
	Castrated male	257	101	90	30
Spain	Entire male	91	12	18	6
	Female	521	83	63	21
	Castrated male	358	27	51	17
Netherlands	Entire male	936	168	162	54
	Female	372	119	132	44
	Castrated male	290	72	111	37
Total	Entire male	1,027	180	180	60
	Female	998	237	240	80
	Castrated male	905	200	252	84
Overall		2,930	617	672	224

Table II. Composition of the training, validation, and test sets by slaughterhouse and sex class.

Deep learning-based method employed

A YOLO11m object-detection model (Jocher and Qiu, 2026), implemented using Ultralytics version 8.3.x and initialised with pretrained weights, was trained to detect the anatomical region of interest and classify it into one of the sex categories. The training subset was used for model fitting, whereas the validation subset was used to monitor model performance and select the confidence thresholds for image-level inference.

Images were resized to 960 × 960 pixels using aspect-ratio-preserving letterboxing. Due to session-duration and GPU-usage limitations imposed by the free-tier Google Colab environment (Tesla T4 GPU), the training was conducted in two consecutive phases for a total of 30 epochs. The first phase ran for 17 epochs with an early-stopping patience of 5 epochs; training was then resumed from the best checkpoint for an additional 13 epochs, with patience increased to 10 epochs. Batch size was automatically determined using the Ultralytics autobatch function and set to 8 during the second phase. The optimiser and initial learning rate were also automatically selected, resulting in AdamW with an initial learning rate of 0.001429, momentum of 0.9, and weight decay of 0.0005, combined with a cosine learning-rate schedule.

Data augmentation included scaling (0.5), translation (0.1), rotation ($\pm 10^\circ$), shear ($\pm 2^\circ$), horizontal flipping (0.5), and variations in hue (0.015), saturation (0.7), and brightness (0.4). Mixup (0.15) and mosaic (1.0) augmentation were also applied, with mosaic disabled during the final epochs of each training phase.

The checkpoint achieving the highest validation fitness, based on mAP50 and mAP50–95, was retained for evaluation on the held-out test set.

Statistical analysis

YOLO11m model performance was evaluated on the test set at both image and animal levels.

For image-level evaluation, a confidence threshold of 0.25 was empirically set based on the validation-set results and

applied to all three classes. When multiple predictions exceeded the threshold within the same image, only the prediction with the highest confidence score was retained. If no prediction exceeded the threshold, the image was assigned a null output, indicating that no valid class prediction was available. Thus, each test image yielded either a single predicted class (entire male, female, or castrated male) or a null output.

For animal-level evaluation, the three images of each carcass were considered jointly as a triplet and classified according to predefined criteria (Table III).

Sex category	Criteria
Female	Detection of the vulva at least in one image of the triplet; no scrotum detected
Entire male	Detection of the scrotum at least in one image of the triplet; no vulva detected
Castrated male	Neither scrotum nor vulva detected in any image of the triplet; perianal region detected at least in one image

Table III. Criteria for animal-level classification of sex.

A triplet was considered invalid when the combination of image-level outputs did not allow the carcass to be assigned to one of the three classes. This included conflicting combinations of predicted classes (i.e., female and entire male), as well as triplets in which no valid prediction was obtained from any of the three images (i.e., three null outputs).

Classification performance at image and animal levels was assessed using accuracy, precision, recall, and F1-score (Sokolova and Lapalme, 2009). Macro-averaged metrics were calculated as the unweighted mean across the three classes. Object-detection performance was assessed using mAP50 (IoU = 0.50) and mAP50-95 (IoU = 0.50-0.95) (Lin et al., 2014; Ultralytics, 2023).

Results

Image-level performance

The complete performance metrics are reported in Table IV, while the corresponding confusion matrix is shown in Figure 3A. Image-level classification achieved an overall accuracy of 97.5% (655 correct predictions out of 672 pictures; 95% Wilson CI: 96.0-98.4%). None of the entire male images was misclassified as female, and vice versa. All other errors involved castrated males, either as the true or predicted class. No null outputs occurred.

Metric	Entire male	Female	Castrated male	Overall/ Macro-average
Precision (%)	99.4	97.1	96.4	97.7
Recall (%)	97.8	97.9	96.8	97.5
F1-score (%)	98.6	97.5	96.6	97.6
Accuracy (%)	-	-	-	97.5
mAP50 (%)	-	-	-	94.4
mAP50-95 (%)	-	-	-	53.1

Table IV. Image-level performance of the YOLO11m model on the held-out test set. Precision, recall, and F1-score are reported for each class and as macro-averaged values. Accuracy represents overall classification accuracy. (655/672 correctly classified images). The metrics mAP50 and mAP50-95 refer to object-detection performance at an IoU threshold of 0.50 and averaged across IoU thresholds from 0.50 to 0.95, respectively.

Animal-level performance

At the animal level, 219 out of 224 test carcasses were correctly classified, corresponding to an overall accuracy of 97.8% (95% Wilson CI: 94.9–99.0%). Five carcasses (2.2%) were misclassified, while no triplet yielded an invalid classification. Class-specific and macro-averaged performance metrics are reported in Table V, and the corresponding confusion matrix is shown in Figure 3B. Representative examples of misclassifications are shown in Figure 4.

Metric	Entire male	Female	Castrated male	Overall/ Macro-average
Precision (%)	98.4	95.2	100	97.9
Recall (%)	100	100	94	98
F1-score (%)	99.2	97.6	96.9	97.9
Accuracy (%)	-	-	-	97.8

Table V. Animal-level performance based on triplet aggregation in the held-out test set. Precision, recall, and F1-score are reported for each class and as macro-averaged values. Overall accuracy was calculated over all 224 test triplets.

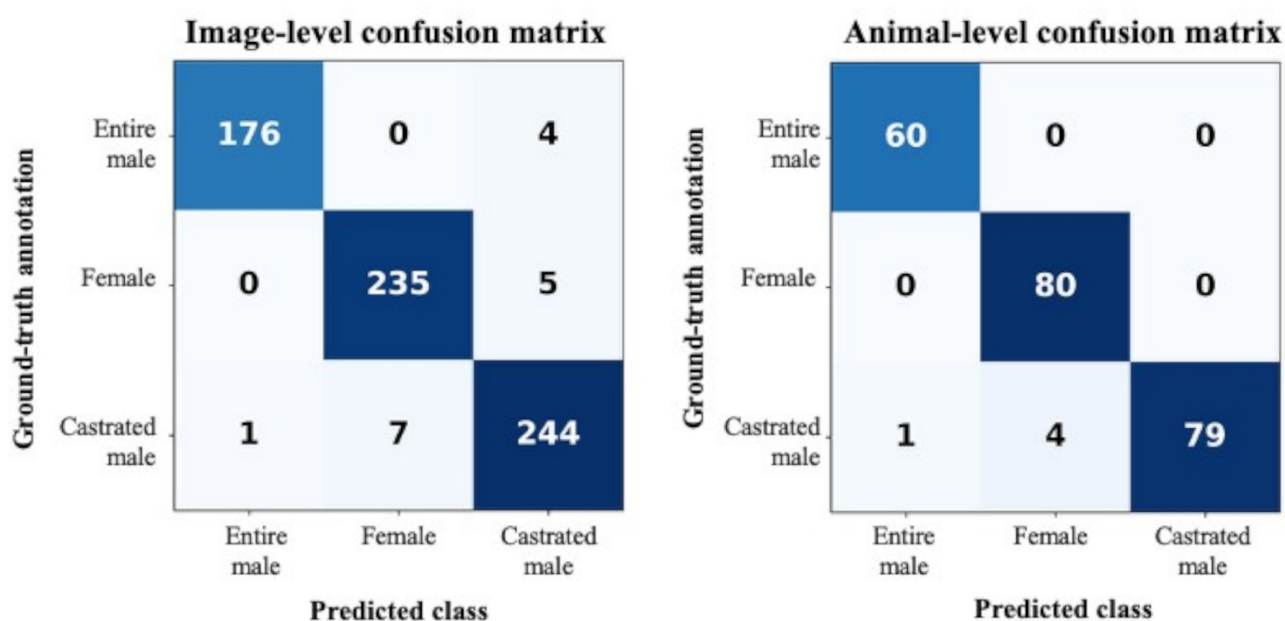


Figure 3. Confusion matrices for sex classification of pig carcasses at image and animal levels. Rows represent the sex class detected by investigators (“ground-truth annotation”), whereas columns show the sex class predicted by the deep learning-based model. Values indicate the number of images (image-level) or carcasses (animal-level) assigned to each class.

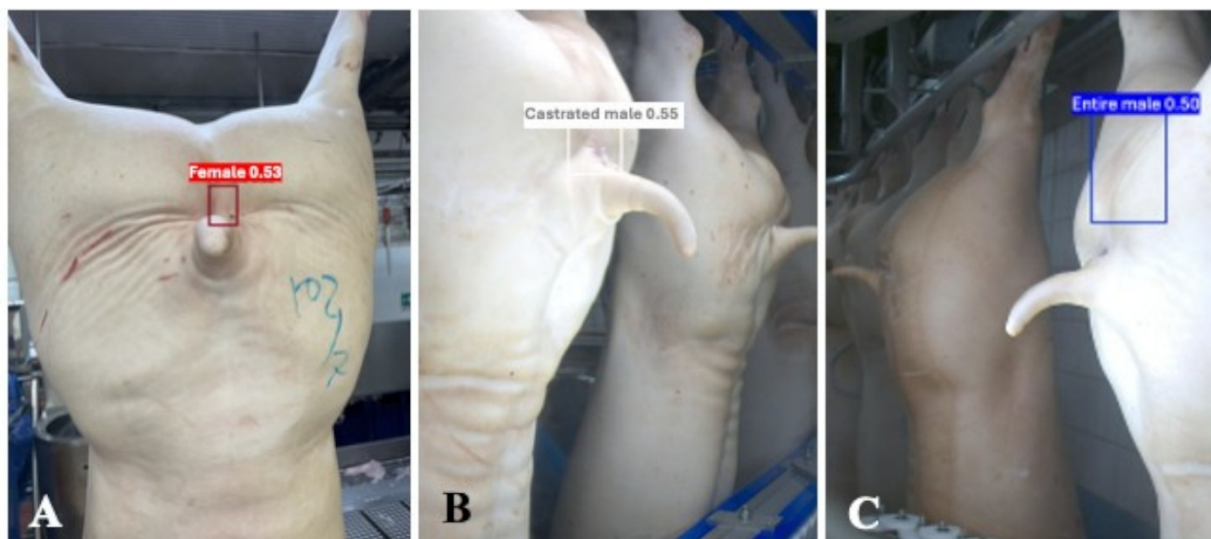


Figure 4. Misclassification of sex categories. A castrated male was incorrectly classified as female (A) because a skin fold/discolouration in the perineal region was misidentified as the vulva. An entire male was incorrectly classified as castrated male (B) because the scrotum was not correctly detected. Conversely, a castrated male was misclassified as an entire male (C) because the contour of the thigh was incorrectly recognised as the scrotum.

Discussion

Sex and castration status are relevant sources of biological and productive variation in pig production. Entire males generally show better feed efficiency and greater lean-tissue deposition, whereas surgical castration is associated with increased feed intake and fat deposition. These differences also extend to the technological and sensory properties of pork, including fat composition, intramuscular fat content and suitability for processing (Batorek et al., 2012; Bee et al., 2020; Čandek-Potokar et al., 2020; Škrlep et al., 2020).

The distinction among sex categories is particularly relevant in Europe, where surgical castration remains a controversial practice. It has traditionally been used primarily to prevent boar taint and reduce sexual and aggressive behaviour. However, the pain associated with the procedure raises important animal-welfare concerns and has stimulated the development of alternative strategies (Bonneau and Weiler, 2019; Squires et al., 2020). Among these is immunocastration, which substantially reduces boar-taint compounds while retaining some of the productive advantages of entire males (Batorek et al., 2012; Bee et al., 2020). Consequently, females, entire males, surgical castrates and immunocastrates coexist across European production systems, with marked differences among countries and production chains.

Overall, this deep learning-based method showed high classification performance at both single-image and animal levels. The comparatively low mAP50–95 (53.1%) likely reflects the poorly defined boundaries of the annotated regions and is of limited relevance for this classification task.

Most errors involved castrated males, particularly misclassification between castrated males and females. Notably, the aggregation rule (Table III) gives precedence to the detection of a vulva or scrotum, accounting for the lower recall of castrated males (94.0%) at the animal level.

Misclassifications may partly reflect the image-acquisition protocol, which was originally designed for tail assessment rather than sex classification. Consequently, the tail occasionally overlapped the vulva, making discrimination between females and castrated males more difficult. Increasing the size and variability of the training dataset should further improve the model's ability to discriminate among sex categories. Moreover, a slightly higher camera position could provide a clearer view of the perineal region and further improve classification performance. These adjustments, along with appropriate carcass positioning, could also minimise the occurrence of unsuitable images, which were relatively common and mainly associated with carcass rotation. The generalisability of this deep learning-based model to carcasses from other slaughterhouses, genetic types and image-acquisition set-ups remains to be assessed. Accordingly, the reported performance applies to images with adequate anatomical visibility, and acquired under the conditions of the three participating slaughterhouses; applicability to other slaughterhouses or image-acquisition settings requires further evaluation.

Future developments could extend the method beyond routine classification of sex categories. For instance, targeted training could enable the detection of atypical genital conditions, such as cryptorchidism and intersex conditions (Hunter and Greve, 1996).

Conclusion

In conclusion, the present study demonstrates the feasibility of deep learning-based sex classification of pig carcasses. Further optimisation of image acquisition and expansion of the training dataset may improve classification performance and potentially enable the automated detection of atypical or pathological conditions affecting the genital region. These findings should be interpreted within the acquisition conditions of the participating slaughterhouses and for carcass images providing adequate visibility of the relevant anatomical region.

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Ethical approval

Ethical approval was not required for the study involving animals in accordance with the local legislation and institutional requirements because ethical review and approval were waived for this study. Investigations were carried out on pigs regularly slaughtered according to the EU legislation. Slaughtering procedures were performed in strict compliance with respecting the European legislation on the protection of animals at the time of killing (European Community Council Regulation No. 1099/2009).

Conflict of interest

A.C.D. is CEO and founder of Farm4Trade s.r.l., an Italian tech company specialised in AI-based data and software solutions for the livestock and meat-production chain. R.D. is an employee, of Farm4Trade s.r.l., an Italian tech company specialised in AI-based data and software solutions for the livestock and meat-production chain. R.D. is an employee of Farm4Trade s.r.l.

The remaining author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

Conceptualisation: A.C.D., G.M., D.R., A.R. ; Methodology: M.D., A.C.D., R.D.; Formal analysis: M.D., R.D.; Investigation: M.D., B.A., G.M.; Writing original draft preparation: M.D., G.M.; Writing, review and editing: M.D., R.D., B.A., A.C.D., A.R., D.R., G.M.; Visualisation: M.D., G.M. ; Supervision: A.C.D.; Project administration: A.C.D.; Funding acquisition: A.C.D., G.M. All authors have read and agreed to the published version of the manuscript.

Data availability

The images included in this study were collected in commercial slaughterhouses under confidentiality agreements. Therefore, they are not publicly available and may be obtained from the corresponding author upon reasonable request, subject to the agreement of the slaughterhouses.

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References

- Batorek N., Čandek-Potokar M., Bonneau M. & Van Milgen J. (2012). Meta-analysis of the effect of immunocastration on production performance, reproductive organs and boar taint compounds in pigs. *Animal*, 6 (8), 1330-1338. doi: 10.1017/S1751731112000146.
- Bee, G., Quiniou, N., Maribo, H., Zamaratskaia, G., & Lawlor, P. G. (2020). Strategies to Meet Nutritional Requirements and Reduce Boar Taint in Meat from Entire Male Pigs and Immunocastrates. *Animals : an open access journal from MDPI*, 10(11), 1950. <https://doi.org/10.3390/ani10111950>.
- 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, 107934. <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 : an open access journal from MDPI*, 11(11), 3290. <https://doi.org/10.3390/ani11113290>.
- Bonneau, M., & Weiler, U. (2019). Pros and Cons of Alternatives to Piglet Castration: Welfare, Boar Taint, and Other Meat Quality Traits. *Animals : an open access journal from MDPI*, 9(11), 884. <https://doi.org/10.3390/ani9110884>.
- Bottacini, M., Scollo, A., Edwards, S. A., Contiero, B., Veloci, M., Pace, V., & Gottardo, F. (2018). Skin lesion monitoring at slaughter on heavy pigs (170 kg): Welfare indicators and ham defects. *PloS one*, 13(11), e0207115. <https://doi.org/10.1371/journal.pone.0207115>.
- Čandek-Potokar, M., Škrlep, M., Kostyra, E., Żakowska-Biemans, S., Poklukar, K., Batorek-Lukač, N., Kress, K., Weiler, U., & Stefanski, V. (2020). Quality of Dry-Cured Ham from Entire, Surgically and Immunocastrated Males: Case Study on Kraški Pršut. *Animals : an open access journal from MDPI*, 10(2), 239. <https://doi.org/10.3390/ani10020239>.
- D'Angelo, M., Sciota, D., Romano, A., Rosamilia, A., Guarnieri, C., Cecchini, C., Olivastri, A., & Marruchella, G. (2025). Detecting ear lesions in slaughtered pigs through open-source convolutional neural networks. *Porcine health management*, 11(1), 29. <https://doi.org/10.1186/s40813-025-00442-9>.
- De Luca, S., Zanardi, E., Alborali, G. L., Ianieri, A., & Ghidini, S. (2021). Abattoir-Based Measures to Assess Swine Welfare: Analysis of the Methods Adopted in European Slaughterhouses. *Animals : an open access journal from MDPI*, 11(1), 226. <https://doi.org/10.3390/ani11010226>.
- Eurostat. 2025a. EU livestock populations continued to decrease in 2024. Eurostat, European Commission, Luxembourg. <https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20250626-1> (accessed on 18 September 2026).
- Eurostat. 2025b. Key figures on the European food chain – 2025 edition. Publications Office of the European Union, Luxembourg. doi: 10.2785/8194502.
- FAO. 2025. World Food and Agriculture – Statistical Yearbook 2025. Food and Agriculture Organization of the United Nations, Rome. doi: 10.4060/cd4313en.
- Grandin T. (2017). On-farm conditions that compromise animal welfare that can be monitored at the slaughter plant. *Meat science*, 132, 52–58. <https://doi.org/10.1016/j.meatsci.2017.05.004>.
- Huanca-Marca, N. F., Estévez-Moreno, L. X., Espinosa, N. L., & Miranda-de la Lama, G. C. (2025). Assessment of pig welfare at slaughterhouse level: A systematic review of animal-based indicators suitable for inclusion in monitoring protocols. *Meat science*, 220, 109689. <https://doi.org/10.1016/j.meatsci.2024.109689>.

Hunter, R. H., & Greve, T. (1996). Intersexuality in pigs: clinical, physiological and practical considerations. *Acta veterinaria Scandinavica*, 37(1), 1–12. <https://doi.org/10.1186/BF03548114>.

Jocher G. & Qiu J. (2024). Ultralytics YOLO11, version 11.0.0 [computer software]. Ultralytics. <https://github.com/ultralytics/ultralytics> (accessed on 16 September 2026).

Kim, J., Kwon, Y. K., Kim, H. W., Seol, K. H., & Cho, B. K. (2023). Robot Technology for Pork and Beef Meat Slaughtering Process: A Review. *Animals : an open access journal from MDPI*, 13(4), 651. <https://doi.org/10.3390/ani13040651>.

Lin T. Y., Maire M., Belongie S., Hays J., Perona P., Ramanan D., Dollár P. & Zitnick C.L. (2014). Microsoft COCO: common objects in context. In *Computer Vision – ECCV 2014* (Fleet D., Pajdla T., Schiele B. & Tuytelaars T., eds), *Lecture Notes in Computer Science*, vol. 8693. Springer, Cham, 740–755. doi: 10.1007/978-3-319-10602-1_48.

Nguyen V. A. (2026). AnyLabeling: effortless AI-assisted data labeling [computer software]. <https://github.com/vietanhdev/anylabeling> (accessed on 16 September 2026).

Romano, A., Golunova, E., Marruchella, G., Capobianco Dondona, A., Bernabò, N., Del Negro, E., Pettinella, S. D., Naadland, S. S., Jensen, A. D., Alvseike, O. A., & Nagel-Alne, G. E. (2025). Automated detection and scoring of pleurisy in Norwegian slaughtered pigs: A field trial. *Food Control*, 178, Article 111514. <https://doi.org/10.1016/j.foodcont.2025.111514>.

Romano, A., Baghini, S., Capobianco Dondona, A., Bernabò, N., & Marruchella, G. (2026). Image-based assessment of tail docking and tail biting in slaughtered pigs across three European countries. *Frontiers in veterinary science*, 13, 1751411. <https://doi.org/10.3389/fvets.2026.1751411>.

Russell, B. C., Torralba, A., Murphy, K. P., & Freeman, W. T. (2008). LabelMe: A database and web-based tool for image annotation. *International Journal of Computer Vision*, 77(1–3), 157–173. <https://doi.org/10.1007/s11263-007-0090-8>.

Schimitzek, P. (2019). Device for optically identifying the sex of a slaughter pig (U.S. Patent No. 10,165,782 B2). U.S. Patent and Trademark Office. <https://patents.google.com/patent/US10165782B2> (accessed on 18 September 2026).

Škrlep, M., Tomašević, I., Mörlein, D., Novaković, S., Egea, M., Garrido, M. D., Linares, M. B., Peñaranda, I., Aluwé, M., & Font-I-Furnols, M. (2020). The Use of Pork from Entire Male and Immunocastrated Pigs for Meat Products-An Overview with Recommendations. *Animals : an open access journal from MDPI*, 10(10), 1754. <https://doi.org/10.3390/ani10101754>.

Sokolova, M., & Lapalme, G. (2009). A systematic analysis of performance measures for classification tasks. *Information Processing & Management*, 45(4), 427–437. <https://doi.org/10.1016/j.ipm.2009.03.002>.

Squires, E. J., Bone, C., & Cameron, J. (2020). Pork Production with Entire Males: Directions for Control of Boar Taint. *Animals : an open access journal from MDPI*, 10(9), 1665. <https://doi.org/10.3390/ani10091665>.

Tholen, J., Kirse, A., Voß, A., Schulze Althoff, G., Strotkötter, L., Kreienbrock, L., & Upmann, M. (2026). Detection of carcass contamination using video image analysis during industrial pig slaughter. *Frontiers in Food Science and Technology*, 6, Article 1698416. <https://doi.org/10.3389/frfst.2026.1698416>.

Ultralytics. (2023). YOLO performance metrics. Ultralytics documentation. <https://docs.ultralytics.com/guides/yolo-performance-metrics/> (accessed on 16 September 2026).

van Staaveren, N., Doyle, B., Manzanilla, E. G., Calderón Díaz, J. A., Hanlon, A., & Boyle, L. A. (2017). Validation of carcass lesions as indicators for on-farm health and welfare of pigs. *Journal of animal science*, 95(4), 1528–1536. <https://doi.org/10.2527/jas.2016.1180>.