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Computer Vision Techniques to Support Animal Welfare And Veterinary Public Health

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ABSTRACT

The application of artificial intelligence in animal husbandry and veterinary medicine is gaining increasing attention. Using computer vision systems for assessing animal welfare seems promising in the latter field. The Istituto Zooprofilattico Sperimentale delle Venezie (IZSVe) is developing systems for assessing animal welfare based on innovative technological tools leveraging deep learning algorithms for complex computer vision tasks. These tools enable the automation of data processing, significantly increasing efficiency and scalability. By replacing labor-intensive manual analysis, the system allows for the rapid processing of large volumes of data, ensuring the extraction of critical information that would otherwise be lost or impractical to obtain through conventional methods.

Keywords: Computer Vision, YOLO, DeepLabCut, Precision Livestock Farming, Animal Welfare, Laying Hens, Swine.

1. BACKGROUND

In recent years, computer vision systems have extended to several areas, including livestock science and veterinary medicine. More specifically, computer vision techniques could be applicable in veterinary public health sectors as a valuable support in the routine official inspections. The application of this technology makes it possible to facilitate, speed up, and standardize the activities carried out daily by trained personnel. Moreover, their use can be applied to all stages of the production chain, from breeding to slaughter and subsequently to the assessment of the quality and safety of animal products intended for human consumption.

Animal welfare assessment is an area that benefits significantly from advancements in technology and data analysis. In Europe, awareness of animal welfare issues has risen sharply in recent years, accompanied by the enactment of various EU regulations protecting animal welfare. Several European regulatory references govern specific structural and management requirements for each species at all stages of production (on farm, during transportation and at the abattoir). Italy, over time, has incorporated these regulations and adapted to European requirements by issuing specific checklists for animal welfare control made public online in the ClassyFarm system [1] by the National Reference Centre for Animal Welfare (CReNBA).

An important part of welfare checks carried out on farms involves the evaluation of so-called animal-based measures (ABMs), measures carried out directly on the animals that indicate the impact that structural or management elements of the farm have on the welfare of the animals themselves, even when environmental conditions are not found to be compliant. The assessment of ABMs requires appropriately trained personnel, sufficient time, and cannot be effectively conducted through isolated spot checks. Evaluating ABMs on the farm is challenging, so the focus is shifting towards evaluations that can be carried out in more standardized contexts, such as the slaughterhouse. For these reasons, the IZSVe, within the framework of two research projects, has recently developed and applied these techniques to assess animal welfare in different contexts and species to identify lesions in animals that can be traced back to improvable farm welfare situations.

2. WELFARE ASSESSMENT

The first experiment was conducted at the slaughterhouse to assess keel bone lesions in laying hens at the end of lay period [2]. Slaughterhouses represent an important public health safeguard thanks to the constant surveillance of zoonotic agents by the Veterinary Services. However, they are also a valuable epidemiological observatory for the large-scale study of numerous animal health and welfare issues.

In Northeastern Italy, poultry breeding is highly developed, with laying hen rearing standing out as one of the most critical sectors for animal welfare due to its long production cycles. Laying hens often arrive at the slaughterhouse in compromised physiological conditions and with manifestations of malformations linked to the rearing phase [3]. Amongst these, one of the main indicators of poor welfare on the farm is keel bone lesions (i.e. fractures and deviations), a multifactorial problem that can reach high frequencies in laying hens at the end of the production cycle. Keel bone lesions can be assessed directly on the farm or slaughterhouse. The latter option is more promising and more readily applicable as the slaughterhouse processes a large number of animals daily without the need for additional handling, hence avoiding further stress for the animals themselves. Therefore, surveillance on such high numbers could benefit significantly through technological innovation and automation and could facilitate the task of the official veterinarian in visually assessing lesions in carcasses in production plants that now work at a breakneck pace.

Pig farming faces significant animal welfare challenges as well. Among these, one of the most concerning is tail-biting, a complex, multifactorial problem typical of the weaning phase [4] that reflects a general condition of discomfort on the farm. In addition to its implications for animal welfare, this phenomenon also negatively impacts the productivity of the farm, with economic consequences for the farmers themselves [5], such as the risk of bitten animals being eliminated early due to complications. As a result, tail docking has been adopted in commercial farms to prevent and manage tail biting. In the EU, tail docking is not routinely allowed for all pigs, promoting the breeding of long-tailed pigs [6]. On-farm image analysis techniques can be applied to identify and prevent this phenomenon and develop an alert system.

3. METHODOLOGY

To assess animal welfare through computer vision, we developed deep learning-based approaches leveraging state-of-the-art frameworks. Specifically, we employed DeepLabCut [7] for pose estimation tasks and YOLO [8] for object detection and classification. Given the high computational demands of these tasks, we utilized a cloud-based infrastructure, deploying our models on an Azure virtual machine equipped with an NVIDIA A100 GPU. This setup ensured the necessary computational power to handle large datasets and accelerate model training and inference.

3.1. Methodology Applied to Welfare Assessment In Laying Hens

A YOLOv11 model was trained to detect keel bones from video footage of laying hens on a conveyor belt at the slaughterhouse, with the aim of assessing keel bone quality. The model also classified keel bones into three categories (Figure 1): 0 (intact keel bone), 1 (visibly damaged keel bone), and NC (unclassifiable keel bone due to factors such as angle, lighting conditions, or occlusions). The dataset used for training consisted of approximately 600 annotated images. Each image was manually labeled by a team of three veterinarians using Roboflow [9], with bounding boxes and corresponding scores indicating the keel bone status. Each image contained an average of 4–5 keel bone instances, resulting in a rich dataset of annotated regions. To expand the training set and improve model

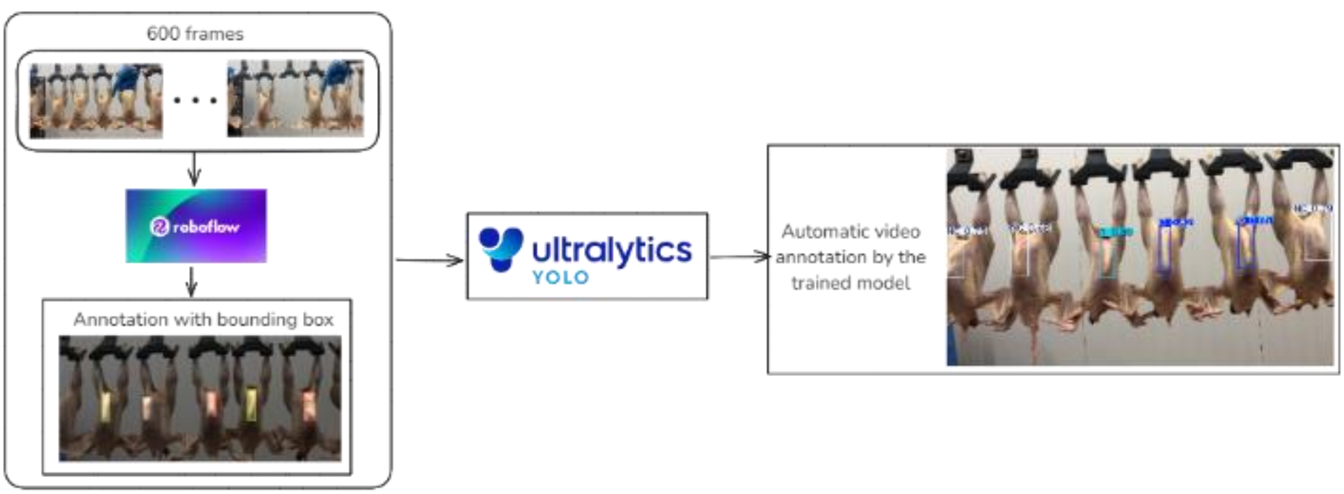

Figure 1. Workflow of keel bone detection and classification using deep learning. A dataset of 600 video frames was annotated with bounding boxes in Roboflow. The labeled data were then used to fine-tune a YOLOv11 model, which was subsequently deployed to perform automated keel bone detection and classification in video footage.

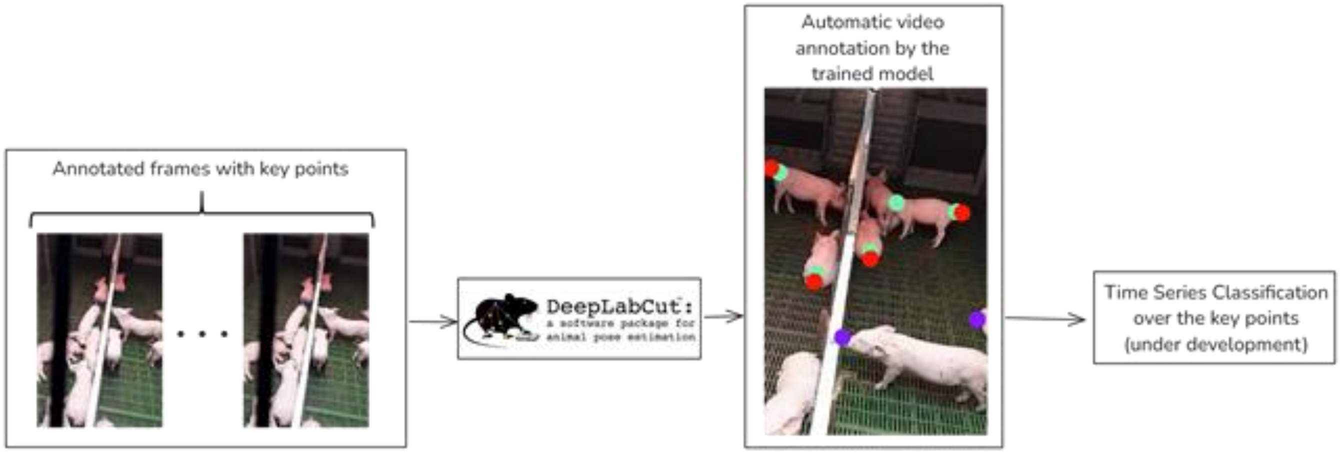

Figure 2. Workflow for detecting tail-biting behavior using deep learning-based pose estimation. Frames were annotated with key points and used to train a DeepLabCut model for automatic pose estimation in video footage. The extracted key points will be used in a future phase for time series classification to analyze movement patterns and improve tail-biting behavior detection.

generalization, data augmentation techniques were applied using the Albumentations library [10]. Augmentations included random rotations, flips, brightness and contrast adjustments, effectively increasing the dataset size to approximately 1,400 training samples. The labeled and augmented data were then used to fine-tune a pre-trained YOLOv11 model on this specific dataset, resulting in a model capable of performing real-time detection and classification over a video stream.

3.2. Methodology Applied to Welfare Assessment in Swine

The project aims to develop a framework capable of detecting tail-biting behavior and, in a potential later phase, identifying the biting pig through automatic ear tag recognition. We are developing a deep learning-based pose estimation system to detect tail-biting behavior by analyzing pigs' body posture and interactions within the enclosure (Figure 2). For the initial development of the pose estimation model, approximately 300 frames were manually annotated. These frames were extracted from four different videos recorded under real-world farming conditions, each captured from slightly different angles to maximize variability and improve model generalization. The videos were recorded at a resolution of 4K to preserve spatial detail, with a frame rate of 4 frames per second (fps). This relatively low frame rate was chosen deliberately to significantly reduce the video file size, enhancing data portability without compromising the quality of the movement analysis. Once the pose estimation model is fully developed, a time series classification approach will be explored to analyze movement patterns over time and improve the detection of biting events. Future developments may also address individual recognition as a separate challenge. This task remains particularly complex due to the recording setup: the enclosure is relatively small and low, preventing overhead shots at a 90-degree angle. Additionally, since this is a real-world scenario, each pen contains approximately 35 pigs, making individual recognition significantly more difficult compared to similar studies [11].

4. CONCLUSION AND FUTURE DEVELOPMENTS

Developing and implementing computer vision systems applied to welfare assessment can provide valuable support to the official veterinarian. Especially in the case of assessments carried out directly at the slaughterhouse, it is possible to identify those batches that present poor welfare conditions and address the competent authorities towards targeted on-farm checks for those more critical situations found in order to improve welfare conditions or promote those breeding realities that are more virtuous. Moreover, the automatic and standardized analysis of thousands of images could be exploited in scientific research for animal welfare or implemented in veterinary inspection activities to identify pathologies that exclude animal products from human consumption.
Developing computer vision systems in commercial husbandry settings presents significant challenges, particularly under non-experimental conditions. Detecting tail-biting in pigs is complex due to excessive crowding in pens, which makes accurate pose estimation difficult. An even more significant challenge is individual recognition, as low video resolution, crowding, and suboptimal camera angles significantly hinder the readability of ear tags. However, implementing computer vision could facilitate early detection of tail-biting behavior, and when combined with reliable individual recognition, it may also help identify the responsible animals.

5. ACKNOWLEDGEMENTS

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