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Editorial

Recent Advancements in Precision Livestock Farming

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The increasing global demand for sustainably sourced animal-derived food has prompted the development and application of smart technologies to address environmental, economic, and societal concerns, resulting in precision livestock farming (PLF) applications. PLF can be defined as "individual animal management by continuous real-time monitoring of health, welfare, production/reproduction, and environmental impact" [1]. This approach includes the implementation of digital tools, sensors, and automation technologies applied with different degrees of integration [2–4]. PLF can provide farmers with continuous, contactless, and objective data collection, allowing for the detection of small but significant variations in behavioural patterns or other significant parameters, greatly improving farmers' decision management and resource use efficiency [5].

The focal point of this Special Issue, "Recent Advancements in Precision Livestock Farming", delves into this subject matter from multiple perspectives, aiming to provide novel insights, current challenges, and future trends for the sustainable application of PLF approaches and systems.

Researchers across Asia and Europe have contributed 11 papers (10 research and 1 review article) published in this issue. They cover a wide range of aspects related to the performance modelling of PLF approaches, such as animal body measurement systems and automation in livestock environments.

Several authors reported on PLF approaches with the aim of measuring and predicting animal body parameters to improve the maintenance of animal health and to maximise production efficiency.

In pig production, Yang et al. [6] implement an optimised system for determining the shipping schedule for pigs with a predictive model that uses machine learning based on a large amount of data. Such prediction is achieved using a machine-learning model that considers the weight gain trend pattern of abdominal fat-forming pigs to predict weight, and eventually allows for the definition of the optimal shipping time.

Similarly, Preethi et al. [7] developed an Artificial Neural Network (ANN) model to predict the body weight of Landlly piglets at different growth stages based on linear body measurements and compared it with non-linear regression models. The results of the ANN models were comparable to those given by the non-linear regression models at all growth stages.

Moreover, Li et al. [8] introduced a hybrid CNN-ViT (Vision Transformer, ViT) model for measuring sows' backfat thickness (BF). The model was tested on seven groups of pregnant sows (106 animals in total). The results gave evidence of the high performance of the CNN-ViT, with a Mean Absolute Error MAE = 0.83 mm, a Root Mean Square Error RMSE = 1.05 mm, a Mean Absolute Percentage Error MAPE = 4.87%, and a coefficient of

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determination $R^2 = 0.74$. Finally, Hu et al. [9] proposed and evaluated a novel curve skeleton extraction method for point clouds. The extracted skeleton allows for the evaluation of a pig's posture, which can assist in selecting data suitable for body size measurements.

Also within the pig sector, a new interesting application of pig face recognition was reported by Wang et al. [10]. This study establishes an improved ResNAM network as a backbone network for pig face feature extraction by combining an NAM (normalisation-based attention module) attention mechanism and a ResNet model to probe non-contact open-set pig face recognition. The experimental results highlighted an accuracy of 95.28%, which is over 2% higher than a human face recognition model.

Regarding beef cattle production, Ruchay et al. [11] described a new model for predicting live weight based on augmenting three-dimensional clouds through flat projections and image regression with deep learning. Tests on farm conditions reported an accuracy as high as 91.6% on weight measurements based on the proposed model. Furthermore, a highly efficient and automatic method was developed by Li et al. [12] to measure beef cattle's body dimensions based on the reconstructed three-dimensional point cloud. The results showed that the errors of calculated body dimensions, i.e., the oblique length, height, width, abdominal girth, and chest girth, were always lower than 3%. The proposed algorithm gave evidence of the negligible influence of the different postures of beef cattle.

Regarding the dairy sector, the importance of cow oestrus behaviour detection is evident in the contribution by Wang et al. (2022) [13]. The authors proposed a cow oestrus detection method based on the improved YOLOv5 to improve the inference speed and accuracy in natural scenes. The experimental results show that the average accuracy of the improved model was 94.3%, the precision was 97.0%, and the recall was 89.5%: such performance was shown to be higher than those of mainstream models such as YOLOv5, YOLOv3, and Faster R-CNN.

In the field of dairy production, Pavkin et al. [14] presented an algorithm for automatic positioning and a mobile remote-control system for a feed-pushing robot on a dairy farm. This research made it possible to eliminate the inductive sensors from the system and reduced the labour required to assemble the feed alley's contour wire.

In the poultry sector, Jia et al. [15] systematically reviewed the key techniques for the in ovo sexing of chicken eggs before hatching, and presented recent research on molecular-based, spectral-based, acoustic-based, morphology-based, and volatile organic compound (VOC)-based technologies. To identify the chicken's sex, an identification model was developed by Jia et al. [16] based on an improved YOLOv7 deep learning algorithm. The results highlighted a mean average precision of 88.79%.

The presented works contribute towards solving issues regarding the development, research, and optimisation of engineering innovations in precision livestock farming systems. The reported results addressing cattle, pig, and poultry are of interest to specialists and scientists involved not only in research but also in daily farm support and management.

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