Multi-Object Keypoint Detection and Pose Estimation for Pigs

Qinghua Guo[1], Dawei Pei[1], Yue Sun[1,3], Patrick P. J. H. Langenhuizen[1], Clémence A. E. M. Orsini[2], Kristine Hov Martinsen[4], Øyvind Nordbø[4], J. Elizabeth Bolhuis[2], Piter Bijma[2] and Peter H. N. de With[1]

[1] *Department of Electrical Engineering, Eindhoven University of Technology, Eindhoven, The Netherlands*

[2] *Department of Animal Sciences, Wageningen University & Research, Wageningen, The Netherlands*

[3] *Faculty of Applied Science, Macao Polytechnic University, Macao Special Administrative Region of China*

[4] *Norsvin SA, Hamar, Norway*

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Abstract: Monitoring the daily status of pigs is crucial for enhancing their health and welfare. Pose estimation has emerged as an effective method for tracking pig postures, with keypoint detection and skeleton extraction playing pivotal roles in this process. Despite advancements in human pose estimation, there is limited research focused on pigs. To bridge this gap, this study applies the You Only Look Once model Version 8 (YOLOv8) for keypoint detection and skeleton extraction, evaluated on a manually annotated pig dataset. Additionally, the performance of pose estimation is compared across different data modalities and models, including an image-based model (ResNet-18), a keypoint-based model (Multi-Layer Perceptron, MLP), and a combined image-and-keypoint-based model (YOLOv8-pose). The keypoint detection branch achieves an average Percentage of Detected Joints (PDJ) of 48.96%, an average Percentage of Correct Keypoints (PCK) of 84.85%, and an average Object Keypoint Similarity (OKS) of 89.43%. The best overall accuracy obtained for pose estimation is 99.33% by the YOLOv8-pose model, which indicates the superiority of the joint image-keypoint-based model for pose estimation. The conducted comprehensive experiments and visualization results indicate that the proposed method effectively identifies specific pig body parts in most monitoring frames, facilitating an accurate assessment of pig activity and welfare.

1 INTRODUCTION

Since pigs are common livestock animals worldwide, their health and welfare are crucial in shaping the societal and economic landscape of the pig breeding industry. To mitigate the risk of disease and injury in pigs (Racewicz et al., 2021), automated monitoring systems have emerged as essential tools for assessing pig health and welfare (Yang and Xiao, 2020). These systems are typically based on video surveillance offering non-invasive, real-time monitoring, which significantly reduces the need for labor-intensive manual inspections. In particular, this approach facilitates the detection of activity levels, postural changes, and behavioral patterns, which are often indicative of animal health and welfare status. Accurately identifying these postures allows the monitoring and analysis of interactions between pigs, enabling the early detection and prevention of negative social behavior, such as aggression or competition for resources. Such analysis can contribute to improved disease prevention and overall enhancement of animal welfare (Volkmann et al., 2022; Zhuang et al., 2018).

The growing demand for animal monitoring in commercial farms has led to the development of various methodologies related to animal pose estimation. These methodologies include wearable and physical sensors, as well as camera-based monitoring systems that leverage advanced computer vision techniques (Lee et al., 2016; Yang and Xiao, 2020). However, the application of physical sensors presents several practical challenges, such as the installation and maintenance of these devices. Additionally, the effectiveness of such sensors is influenced by the individual characteristics of different farms, including spatial layout, animal density, and environmental conditions. In contrast, video-based solutions have drawn significant attention because of their contactless, low-cost, scalable, and sustainable attributes. These systems leverage advanced computer vision techniques to analyze animal behavior without direct physical interaction, which not only minimizes stress on the animals but also facilitates continuous and automated monitoring. Numerous studies have investi-

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gated video-based monitoring techniques applicable to human datasets. In contrast to human pose estimation, pig farming frequently necessitates the monitoring of large groups in shared environments. This requirement underscores the importance of accurately estimating the poses of multiple animals, even under challenging conditions where occlusion caused by the camera perspective and pig activity may occur.

Related works: As computer vision techniques based on deep learning garner increasing attention, related applications within agriculture, e.g. pig monitoring on commercial farms, are becoming more prevalent (Yang and Xiao, 2020). Implementing pose estimation for pigs using machine learning can involve various types of features, including bounding boxes, keypoints, and segmentation contours, each serving as critical inputs for neural networks. The selection of specific features is crucial for achieving effective and efficient model performance.

Wutke *et al.* constructed a custom convolutional neural network using keypoints to detect and track pigs (Wutke et al., 2021). They highlighted the advantages of using keypoints compared to bounding boxes, noting that while bounding boxes provide positional information, they fail to capture interactions driven by specific body parts. It demonstrated that keypoints can convey more detailed feature information than bounding boxes, thereby enhancing the effectiveness of pose estimation models in agricultural applications.

Keypoint data is a widely used input for machine learning in pose estimation tasks. However, compared to its extensive use in human-related research, there is only a limited number of studies focused on animal keypoint detection. Notable examples from human pose estimation literature include OpenPose (Cao et al., 2019), AlphaPose (Fang et al., 2022), and You Only Look Once (YOLO) Version 8 (Jocher et al., 2023). OpenPose is designed for human pose estimation in multi-object scenarios, utilizing skeleton and keypoint information to optimize network depth (Cao et al., 2019). AlphaPose employs a top-down approach to achieve pose estimation (Fang et al., 2022), that begins with bounding-box detection, followed by the prediction of keypoints, where human poses are derived from features extracted from the bounding boxes. In contrast, bottom-up approaches directly detect keypoints for the entire frame and subsequently construct skeletons using these detected keypoints for pose estimation. While OpenPose exhibits approximately twice the inference speed of AlphaPose (Cao et al., 2019), AlphaPose achieves a higher accuracy, reaching 57.7% on the COCO-WholeBody dataset compared to OpenPose's accuracy of 33.8% on the same dataset. However, in terms of inference speed and efficiency, both OpenPose and AlphaPose are computationally expensive compared to YOLOv8-pose, which is designed with efficiency and execution speed. The efficient architecture of YOLOv8-pose further enhances its ability to handle multiple objects simultaneously, making it a competitive option for high-speed pose estimation.

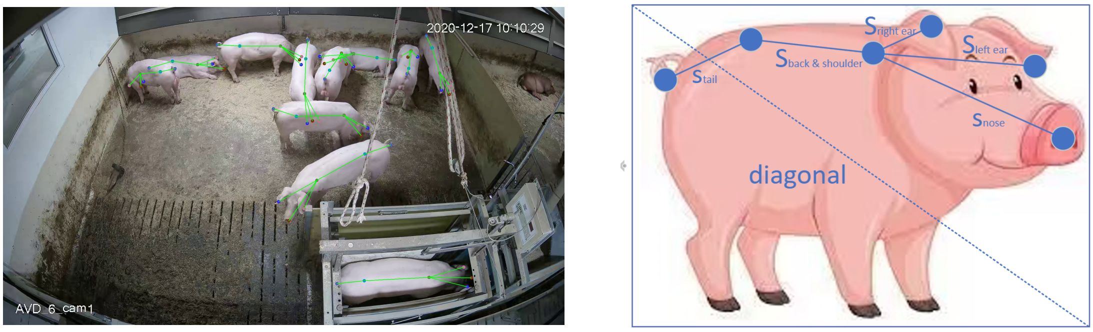
Proposed research direction: In this work, we propose a keypoint detection algorithm specifically designed for pigs to facilitate the performance of posture recognition for pigs. We utilize YOLOv8-pose as the backbone framework for the keypoint detection (Jocher et al., 2023). As a result of the existing limitations in animal research, we re-define the evaluation metrics that are tailored to human pose estimation to pigs such that the model performance can be assessed comprehensively. Furthermore, we employ the YOLOv8-pose model for posture recognition of pigs, demonstrating that the integration of the keypoint features with the image features significantly enhances the performance of pose estimation. This work yields the following key contributions of keypoint detection and pose estimation for pigs.

- The performance of the following pose estimation methods is benchmarked: (1) ResNet-18 (image-based method), (2) Multi-layer Perceptron (MLP) (keypoint-based), (3) YOLOv8-pose (combining image and keypoint features).
- Suitable evaluation metrics are re-defined specifically for animals, which are sourced from research on human pose estimation. The SOTA detection model YOLOv8-pose is implemented to perform multi-object keypoint detection of pig body parts.
- Two pig datasets are specifically constructed for proper validation and based on manual annotation: (1) The Norwegian dataset provides the ground-truth information in bounding boxes, segmentation contours, keypoints, and skeleton information, and (2) The German dataset offers ground-truth information in bounding boxes, keypoints, skeletons, and posture labels.

2 METHODS

2.1 Data Description

The proposed work is based on two collected video datasets, called the Norwegian and German datasets, which are used for keypoint detection and pose estimation, respectively.



(a)

(b)

Figure 1: Localization information for six keypoints, indicating the tail, back, shoulder, nose, left ear, and right ear. (a) Sample frame showing the annotated keypoints along with the corresponding skeleton, highlighted in green. (b) Visualization of the criteria used for pig keypoint annotation.

The Norwegian dataset utilizes videos which are captured from the Genes2Behave project (321409 - IPNÆRINGSLIV20, G2B). This dataset comprises 1,191 randomly selected frames from Norsvin SA, with an image resolution of 2,688×1,520 pixels. A sample frame with visualized keypoints and skeletons is shown in Fig. 1(a). The manual annotation of Norwegian data is in the COCO format, covering the bounding box, segmentation contour, keypoints, and skeleton information. There are 6 keypoints annotated for each pig, i.e., tail, back, shoulder, nose, left ear, and right ear. Fig. 1(b) provides an illustrative example of the annotated keypoints and their corresponding skeletons.

The pose estimation utilizes the German dataset, which comprises five videos containing 876 frames. Each frame is captured at a resolution of 1280×720 pixels. Annotation within the dataset is in the COCO format, including the bounding box, keypoints, and 3 posture class labels, i.e., lying, sitting, and standing. The postures are defined according to an ethogram developed by animal scientists at Wageningen University & Research. Standing is labeled if pigs are supported by three or four stretched legs. The posture is labeled as lying if pigs are lying centrally or on a side, potentially with legs tucked underneath the body. If the pig body is supported by hindquarters while the front legs are stretched, the posture is defined as sitting.

2.2 Keypoint Detection

2.2.1 Network Architecture Overview

In the YOLOv8-pose architecture, the backbone network is constituted by the Cross-Stage Partial Network (CSPNet), while the neck network is represented by the combination of the Feature Pyramid Network and the Path Aggregation Network (FPN-PAN), and the head network is implemented as PANet. The CSPNet, which is based on DenseNet, employs a cross-stage hierarchy and is characterized by reduced memory consumption and rapid inference speed (Wang et al., 2020). The FPN-PAN architecture uses both top-down and bottom-up approaches for up-sampling and down-sampling, enhancing feature extraction through increased diversity and completeness (Niu and Yan, 2023). Furthermore, YOLOv8-pose adopts a decoupled head structure for object detection, utilizing distinct branches for object classification and bounding-box prediction (Niu and Yan, 2023).

Loss functions: The weighted loss is shown in Fig. 2, the YOLOv8-pose model improves its predictions for both object detection and pose estimation by minimizing the total loss. The localization loss measures how well the predicted bounding boxes fit the ground-truth boxes using the Complete Intersection over Union (CIoU) loss. The classification loss uses the Binary Cross-Entropy (BCE) loss to predict the object loss. The objectness loss indicates how confident the model is that a particular box contains an object, YOLOv8-pose uses BCE loss with Logits for the objectness prediction. The keypoint/pose loss measures the Mean Squared Error (MSE) loss between the predicted and ground-truth coordinates of each keypoint.

2.2.2 Evaluation Metrics

The field of keypoint detection for pigs currently lacks standardized evaluation metrics tailored specifically for animal subjects, since most existing metrics are designed primarily for human data. Drawing inspiration from SOTA methods used in human keypoint detection, we re-define several evaluation metrics to

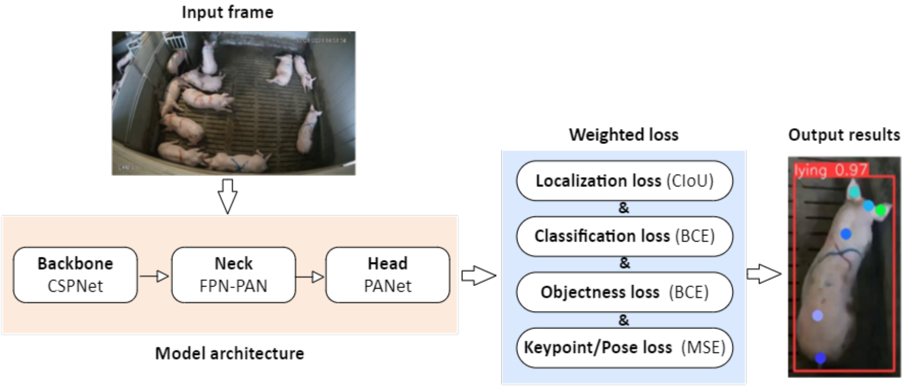


Figure 2: Joint system of keypoint detection and pose estimation introducing model architecture and loss calculation, which contains the YOLOv8-pose as the baseline model.

adapt them to pig-specific data (Lin et al., 2014; Toshev and Szegedy, 2014).

In this study, we employ the following evaluation metrics to assess the performance of keypoint detection algorithms: (1) Percentage of Detected Joints (PDJ), (2) Percentage of Correct Keypoints (PCK), and (3) Object Keypoint Similarity (OKS). For all three metrics, a higher value indicates the improved keypoint detection performance. Fig. 1(b) illustrates the keypoint layout and corresponding skeletons connecting these keypoints. The definitions of these metrics are as follows.

The Percentage of Detected Joints (PDJ) is specified by

$$P_{\mathrm{DJ}} = \frac{\sum_{i=1}^{n} \mathrm{Bool}(d_i < 0.05 \cdot d_{\mathrm{diagonal}})}{n}, \tag{1}$$

where n represents the total number of keypoints in a frame, parameter d_i denotes the Euclidean distance between the i_{th} predicted keypoint and its corresponding ground-truth keypoint, and $d_{diagonal}$ indicates the diagonal length of the bounding box (Toshev and Szegedy, 2014). The function Bool$(\cdot)$ returns a unity value if the criterion in the argument is satisfied, otherwise it is zero.

Similar to the PDJ, the Percentage of Correct Keypoints (PCK) is specified by

$$P_{\mathrm{CK}} = \frac{\sum_{i=1}^{n} \mathrm{Bool}(d_i < 0.5 \cdot s_i)}{n}, \tag{2}$$

where parameter s_i is the length of the i_{th} skeleton, replacing the diagonal length of the bounding box used in the PDJ calculation. Because the pig movement is undirected, the center of its body is not always relevant to the diagonal of the bounding box. In this case, the longest skeleton between keypoints of body parts is more relevant. Thus, as shown in Fig. 1(b), the skeleton length between back and shoulder keypoints is selected as the value of s_i, see (Insafutdinov et al., 2016).

Finally, the Object Keypoint Similarity (OKS) is specified by

$$P_{\mathrm{OKS}} = exp(-\frac{d_i^2}{2A \cdot k_i^2}), \tag{3}$$

where A represents the area of the object segment, and k_i is a coefficient assigned to weigh each keypoint. It should be noted that there is currently no established k_i specific to pigs. To address this omission, we utilize the coefficients k_i derived from the human skeleton in the COCO dataset, more specifically $k_i = [0.089, 0.107, 0.079, 0.026, 0.035, 0.035]$ for the tail, back, shoulder, nose, left ears, and right ears, respectively. Given that these k_i values are computed from human data, we re-calibrate the coefficients using the same method to derive the values for k_i for the pig dataset, resulting in $k_i = [0.464, 0.429, 0.342, 0.482, 0.485, 0.482]$, see (Lin et al., 2014). These coefficients are specifically computed from the validation set. The k_i from the pig dataset is specified by

$$k_i = 2\sqrt{\mathbb{E}[d_i^2/A]}, \tag{4}$$

where A denotes the object segment area, parameter $\mathbb{E}[\cdot]$ represents statistical expectation (Lin et al., 2014).

2.3 Pose Estimation

2.3.1 Network Architecture Overview

To our knowledge, there is limited research investigating the influence of combining keypoint features and image features on the performance of pig pose estimation. In the context of classification of human behaviors, the Multi-layer Perceptron (MLP) model is capable of utilizing only keypoint data to classify human postures (Rosenblatt, 1958). ResNet classifies human postures by extracting information from the pixels within the bounding box (He et al., 2016). The YOLOv8 model computes multi-object poses that are based on both keypoint and image features to individually assess the posture of each object in every frame (Jocher et al., 2023). This study aims to investigate the efficacy of combining image features and keypoint features in pose estimation tasks. To this end, we conduct a comparative analysis employing three distinct feature-based models: (1) the ResNet-18 model (image-based), (2) the MLP model (keypoint-based), and (3) the YOLOv8 - Pose estimation model (YOLOv8-pose) (combined features of image and keypoints).

In this research, the ResNet model serves as an image-based strategy for classification, with images containing multiple pigs, serving as the input data. We adopt the ResNet-18 model for its flexibility in adjusting the depth of the architecture, which is beneficial for our specific problem. Additionally, the ResNet-18 model capacity for model generalization is suitable for deploying it in our study (He et al., 2016).

The Multi-layer Perceptron (MLP) model represents a conventional neural network architecture that employs hidden layers with activation functions to facilitate decision-making for classification tasks. In this study, the MLP model serves as a keypoint-based method, where the input comprises of a 12-dimensional vector representing a set of keypoints. We select the MLP model for this application because of its scalability, particularly given that our dataset is relatively small. The MLP architecture allows for customizing the model size to align with our limited dataset (Rosenblatt, 1958).

The YOLOv8-pose network architecture for pose estimation is the same as employed for keypoint detection, which is introduced in Section 2.2.1.

2.3.2 Evaluation Metrics

To evaluate the performance of the posture recognition model, we consider the problem as a classification task. The overall accuracy provides a general sense of performance, calculated as the ratio of correctly predicted instances to the total number of instances. This accuracy A_{cc} is specified by

$$A_{\mathrm{cc}} = \frac{N_{\mathrm{TP}} + N_{\mathrm{TN}}}{N_{\mathrm{TP}} + N_{\mathrm{TN}} + N_{\mathrm{FP}} + N_{\mathrm{FN}}}, \tag{5}$$

where N_{TP} denotes the number of true positives (TP), and N_{TN} is the number of true negatives (TN). Likewise, FP stands for false positives and FN for false negatives.

In addition to the overall accuracy, we use recall as a key metric for each category, which measures the model's ability to measure the ratio between the amount of correct detections and the total number of detections. Hence, the recall R_{c} is specified by

$$R_{\mathrm{c}} = \frac{N_{\mathrm{TP}}}{N_{\mathrm{TP}} + N_{\mathrm{FN}}}, \tag{6}$$

which identifies all relevant instances, particularly in scenarios where class imbalance exists.

3 EXPERIMENTAL RESULTS

In this section, there are two separate subsections for keypoint detection and pose estimation.

3.1 Keypoint Detection

The results are divided into three descriptions, first the outline of the dataset, then the implementation details, and finally the results.

Table 1: Statistics of the Norwegian dataset for keypoint detection. The numbers indicate the data distribution across the number of frames, pigs, and keypoints in each experimental dataset.

Dataset parts	No. of Frames	No. of Pigs	No. of Keypoints
Training set	972	10,058	60,348
Validation set	97	1,021	6,126
Testing set	91	802	4,812
Overall	1,160	11,881	71,286

3.1.1 Dataset Summarization

The Norwegian dataset is utilized for the development of the keypoint detection model and for evaluating its performance. The manually annotated dataset of pigs is summarized as shown in Table 1.

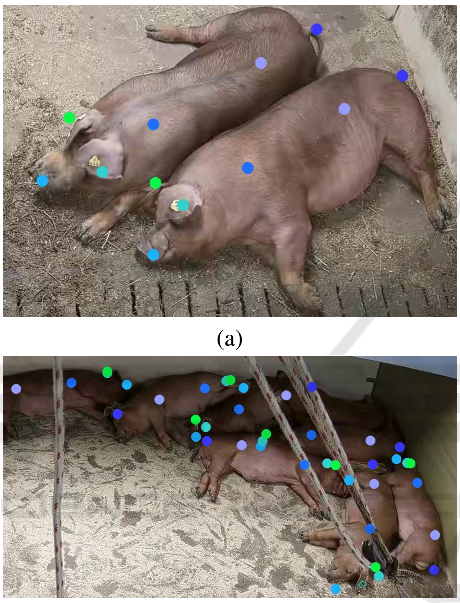
3.1.2 Implementation Details

The backbone model employed in this study is the YOLOv8x-pose-p6 architecture (Jocher et al., 2023). The learning rate is set to 0.01, while the early stopping criterion is defined with a patience parameter of 50 epochs. The batch size is configured to be 16. The model is trained for a maximum of 400 epochs, to ensure that early stopping can be effectively triggered. Additionally, we leverage a COCO-pretrained model to further fine-tune the keypoint detection model using the Norwegian dataset. All keypoint detection experiments are conducted on a GeForce GTX 3090 GPU (Nvidia Corp, Santa Clara, CA, USA).

Table 2: Performance of keypoint detection evaluated within the Norwegian dataset, using distinct metrics for each specific body part, along with the overall results. Metric P_{DJ} denotes the percentage of detected joints, P_{CK} is the percentage of correct keypoints, $P_{\mathrm{OKS_{human}}}$ stands for the object keypoint similarity using human coefficients, and $P_{\mathrm{OKS_{pig}}}$ represents the object keypoint similarity using pig coefficients.

	Tail	Back	Shoulder	Nose	Left ear	Right ear	Overall
P_{DJ}	59.48	25.44	43.52	58.35	52.37	54.61	48.96
P_{CK}	69.95	93.89	94.14	85.54	82.79	83.42	84.85
$P_{\mathrm{OKS_{human}}}$	53.57	37.05	36.18	10.95	16.00	16.76	28.53
$P_{\mathrm{OKS_{pig}}}$	90.81	87.23	87.42	90.89	90.64	91.10	89.43

3.1.3 Results



(a)

(b)

Figure 3: Magnified visualization examples, (a) where all keypoints are correctly detected, and (b) where some keypoints are incorrectly detected because of occlusion and pigs overlapping each other.

The keypoint detection model is developed using the Norwegian dataset. Table 2 lists the average testing results, resulting in a PDJ of 48.96%, a PCK of 84.85%, an OKS$_{human}$ of 28.53%, and an OKS$_{pig}$ of 89.43%. There are also keypoint detection evaluation results for specific body parts of the pig, as shown in Table 2. It can be observed that the back and shoulder obtain higher PCK values compared with other body parts. We calculate the PCK using the skeleton between back and shoulder keypoints as a threshold, which is the longest length among all skeletons. The back and shoulder obtain lower the PDJ values than other body parts. Concerning 802 individual pigs in the testing set, 31 pigs failed to be detected (false negative), and 5 non-existing pigs got the wrong detection (false positive). It can be noticed that keypoints are detected correctly in Fig. 3(a), while keypoint detection failures are occurring in Fig. 3(b) because the pigs are clustered together.

3.2 Pose Estimation

This section has the same structure as Section 3.1.

3.2.1 Dataset Summarization

The German dataset is employed to develop the models for pose estimation, which are compared and evaluated for feature-based methods. We employ two-fold cross-validation to ensure a fair evaluation of the model performance. The class distribution in each fold is listed in Table 3.

3.2.2 Implementation Details

To ensure a fair comparison, all experiments related to pose estimation are conducted on a GPU device, specifically an RTX 2080Ti GPU (Nvidia Corp, Santa Clara, CA, USA), without employing any pretraining.

Table 3: Statistics of the German dataset for pose estimation, which randomly splits frames from all video segments into two folds (K1, K2). The table lists the counts of instances of three types of pig postures in each fold.

Dataset K-fold	**No. of Frames**	**Count Lying**	**Count Sitting**	**Count Standing**
K1	438	2,936	473	1,409
K2	438	2,926	502	1,390
Overall	876	5,862	975	2,799

For the MLP model, the initial learning rate is set to 0.0001. In this research, the input data consists of a 12-dimensional vector, representing the (x,y) coordinates from the six keypoints for each pig. For the ResNet model, the images enclosed by ground-truth bounding boxes in the training dataset serve as training samples. The initial learning rate is set to 0.001 with adaptive decay. The batch size is 4, and the model is trained for a total of 200 epochs. For the YOLOv8-pose model, the experimental settings are the same as used in Section 3.1.2, except for the input which is the German dataset that outputs the pose estimation results.

3.2.3 Results

As shown in Table 4, the performance of different models and input feature combinations for pose estimation of the pigs are evaluated. Table 3 illustrates that the pose estimation dataset exhibits a significant class imbalance (approximately 61% of the data is labeled as 'lying', 10% as 'sitting', and 29% as 'standing'), and suffers from insufficient data volume. Despite these challenges, the YOLOv8-pose model, which utilizes both ground-truth keypoints and image data, achieves the highest overall accuracy of 99.33%, with exceptional performance across all pose categories (lying: 99.88%, sitting: 98.88%, and standing: 99.25%). By visualizing the results of both keypoint detection and pose estimation in Fig. 4, all pig posture classes are also predicted correctly by the YOLOv8-pose model. These results demonstrate the superiority of combining image features and keypoint features for robust pose estimation, despite the imbalanced dataset. In contrast, the MLP model achieves a lower overall accuracy of 95.69%, indicating that keypoint-based features only are less effective without additional image features. The overall accuracy of the ResNet model across all postures is 61.54%, which is considerably lower than the models incorporating keypoint features.

From the above analysis, it can be concluded that combining keypoint features and image features significantly enhances the accuracy of pose estimation.

4 DISCUSSION

This section discusses key aspects and limitations of this work.

Data limitation: This study is based on two pig datasets constructed from real-world farm environments in Norway and Germany. The imbalanced data distribution and limited data volume pose significant challenges to the generalization capability of the proposed models. For example, in the German dataset, the number of images representing the sitting posture is considerably lower than those of the other two postures, which complicates the task of pose estimation, especially for this specific pose. Furthermore, the small size of the datasets exacerbates the difficulty in achieving a robust generalization.

The datasets also exhibit a lack of diversity. For instance, all frames in the Norwegian dataset are captured under similar lighting conditions and share a consistent RGB value distribution. When frames are taken from different environments, such as darker scenes, the model predicts some keypoints incorrectly, as demonstrated in Fig. 3(b). Another example of this limitation arises when ropes appear in certain scenes within the training dataset. In these cases, keypoints are occasionally incorrectly predicted on the rope rather than on the pig body parts. As shown in the quantitative and qualitative results in Table 2 and Fig. 3, respectively, most test set achieve high keypoint detection accuracy, though some challenging cases remain.

Occluding behavior: Difficult cases remain as result of occluding behaviors of the animals. Specifically, Table 2 indicates that the model performs less accurately for the tail compared to other body parts, such as the ear, nose, and shoulder. This discrepancy likely arises from the fact that the tail is often occluded or indistinguishable due to the low resolution of the images, limiting the model exposure to sufficient tail features.

Keypoint detection: As depicted in Table 2, the PDJ value obtains lower performance compared to the PCK value. The main reason is that most diagonal lengths in the bounding boxes differ from the skeleton lengths of pigs, as shown in Fig. 1(b). In this case, the metric PDJ may not be as suitable as the metric PCK. The PCK calculation involves the length of the pig skeleton for the evaluation, which ensures that all parameters used in the PCK metric are directly derived from the pigs themselves, making it more suitable for pig keypoint detection. The PCK metric also obtains an accuracy over 90% in correctly detecting the back and shoulder keypoints. When the annotator makes a label for the keypoint, the back and shoulder have a larger area to place the keypoint compared to other parts. Therefore, we pick the longest skeleton which is between the back and shoulder keypoints as s_i for calculating the metric. The longest skeleton causes back and shoulder keypoints to have a reasonable threshold for a true prediction. Since the pig movement is undirected, the center of its body is not always relevant to the diagonal of the bounding box.

The OKS_{human} metric uses coefficients k_i determined for humans, which are for the ankles, back, shoulder, nose, left ear, and right ear, respectively. Since humans do not have tails, we apply the coefficient for human ankles to the pig's tail. However, the OKS results for the nose and ears are suboptimal. In human keypoint detection research, the nose and ears are not as critical, and thus, lower weights are

Table 4: Performance comparison of three models for pose estimation accuracy. The evaluation is based on twofold cross-validation, using different input features utilized by the models based on YOLOv8-pose, ResNet-18, and MLP. The values under lying, sitting, and standing are the average recall values for the test set of the corresponding data fold. The bold values are the highest scores, GT means ground truth.

Dataset	**Input features**	**Model**	**Recall Lying**	**Recall Sitting**	**Recall Standing**	**Accuracy (overall)**
K1	GT keypoint	MLP	98.75	69.74	94.11	94.47
	GT image	ResNet-18	65.53	68.29	27.89	54.79
	GT image + keypoint	YOLOv8-pose	**99.93**	**99.15**	**99.36**	**99.48**
K2	GT keypoint	MLP	99.28	81.33	97.36	96.91
	GT image	ResNet-18	76.49	49.20	57.91	68.29
	GT image + keypoint	YOLOv8-pose	**99.82**	**98.61**	**99.14**	**99.18**
Complete data	GT keypoint	MLP	99.02	75.54	95.74	95.69
	GT image	ResNet-18	71.01	58.75	42.90	61.54
	GT image + keypoint	YOLOv8-pose	**99.88**	**98.88**	**99.25**	**99.33**

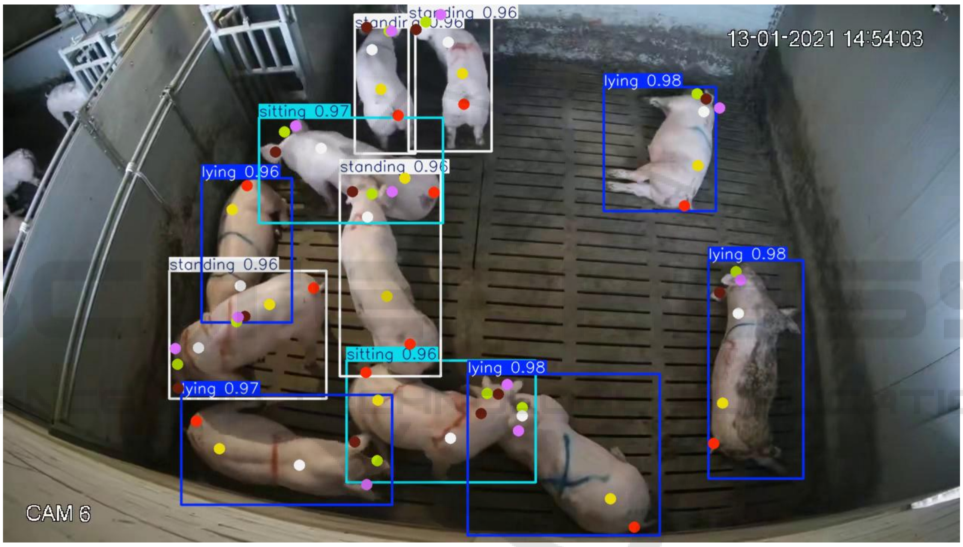


Figure 4: Visualization example result of the best-performing model, YOLOv8-pose. The results show both the keypoint detection and pose estimation, and their individual confidence scores for the considered image.

assigned to these keypoints in the k_i coefficients used by OKS (Lin et al., 2014). Unlike humans, pigs have proportionally larger noses and ears relative to their overall body size, which suggests that higher values of k_i should be assigned to these features. As a result, we calculated tailored k_i coefficients for pigs to improve the accuracy of keypoint detection in these areas.

The six annotated keypoints are positioned on the pig's head and body, excluding the legs. However, the three posture class labels—lying, sitting, and standing—exhibit distinguishing features primarily associated with the legs. Therefore, incorporating additional keypoints along the legs or back may potentially enhance detection performance.

5 CONCLUSIONS

In this work, we have developed a joint model using YOLOv8-pose for multi-object keypoint detection and pose estimation, tailored specifically for pigs. Two pig datasets have been manually annotated, one dedicated to keypoint detection and the other for pose estimation. The keypoint detection achieved a PDJ value of 48.96%, a PCK value of 84.85%, an OKS_{human} value of 28.53% and an OKS_{pig} value of 89.43%, on average. We have compared three methods with different feature-based strategies to estimate pig postures, including (1) the ResNet-18 model (image-based), (2) the Multi-layer Perceptron (MLP) model (keypoint-based), (3) the YOLOv8-

pose model (image-based and keypoint-based). The best pose estimation performance is obtained by the YOLOv8-pose model, which demonstrates that combining keypoint features and image features enhances the pose estimation results. This work demonstrates the capability of the proposed algorithm to accurately recognize specific body parts using keypoint detection, thereby providing a concurrent assessment of pig-posture status. Overall, the results demonstrate that combining image features and keypoint features yields the most accurate pose estimation. The YOLOv8-pose model consistently outperforms both the MLP model and the ResNet-18 model, highlighting the effectiveness of integrating multiple feature types. The presented approach provides a promising foundation for future research aimed at detecting more complex behaviors, such as social interactions among pigs, further enhancing animal welfare and monitoring capabilities.

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