Dynamic coupling analysis of group-housed pig behaviors and pigsty environmental factors based on the PIG-Net model

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Abstract: Behavioral responses of group-housed pigs are strongly influenced by pigsty environmental conditions, yet their dynamic coupling is difficult to quantify under commercial farming scenarios. This difficulty arises from high inter-pig similarity, complex interactions, and rapidly changing environmental conditions, which pose significant challenges for existing vision-based multi-pig behavior detection and tracking methods. To address these challenges, this study proposes a PIG-Net–based dynamic coupling analysis framework that integrates behavior detection, multi-pig tracking, and behavior-environment interaction analysis. The model uses an EfficientRepBiFusion backbone with bidirectional feature fusion and a lightweight LSDGCD detection head, achieving mean Average Precision (mAP) of 93.5% for PIG YOLO on four pig behaviors—standing, dog-sitting, lateral lying, and prone lying. The integrated PIG-Net system achieves stable tracking performance with identification average rate (IDF1) of 90.7%, multiple object tracking accuracy (MOTA) of 88.6%, and a real-time processing speed of 26 FPS, while environmental sensors continuously record temperature, humidity, and CO_2 levels for long-term correlation analysis. Based on long-term monitoring, Pearson correlation analysis was applied to quantify the associations between pig behaviors and environmental factors, highlighting significant correlations with coefficients $|r|$ ranging from 0.65 to 0.76. By combining these quantitative results with temporal and dimensionality reduction analyses, temperature, humidity, and CO_2 were identified as the primary environmental drivers. Active behaviors decreased under elevated temperature and humidity and increased during cooler and drier periods, whereas prone lying and lateral lying increased under thermal and moisture stress. Elevated CO_2 concentrations further suppressed activity, reflecting inhibitory effects of degraded air quality. These findings provide a quantitative basis for behavior-environment coupling assessment and early health warning in group-housed pigs.

Keywords: pig behavior detection, environmental dynamics, PIG-Net, behavior–environment coupling, animal welfare assessment

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1 Introduction

In the livestock industry, the pig breeding sector is actively responding to market demands and industrial development trends, rapidly moving towards scale and intensification. Animal welfare has become an important indicator for measuring breeding efficiency and the level of sustainable development[1-3]. With the expansion of farming scale, the relationship among pig health status, behavioral performance, and pig house environment has received increasing attention. Therefore, conducting systematic analysis and continuous monitoring of pig behavioral patterns and their surrounding environments has become a key approach to achieving animal welfare goals[4-7].

In group-housed pig production systems, individual behaviors are not only influenced by intrinsic physiological states but are also strongly regulated by external environmental conditions within the pigsty. Numerous studies have demonstrated that environmental factors such as ambient temperature, relative humidity, air quality (e.g., NH_3 and CO_2 concentrations), and particulate matter significantly affect pigs' activity rhythms, resting postures, and social behaviors[8,9]. In intensive housing environments, pigs often exhibit adaptive behavioral responses to environmental stressors,

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such as increased lying time, reduced locomotion, and altered feeding and resting patterns, which can serve as early indicators of discomfort or health deterioration[10]. Behavior-environment association analysis has therefore been increasingly recognized as an effective approach for animal welfare assessment and health management in group-housed pigs. To facilitate large-scale and long-term behavior–environment association analysis, it is essential to obtain accurate, objective, and continuous behavioral information from group-housed pigs. As a result, automated pig behavior detection and recognition technologies have attracted increasing attention.

Current research on pig behavior detection is mainly divided into contact-based and non-contact-based technologies[11,12]. Contact-based approaches attach various types of sensors to the animals to collect behavior-related data for behavior pattern classification. Alghamdi et al.[13] mounted accelerometers and gyroscopes on the backs of pigs to capture motion data, including acceleration and angular velocity, and achieved behavior recognition and classification with F1-scores exceeding 90% for each behavior category by applying machine learning techniques. Similarly, Lin et al.[14] used ear tags embedded with triaxial accelerometers combined with random forest–based strategies to classify pig behavior intensity levels. Achour et al.[15] employed back-mounted inertial measurement units to identify key livestock behaviors with over 91% accuracy without manual labeling. However, contact-based sensor methods tend to induce stress responses in animals, which significantly affect detection accuracy and reduce overall system performance[16,17]. With the rapid development of deep learning and edge computing technologies, non-contact vision-based behavior detection methods have become a major research focus in precision livestock farming[18-20]. However, practical group-farming scenarios still pose prominent technical challenges, namely dense target occlusion and the contradiction between model lightweighting and detection accuracy. Alameer et al.[21] used grayscale images combined with an improved Google Net network to successfully recognize pig feeding behavior, achieving an accuracy of 99.4%. Ma et al.[22] successfully achieved the automatic detection of pig faces in a pigsty environment by using the YOLOv4 algorithm. Tong et al.[23] utilized an improved YOLOv8 algorithm to classify standing, walking, side-lying, lying, and feeding behaviors in pigs. Although these image-based methods demonstrate high detection accuracy, the introduction of multiple enhancement modules often increases model complexity and computational cost, limiting their applicability in practical group-housing scenarios. To address this problem, Zhang et al.[24] proposed Sheep-YOLO, a lightweight detection model. Luo et al.[25] developed an improved YOLOv8-based model integrating GhostNet, FasterNet blocks, and attention mechanisms; both methods were deployed on NVIDIA Jetson Orin NX devices to enable real-time animal behavior monitoring. Nevertheless, computational constraints of edge devices and latency in data processing remain challenges for long-term online monitoring. Beyond single-frame behavior recognition, long-term behavior tracking and statistical analysis have been increasingly applied to support pig health assessment and early warning[26]. Tu et al.[27] combined YOLOv5 with ByteTrack to identify and track individual pig behaviors. Li et al.[28] integrated an improved Dual-YOLOX-Tiny detector with ByteTrack to achieve stable multi-pig tracking and behavior sequence analysis. Yin et al.[29] classified pig health status using activity data through statistical analysis and machine learning. Yang et al.[30] combined an improved Mask R-CNN with a SARIMA model to predict activity trends for early health warning. Although these methods support health monitoring and demonstrate their effectiveness, they lack a more intuitive quantification of behavior patterns and fail to adequately assist farmers in early warning and intervention for potential pig health problems.

In contrast to cattle and sheep, which exhibit more dispersed individual activity, pigs are typically reared in groups during daily management. Group-housed pigs display more concentrated behaviors, stronger social interactions, and greater sensitivity to environmental stimuli, often resulting in abrupt group behavior changes[31]. Core postural behaviors, including standing, dog-sitting, lateral lying, and prone lying, are closely associated with pig physiological condition, health status, and welfare level. Standing and dog-sitting behaviors generally reflect activity level and alertness, whereas prolonged lying behaviors are often related to fatigue, thermal discomfort, illness, or reduced welfare. In particular, changes in lying posture, such as increased prone or lateral lying duration, have been widely recognized as early indicators of health abnormalities and environmental stress. However, accurate recognition of these behaviors remains challenging in practice. Individual pigs exhibit similar body sizes and indistinct visual features, and different postural behaviors often present subtle inter-class differences and high intra-class variability, especially under occlusion and group-housing conditions. Moreover, the strong temporal regularity and repetitive nature of pig behaviors require long-term and continuous observation to capture stable behavioral pattern changes related to health and welfare. These challenges highlight the necessity of selecting representative postural behaviors and developing robust behavior recognition and analysis methods for group-housed pigs.

To address the above challenges, a dynamic coupling analysis method for group-housed pig behaviors and pigsty environmental factors based on the PIG-Net model was proposed. This study integrated the PIG-YOLO model with the ByteTrack algorithm to achieve accurate identification and continuous tracking of individual pigs under complex conditions, enhancing spatiotemporal feature extraction from image and video data. Four specific pig behaviors—standing, dog-sitting, lateral lying, and prone lying could be accurately recognized. In addition, a cloud-edge collaborative system for pig behavior recognition and tracking was constructed. Through cloud-edge collaboration, the system could perform pig behavior detection and continuous monitoring of pigsty environmental conditions, which reduces computing resource consumption, lowers costs, decreases latency, and shortens data transmission time. The monitoring results could provide farmers with an intuitive understanding of pig health status and pigsty environmental information. To further support health risk assessment in group-housed pigs, a data-driven dynamic coupling analysis method that integrates long-term pig behavior recognition results with synchronized pigsty environmental data was proposed. By quantitatively modeling the temporal correlations between behavioral patterns and environmental factors, the proposed method could enable the identification of abnormal behavior-environment interactions, providing objective indicators for early health warning and welfare-oriented management.

2 Materials and methods

2.1 Construction of a cloud-edge collaborative system for pig behavior auxiliary analysis

To control costs and maximize the utilization of computing resources, the overall system adopts a cloud-edge collaborative architecture with multi-domain integration. Edge computing nodes are deployed at the pig farm, and work in coordination with the powerful computing and storage capabilities of the cloud center to achieve real-time monitoring and analysis of pig behaviors. System deployment and network testing were completed in August 2024 at a pig farm in Tai'an, Shandong Province. Each pen in the pig house contains a 1.05 m-high stall structure that can accommodate 30 pigs, as shown in the node layout in Figure 1, and the specific equipment parameters are listed in Table 1.

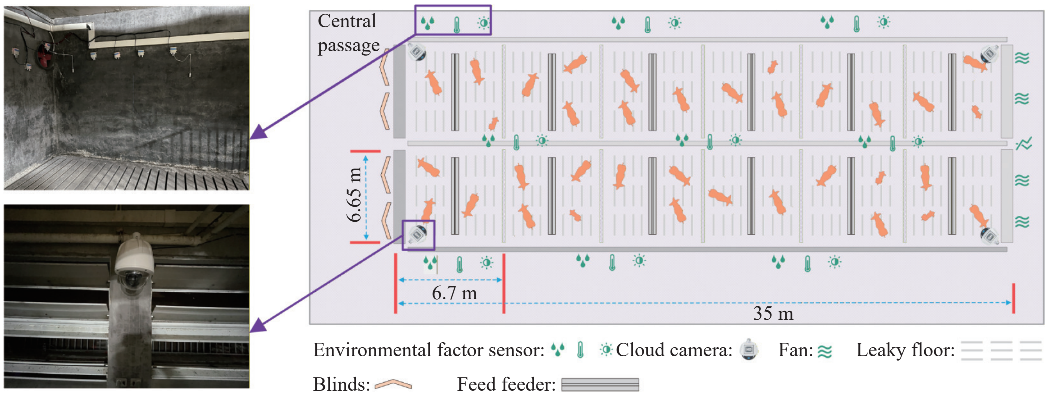


Figure 1　Edge computing nodes and on-site deployment points

Table 1　Sensor selection and performance parameters

Detection index	Model	Range	Precision	Response time/s
Temperature		–40°C to 80°C	±0.5°C	≤90
Humidity	SN-3200Y-CO_2WS-N01	0-100%RH	±3%RH	≤90
CO_2		0-10 000 $\mu g/m^3$	±70 $\mu g/m^3$	≤90
Video/Image	DS-2DC2204IW-D3/W/	NO	1080p	NO

The system is built on edge computing devices such as Jetson Orin Nano and uses LoRa, DTU transparent transmission, and the Message Queuing Telemetry Transport (MQTT) protocol to establish network communication. The Jetson Orin Nano serves as a representative edge platform for real-time behavior analysis and deployment verification, where system performance is primarily characterized by model size and inference speed. A Django-based visualization framework is developed on the cloud server to present, in the form of charts, the number of pigs exhibiting different behaviors at different times within a single pen, along with variations in environmental parameters such as temperature, humidity, and carbon dioxide concentration. Users access the cloud platform through terminal devices to view the analysis results of pig behaviors and environmental conditions inside the pig house, and regulate the farm's environmental settings using equipment such as fans, heaters, and ventilation systems. The system structure is shown in Figure 2.

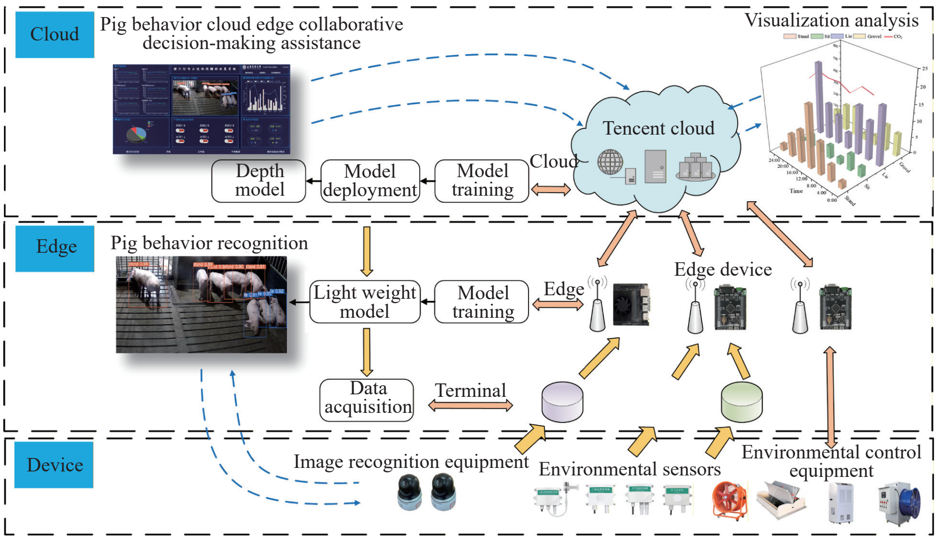


Figure 2　Cloud-edge collaboration framework diagram

Based on design requirements, the study conducts system stability testing and network communication testing. As listed in Table 2, the test results indicate that the volume of incoming messages (received data) is nearly equal to the volume of outgoing messages (sent data), demonstrating that the system functions properly. Comparison across different sampling cycles shows no significant difference in transmission stability, as illustrated in Figure 3. Based on system stability, data processing capacity, and operational requirements, the study selects a 10-min sampling cycle.

Table 2　Sensor selection and performance parameters

Evaluation index	Temperature	Humidity	CO_2	Number of pig behavior
Effective duration/h	24	24	24	24
Number of receivable packages/pieces	8640	8640	8640	144
Actual number of packages received /pieces	8612	8537	8542	144
Number of lost packages/pieces	28	92	68	0
Package loss rate/%	0.324	1.064	0.787	0

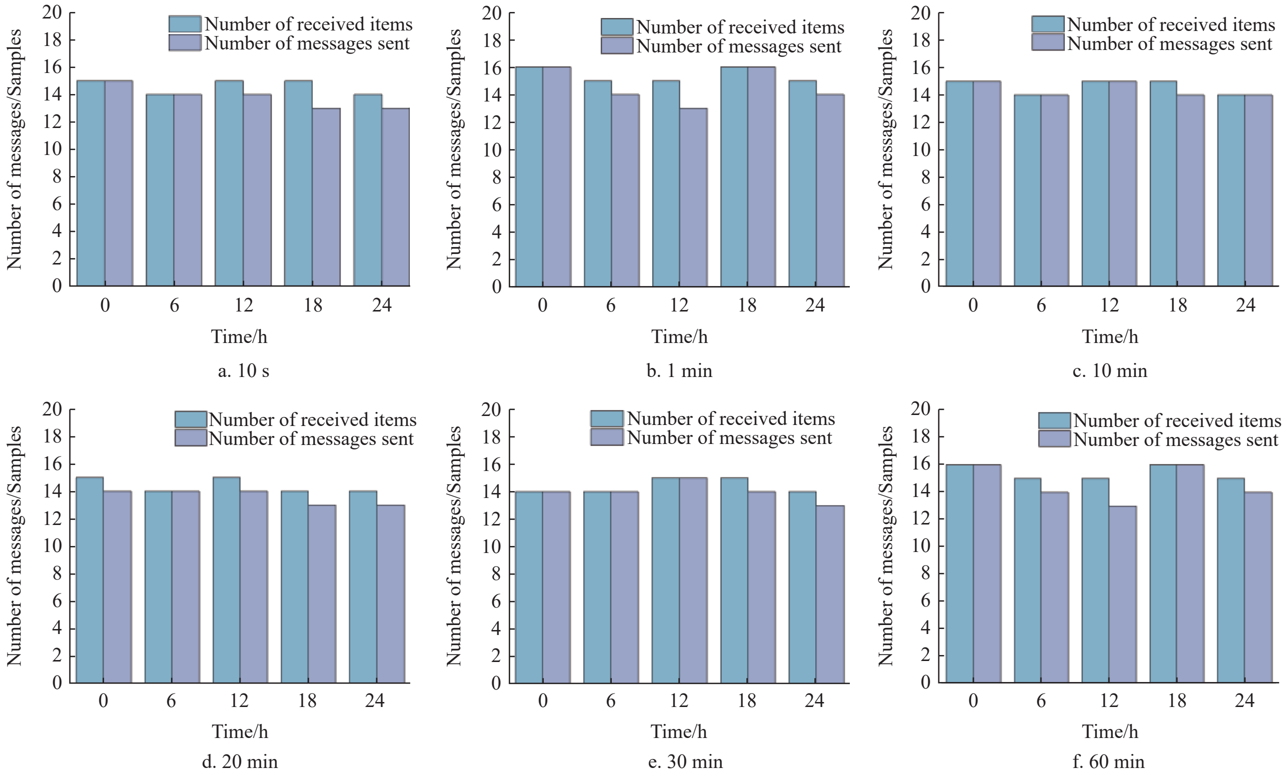


Figure 3 Comparison chart of package loss data under different acquisition frequencies

2.2 Dataset construction and preprocessing

Considering that pigs exhibit distinct behavioral patterns at different growth stages, the experiment is conducted from August 26 to December 4, 2024. This study selects 30 three-way crossbred fattening pigs aged between 60 and 160 d as the experimental subjects and places them in a standard rearing area. A Hikvision DS-2DC2204IW-D3/W surveillance camera is used to capture video data. The images are recorded at a resolution of 1920×1080 pixels. Four types of pig postures—standing, dog-sitting, lateral lying, and prone lying—are recorded, with detailed descriptions shown in Figure 4. A total of 3852 images and 123 video clips are collected. Additionally, 637 images of pigs at different stages were obtained from the publicly available online dataset. To ensure compatibility with the on-site collected data, all online images underwent standardized preprocessing, with the resolution adjusted to 640×640 and the unified annotation format Pascal VOC. Low-quality or irrelevant samples were manually screened out to guarantee the consistency of scene and target features and enhance the diversity, robustness, and credibility of the dataset.

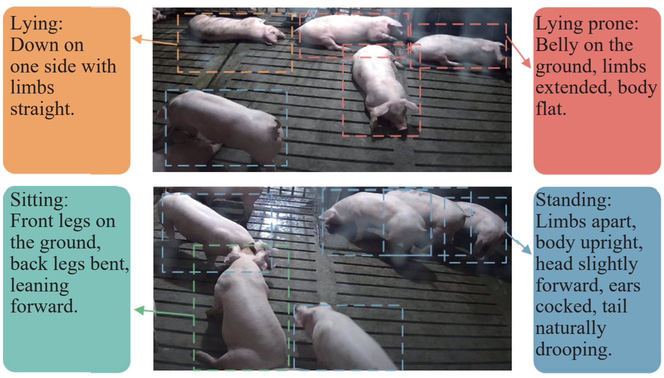


Figure 4 Description of pig behavior

The pig behavior recognition dataset consists of behavior recognition data in VOC format. The specific data augmentation strategies and their detailed process are shown in Figure 5.

The study filters videos of ternary crossbred pigs using FFmpeg and extracts one frame every five frames, selecting the top 50% sharpest images via a Laplacian filter to ensure data quality. A total of 1783 images is enhanced by applying brightness adjustment, Gaussian noise, rotation, median filtering, mirroring, and edge enhancement. These augmentation strategies are applied in a behavior-aware manner to alleviate sample imbalance among different posture categories and to promote a more uniform distribution across behaviors. During dataset construction, the VOC annotations are cleaned and standardized, and YOLOv8n-based augmentation and optimization strategies are employed to improve annotation accuracy and model generalization across diverse shooting scenarios. After preprocessing and statistics, 4849 annotated behavior bounding boxes are obtained, and 14 264 enhanced images are generated. According to a 7:2:1 split, 9985 images form the training set, 2853 images form the validation set, and 1426 images form the test set. Based on this, a group-housed pig behavior dataset is established, as summarized in Table 3.

Table 3 Dataset partitioning

Argument	Type	Dataset			Total
		Training set	Test set	Validation set	
Number of boxes/ samples	Stand	984	281	141	1406
	Sit	870	248	125	1243
	Lie	746	213	107	1066
	Lie prone	793	226	114	1134

2.3 PIG-Net model

To achieve accurate pig behavior detection and continuous individual tracking in group-housed environments, the PIG-Net model is proposed. This model integrates the PIG-YOLO model used for detecting pig behavior and ByteTrack algorithm. By combining high-precision behavior recognition and real-time identity tracking, PIG-Net enables comprehensive spatiotemporal analysis of individual pigs under complex farming conditions.

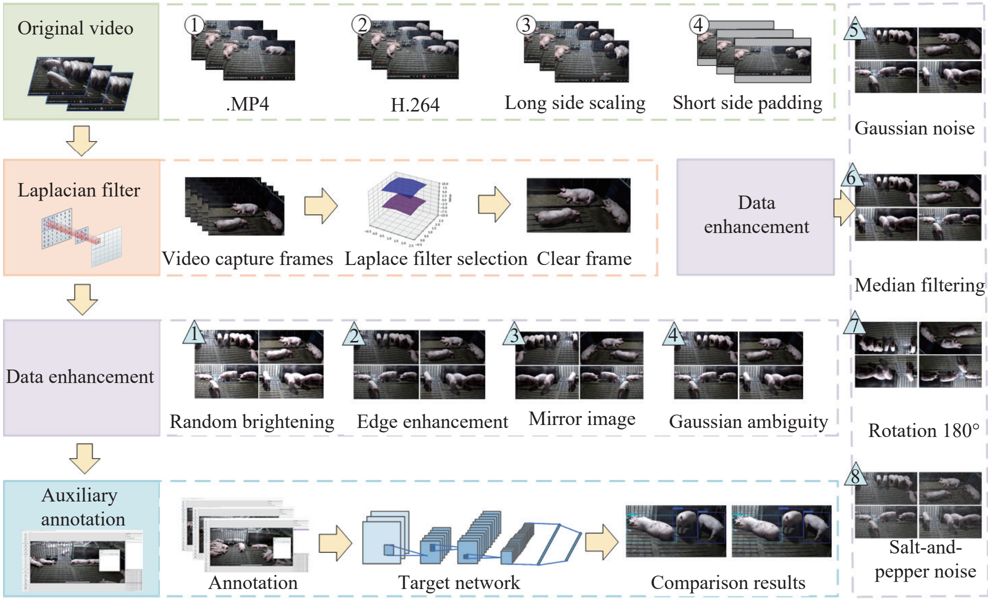
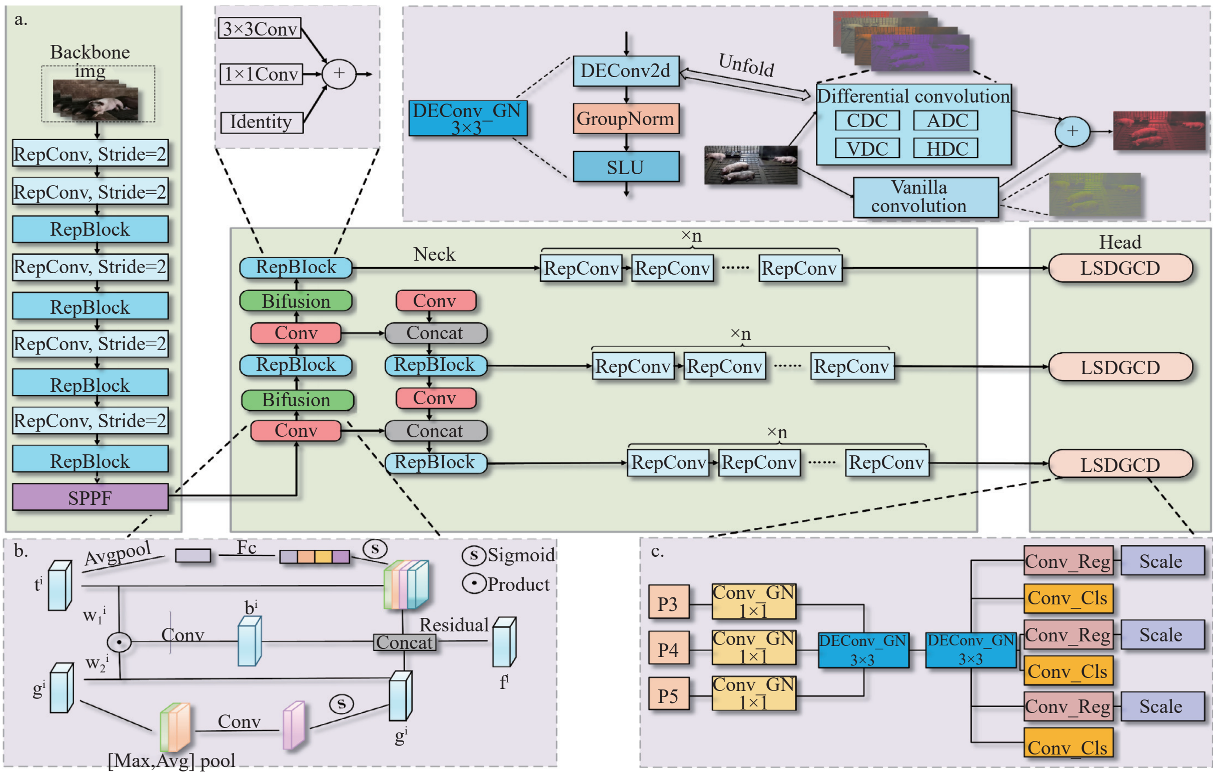


Figure 5 Pig behavior data augmentation process

2.3.1 PIG-YOLO model

To improve multi-scale representation and detail perception under dense interactions and occlusions, this study proposes the PIG-YOLO model, as illustrated in Figure 6. The model integrates two key components: an EfficientRepBiFusion backbone-neck structure and an LSDGCD lightweight detection head.



Note: a. Schematic diagram of PIG-YOLO architecture; b. EfficientRepBiFusion feature network pyramid c. LSDGCD lightweight detection head. d. DEConv_GN

Figure 6 PIG-YOLO network structure

1) LSDGCD lightweight detection head

The DEConv_GN module is designed as shown in Figure 6. The BN layers in the original CBS module are replaced with GN layers. BN assumes that data within each batch follow a similar distribution, but data augmentation introduces distributional differences, which interfere with the normalization effect of BN. In contrast, GN performs normalization based on the statistics within channel groups, thereby avoiding the limitations of BN. This design enhances the robustness of behavior recognition under complex conditions, especially for behaviors such as prone lying and lateral lying that are similar in posture or imbalanced in sample distribution.

In addition, to address the problem of image detail blurring caused by unstable lighting conditions during on-site deployment, which affects the stability and accuracy of pig behavior recognition, as well as to improve the unsatisfactory performance of existing algorithms in distinguishing behaviors such as standing, lying, and dog-sitting, this study proposes corresponding solutions. Therefore, the standard Conv2d is replaced with a Detail-Enhanced Convolution (DEConv). DEConv enhances the feature extraction capability of conventional convolutional layers by integrating difference convolutions. In image dehazing tasks, DEConv effectively captures high-frequency detail information from images.

2) EfficientRepBiFusion module

The EfficientRepBiFusion module enhances bidirectional multi-scale feature fusion, enabling effective interaction between low-level posture details and high-level semantics. Its feature aggregation workflow is presented in Figure 7, where a re-parameterized RepBlock and a dual-path fusion mechanism improve contextual perception while maintaining high inference efficiency.

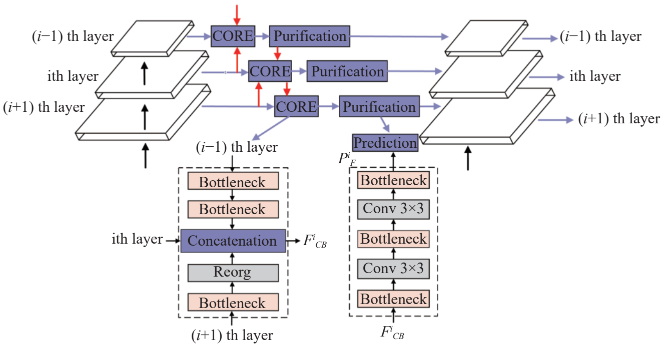


Figure 7 BiFusion feature pyramid

In pig farming environments, target objects often exhibit high similarity to the background, making it difficult to distinguish between positive and negative samples. YOLOv8n by default adopts the Complete Intersection over Union (CIoU) loss function[32], which is formulated as follows in Equation (1):

$$\begin{cases} \mathrm{CIoU} = 1 - \left(\mathrm{IoU} - \dfrac{\rho^2}{c^2} - \alpha \cdot v\right) \\ \mathrm{IoU} = \dfrac{Area\ of\ Overlap}{Area\ of\ Union} \\ \rho = \sqrt{(x_{\mathrm{pred}} - x_{\mathrm{true}})^2 + (y_{\mathrm{pred}} - y_{\mathrm{true}})^2} \\ c = \sqrt{(x_{\max} - x_{\min})^2 + (y_{\max} - y_{\min})^2} \\ v = \dfrac{4}{\pi^2}\left(\arctan\dfrac{\omega_{\mathrm{ture}}}{h_{\mathrm{ture}}} - \arctan\dfrac{\omega_{\mathrm{pred}}}{h_{\mathrm{pred}}}\right)^2 \end{cases} \tag{1}$$

where, IoU denotes the intersection over union between the predicted and ground truth bounding boxes, ρ^2 represents the squared Euclidean distance between their center points, c^2 is the squared diagonal length of the smallest enclosing box covering both bounding boxes, v is the penalty term for the aspect ratio difference, and α is the weighting factor applied to the aspect ratio penalty term.

However, CIoU only considers the spatial alignment of predicted and ground-truth boxes in a single frame, lacking temporal awareness of object motion. To address this limitation, this study replaces the CIoU loss with a flow-guided regression loss that integrates optical flow constraints. The optical flow between consecutive frames is estimated using FlowNet, and the End-Point Error (EPE) is calculated to measure pixel-level motion consistency. The modified regression loss is formulated as Equations (2) and (3):

$$L_{\mathrm{bbox}}^{\mathrm{flow}} = (1 - \mathrm{CIOU}) + \lambda L_{\mathrm{EPE}} \tag{2}$$

$$L_{\mathrm{EPE}} = \frac{1}{N}\sum_{i=1}^{N} \|F_{\mathrm{pred}}(i) - F_{\mathrm{gt}}(i)\|_2 \tag{3}$$

F_{pred} and F_{gt} represent the predicted and ground-truth optical flow, respectively, and λ is a weighting coefficient empirically set to 0.3. The total training objective can thus be expressed as Equation (4) :

$$L_{\mathrm{total}} = L_{\mathrm{cls}} + L_{\mathrm{conf}} + L_{\mathrm{bbox}}^{\mathrm{flow}} \tag{4}$$

This flow-guided loss encourages temporal consistency in bounding-box localization and enhances detection robustness under frequent movement and occlusion in group-housed pig scenarios.

2.3.2 Pig behavior tracking

Accurate and continuous tracking of individual pigs is challenging due to frequent occlusions and complex backgrounds in group-housed environments. Therefore, the lightweight ByteTrack algorithm was adopted to provide real-time and stable identity association without introducing additional computational overhead[33]. ByteTrack maintains both high- and low-confidence detections in its two-stage data association, effectively reducing ID switches and missed detections caused by occlusions or detection uncertainty. The algorithm employs a Kalman filter to predict the motion state of each target and applies the Hungarian algorithm for optimal matching between predicted and detected positions. By integrating motion prediction and multi-level confidence information, ByteTrack ensures robust and stable tracking even during rapid movements or mutual occlusions. Therefore, this study combines the ByteTrack algorithm with the PIG-YOLO model to achieve continuous and accurate behavior tracking of individual pigs. The specific process of ByteTrack is shown in Figure 8.

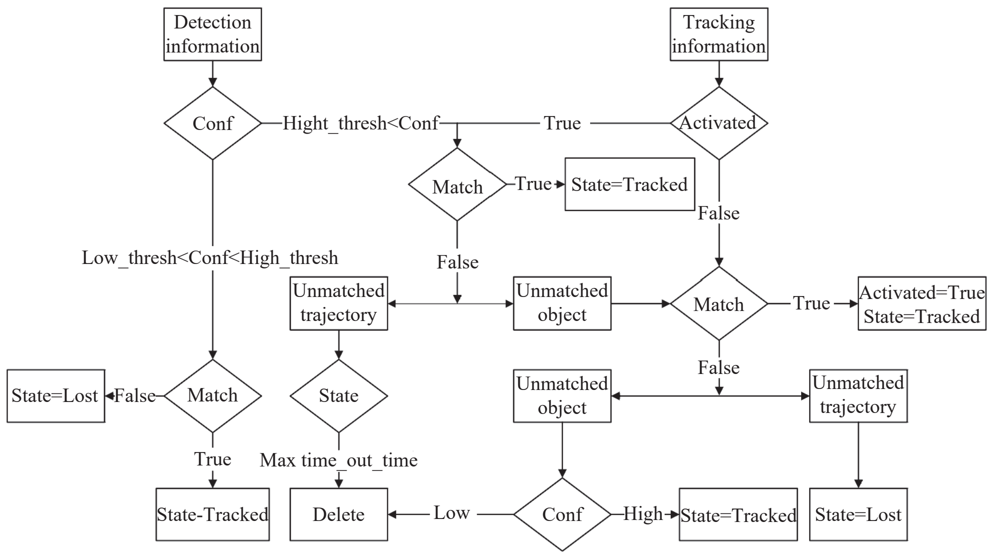


Figure 8 Flowchart of ByteTrack algorithm

2.4 Evaluation index

PIG-YOLO model fast and accurate target area detection has been achieved through a lightweight feature extraction network, an efficient decoding network, and an optimized loss function. In the dynamic detection and tracking of live pigs, the extraction of semantic information is often insufficient, resulting in the loss of details, especially in cases of occlusion or other complex scenarios. At this point, it is crucial to detect individual small pig targets quickly and accurately. This study evaluated the performance of pig detectors using three indicators: detection recall (R), detection precision (P), and mean average precision (mAP). The definitions of these metrics are given by Equations (5)-(8):

$$P = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{5}$$

$$R = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{6}$$

$$A_{\mathrm{P}} = \int_0^1 P(x)\mathrm{d}x \tag{7}$$

$$\mathrm{mAP} = \frac{1}{m}\sum_{i=1}^{m} A_{\mathrm{P}}(i) \tag{8}$$

where, TP represents the number of correct positive samples, FP represents the quantity of samples wrongly marked as positive, and FN is the number of positive samples that were not detected.

In pig behaviors tracking tasks, this study selected three main evaluation metrics: high order tracking accuracy (HOTA)[34], multiple object tracking accuracy (MOTA), and identification average rate (IDF1) for performance comparison. The definitions of these metrics are given by Equations (9)-(14):

$$\mathrm{HOTA} = \sqrt{\mathrm{DetA}\cdot\mathrm{AssA}} = \sqrt{\frac{\sum_{c\in TP} A(c)}{\mathrm{TP+FN+FP}}} \tag{9}$$

$$A(c) = \frac{\mathrm{TPA}(c)}{\mathrm{TPA}(c)+\mathrm{FPA}(c)+\mathrm{FNA}(c)} \tag{10}$$

$$\mathrm{IDP} = \frac{\mathrm{IDTP}}{\mathrm{IDTP+IDFP}} \tag{11}$$

$$\mathrm{IDR} = \frac{\mathrm{IDTP}}{\mathrm{IDTP+IDFN}} \tag{12}$$

$$\mathrm{IDF1} = \frac{2\mathrm{IDTP}}{2\mathrm{IDTP+IDFP+IDFN}} \tag{13}$$

$$\mathrm{MOTA} = 1-\frac{\mathrm{FN+FP+IDSW}}{\mathrm{GT}} \tag{14}$$

where, DetA evaluates inspection accuracy and AssA assesses correlation accuracy, c denotes a point belonging to true positives (TP), and A(c) represents the association accuracy defined by Equation (9). Specifically, TPA(c) is the accuracy of correct associations, FPA(c) refers to the accuracy of predicted tracks from incorrect associations, and FNA(c) denotes the accuracy of unpredicted tracks in correlation predictions. IDTP (identification true positive) refers to the number of correctly identified and consistently tracked target IDs that match actual individual pigs throughout the monitoring sequence, IDFP (identification false positive) represents the number of incorrectly assigned IDs (including duplicates, false IDs for non-targets, or mismatches), and IDFN (identification false negative) indicates the number of actual target IDs that fail to be correctly tracked or identified (such as missing IDs, inconsistent assignments, or failed associations between predicted tracks and ground-truth IDs).

3 Results and discussion

3.1 Experimental setup and hyperparameter settings

The experimental environment is configured on a server running the Ubuntu 22.04 LTS operating system, equipped with an Intel Core i9-13900K CPU and an NVIDIA GeForce RTX 4080 GPU. CUDA 12.1 is installed, and the Python programs are developed using the PyTorch 2.1.0 deep learning framework based on Python 3.9. The hyperparameter settings are listed in Table 4.

Table 4 Hyperparameter settings

Argument	Value
Epoch	300
Batch size	16
Workers	8
Imgsz	640
Lr0	0.01
Momentum	0.937
Weight_decay	0.0005
Optimizer	SGD
Warmup_epochs	3
Learning_rate	0.001

3.2 Model training results

As shown in Figure 9, the PIG-YOLO model achieves faster convergence and lower classification, box regression, and total loss compared with YOLOv8n. Its final loss values are consistently lower and approach 0.5, indicating stronger learning capability in complex environments. Additionally, PIG-YOLO delivers higher mAP and improved precision-recall performance, reaching a mAP@50 of 93.5%, which confirms the effectiveness of the proposed optimization strategies.

3.3 Ablation experiment

The offline augmented group-housed pig dataset is used to compare each improved strategy with the YOLOv8n baseline, as listed in Table 5. Compared with YOLOv8n, Experiments 2, 3, and 4 that introduce the EfficientRepBiFusion (ERB) module, the lightweight spatial-channel decoupling (LSCD) module, and the LSDGCD module all improve P, R, and mAP while reducing parameters, inference speed, and model size, demonstrating better generalization with lower computational cost. Experiment 5, which combines ERB and LSCD, further increases precision, recall, and mAP by 2.95%, 4.02%, and 4.99%, and reduces parameters by 0.26 MB, model size by 1.2 MB, and inference speed by 15.5 fps. Experiment 6 achieves the best overall performance, increasing precision, recall, and mAP by 5.63%, 6.78%, and 7.55%, while the model becomes more lightweight and efficient compared with YOLOv8n, confirming the superiority of the final integrated improvement strategy.

To further verify the effectiveness of the PIG-YOLO model proposed in this study, a comparative analysis is conducted with YOLOv5n, YOLOv8n, YOLOv10n, ERB-YOLOv8n, YOLOv8n-LSCD, YOLOv8n-LSDGCD, and ERB-LSCD. All models are trained for 300 epochs on the same group-housed pig dataset using identical training parameters. The training results, including average precision, mAP, and loss variation curves for each model, are shown in Figure 10.

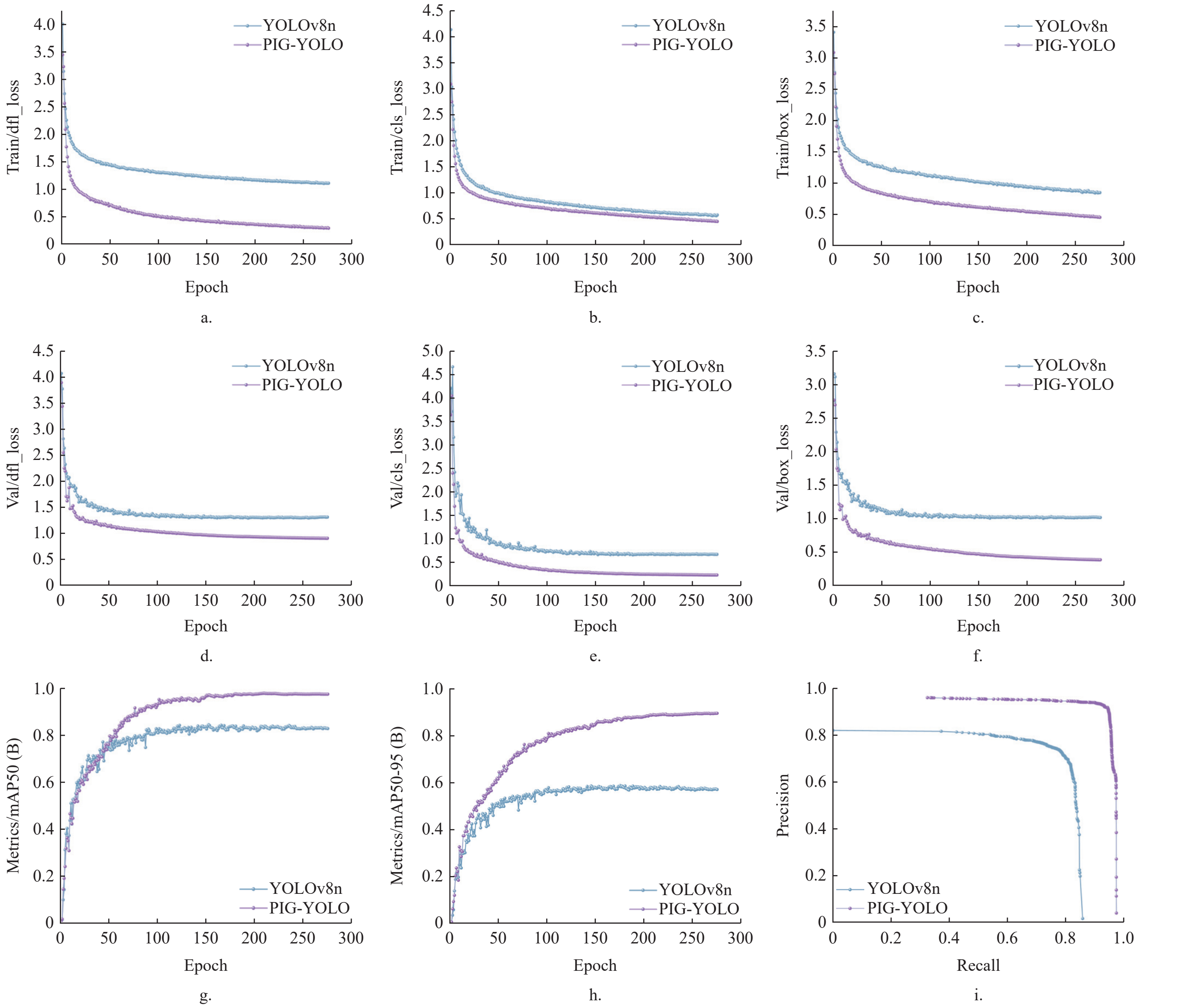


Figure 9 (a)-(i) Loss, mAP, P-R curves of YOLOv8n vs PIG-YOLO

Table 5 Results of ablation experiments

NO.	ERB	LSCD	LSDGCD	Parameter quantity/MB	P/%	R/%	mAP/%	FPS/ (f·s⁻¹)	Model size/MB
1	-	-	-	3.01	90.24	89.14	85.95	80.3	6.5
2	√	-	-	2.81	90.18	90.27	86.56	48.8	5.9
3	-	√	-	2.37	90.55	90.60	87.15	47.6	4.9
4	-	-	√	2.56	92.32	93.73	89.55	53.2	5.1
5	√	√	-	2.75	93.19	93.16	90.94	64.8	5.3
6	√	-	√	2.55	95.57	95.92	92.60	67.7	5.45

3.4 Field verification results

Figure 11 presents the comparison of detection effects between the different algorithms and the PIG-YOLO model with an mAP average recognition rate of 93.5% proposed in this paper. The PIG-YOLO model outperforms other models in recognition accuracy and effectively reduces the misclassification between prone and lateral lying under pig-to-pig occlusion, while also decreasing behavior missed detections in complex background conditions. The specific test results are listed in Table 6.

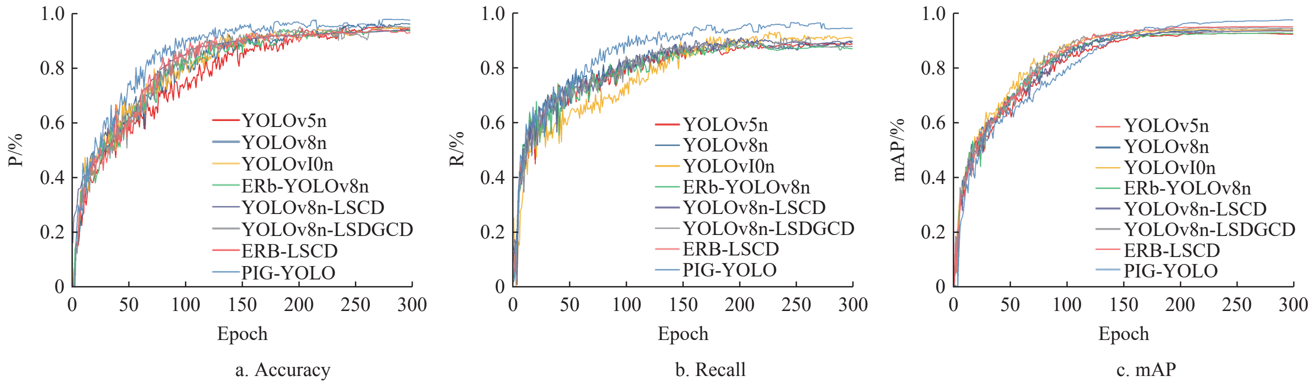


Figure 10 Accuracy, recall, mAP curves of 8 models

Figure 11 Detection effects of 8 models on partial datasets

As shown in Table 7, the combination of PIG-Net achieved the best overall performance in multi-object pig trajectory tracking. It attained the highest IDP, IDR, and IDF1 scores, with an IDF1 of 90.7%, while MOTA and HOTA were improved to 88.6% and 66.2%, respectively. Moreover, the real-time processing speed reached 26 FPS, satisfying practical deployment requirements.

In Figure 12, accurate detection and stable identity maintenance are preserved in real-world scenes with cluttered backgrounds and intensive behaviors, providing reliable data support for behavioral analysis and health monitoring and meeting the requirements of fine-grained management in large-scale pig farming.

To achieve continuous analysis of pig behavior patterns and effective assessment of health status, this study adopts the PIG-Net to accurately capture and record the movement trajectories and activity frequency of the pigs. Pig behavior often reflects their internal physiological states. Under healthy conditions, pigs exhibit periodicity and consistency in key behaviors such as activity and rest. When abnormal behavior occurs, there is typically a deviation from the patterns observed during normal behavior. Therefore, long-term monitoring of pig behavior patterns holds significant importance. Such monitoring not only assists farmers in visually observing the daily behavior of pigs but also provides references for the early identification of health issues, enabling timely alerts for potential abnormalities.

The experiment selects the period from October 19 to October 26, 2024 to evaluate and quantify the behavior patterns of group-housed pigs. The recorded videos and images of group-housed pigs were first processed using the PIG-Net model to recognize behaviors including standing, dog-sitting, lateral lying, and prone lying. To enable long-term monitoring, this study deployed the PIG-Net model on the Jetson Orin Nano. Based on individual pig behavior tracking, the daily proportion of each behavior performed by each pig was calculated, as shown in Figure 13.

Table 6 Results of pig behavior recognition

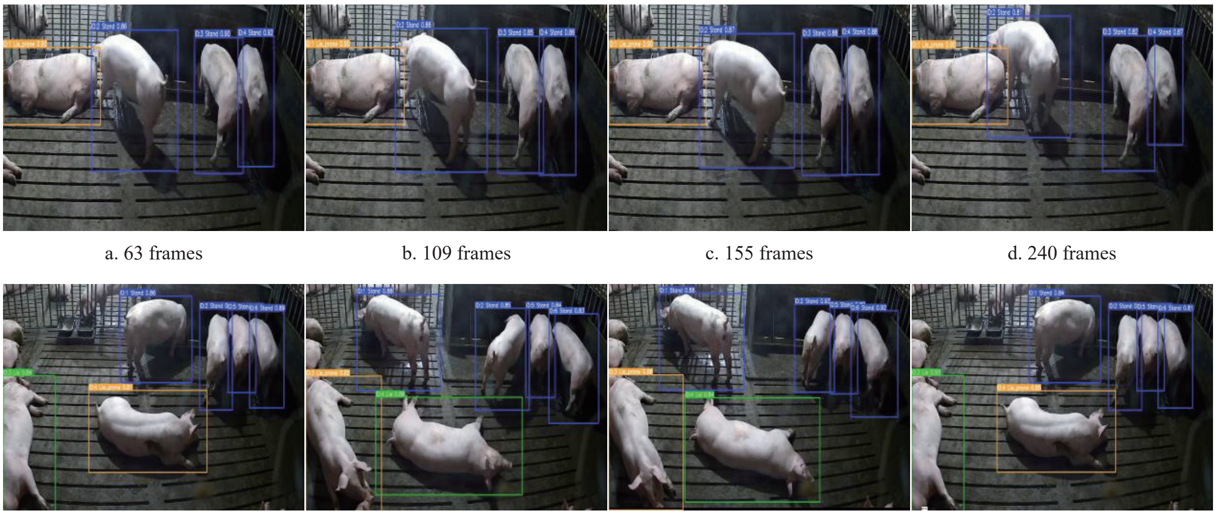
Indicator	Precision/%				Recall/%				mAP/%			
Type	Stand	Sit	Lie	Lie prone	Stand	Sit	Lie	Lie prone	Stand	Sit	Lie	Lie prone
YOLOv5n	90.56	89.82	89.26	88.09	89.97	88.69	87.98	86.46	85.98	85.39	84.86	83.99
YOLOv8n	92.38	91.24	89.48	87.86	91.91	89.24	89.24	85.16	87.54	86.79	85.81	83.66
YOLOv10n	91.42	90.11	89.93	88.84	90.86	88.62	89.13	85.76	86.97	86.65	85.63	83.23
EAB-YOLOv8n	91.41	90.87	90.01	88.43	90.93	90.22	90.09	89.84	87.87	87.19	86.35	84.83
YOLOv8n-LSCD	92.05	91.80	89.60	88.75	92.28	91.81	89.60	88.91	88.38	88.91	86.23	85.08
YOLOv8n-LSDGCD	93.78	92.13	91.23	92.14	94.26	93.74	93.27	93.65	91.09	90.80	87.23	89.08
EAB-YOLOv8n-LSCD	95.10	95.20	90.70	91.76	94.50	94.80	91.10	92.24	92.10	92.20	89.25	90.21
PIG-YOLO	99.20	99.30	93.20	90.37	99.10	99.20	90.40	95.50	93.70	93.90	91.60	91.20

Table 7 The performance of the PIG-Net pig tracking model

Algorithm	IDP/%	IDR/%	IDF1/%	MOTA/%	HOTA/%	FPS
YOLOv8n+ByteTrack	88.7	87.2	87.9	86.5	63.1	32
YOLOv8n+DeepSORT	87.1	85.6	86.3	84.8	61.0	28
YOLOv8n+BoT-SORT	90.2	88.7	89.4	87.5	64.9	29
PIG-Net	91.3	90.1	90.7	88.6	66.2	26

Previous studies demonstrate that the proportion of pig behaviors could be used for the early detection of pig health and welfare issues[35]. The study analyzes the proportion of four behavioral patterns exhibited by pigs throughout a 24-hour period and randomly monitors six pigs for investigation. The postural behaviors of pigs are primarily categorized as standing, dog-sitting, lateral lying, and prone lying. The lateral lying behavior typically accounts for 40% to 60%, standing for 15% to 25%, lying prone for 14% to 25%, and dog-sitting for 1% to 10%. The duration of standing is slightly longer than that of lying prone, which may result from pigs maintaining a standing posture while feeding. Under conditions of limited space or impoverished environments, pigs may increase the frequency of dog-sitting. The occurrence of dog-sitting behavior usually reflects spatial constraints and efforts to avoid crowding. A low proportion of dog-sitting suggests that the living environment is relatively suitable and pigs do not experience crowding or discomfort. The distribution of pig behaviors reflects typical behavioral patterns under normal rearing conditions and suggests a relatively stable physiological state. Deviations from the typical behavioral proportion range may serve as potential indicators of abnormal conditions, which could be associated with health disturbances or environmental stressors.

As shown in Figure 14, Pearson correlation analysis reveals clear associations between pig behaviors and key environmental factors. Temperature and humidity show negative correlations with activity-related behaviors (r=−0.65 to −0.76), indicating reduced activity under hotter and more humid conditions, while CO_2 concentration exhibits a weak negative correlation with overall activity level (r=−0.75), suggesting additional inhibitory effects of degraded air quality. Although light intensity, particulate matter (PM2.5), and NH_3 also exhibit measurable correlations with certain behaviors, their influences are not further analyzed in this study. Specifically, light exposure in the enclosed pigsty followed a fixed and regular lighting schedule, limiting its variability and explanatory power for behavioral dynamics; NH_3 concentrations remained consistently low due to effective ventilation, resulting in negligible behavioral impact; PM2.5 levels were strongly coupled with ventilation conditions rather than pig activity itself, so their variations do not act as a direct driver of behavioral changes. Overall, these results indicate that temperature, humidity, and CO_2 represent the primary environmental drivers underlying the observed behavioral variations in group-housed pigs.



a. 63 frames b. 109 frames c. 155 frames d. 240 frames

e. 63 frames f. 109 frames g. 155 frames h. 240 frames

Figure 12 Tracking results of pig behaviors in Pen 1 and Pen 2 at frames 63, 109, 155, and 240

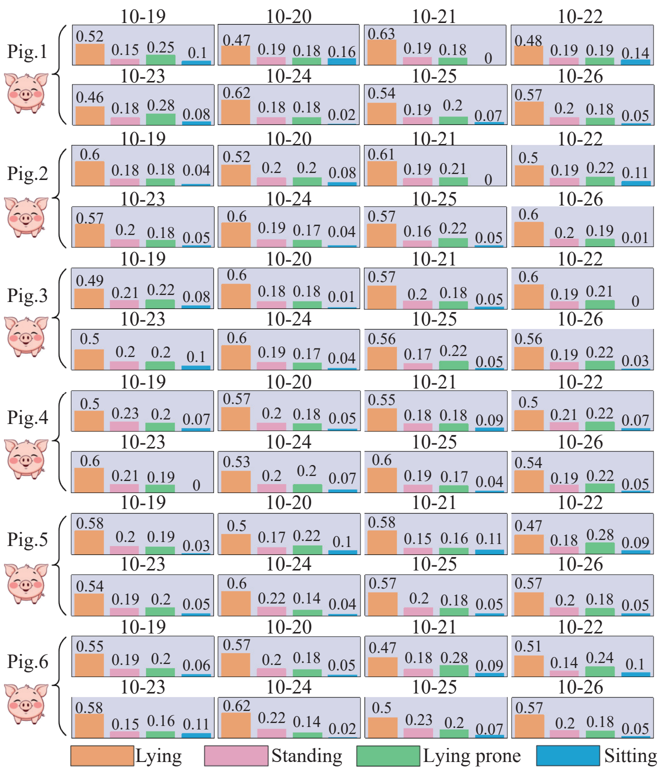


Figure 13 Distribution ratio chart of pig behaviors

Building upon the static correlations between environmental factors and behaviors identified in Figure 14, Figure 15 further focuses on the diurnal dynamics of temperature, humidity, and CO_2 concentrations, alongside their real-time impacts on the distribution of pig behaviors. Herein, temporal variations in temperature, humidity, and CO_2 concentration throughout the day and their influence on behavioral distribution were examined. Temperature and humidity exhibit inverse but relatively stable trends, with temperature peaking around midday and humidity being lowest during the same period, while CO_2 concentrations reach their highest levels in the morning and evening, consistent with the inhibitory association between CO_2 and activity observed in Figure 14. Correspondingly, pigs show increased resting behaviors, particularly prone lying and lateral lying, during periods of higher temperature and humidity, whereas standing and feeding predominantly occur in the cooler morning and evening periods. In low-temperature but high-humidity periods, pigs tend to reduce locomotion and increase resting, suggesting combined effects of thermal discomfort and moisture. Elevated CO_2 concentration further suppresses activity, reinforcing the inhibitory influence of air quality on behavioral expression. These temporal variations provide an intuitive and quantitative basis for evaluating the influence of environmental conditions on daily behavioral rhythms and for identifying periods of potential thermal or air-quality stress in group-housed pigs.

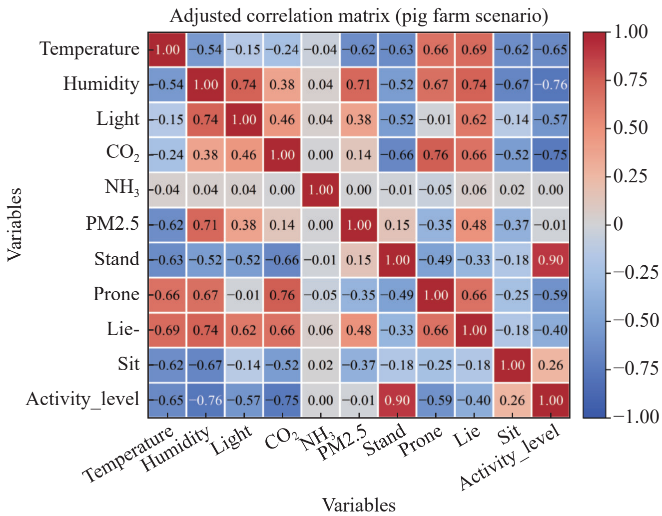


Figure 14 Correlation matrix between environmental and behavioral data

Extending the diurnal behavior-environment rhythms revealed in Figure 15, Figure 16 further expands the analysis to a long-term observation from July to November, to validate the cross-temporal coupling between environmental fluctuations and pig behavioral states. Under conditions of elevated temperature and humidity, pigs exhibit reduced activity, with behaviors predominantly shifting toward prone lying and lateral lying, reflecting thermoregulatory adaptation to heat stress. When temperature and humidity remain low, pigs show higher activity levels, characterized by increased standing and feeding behaviors. In low-temperature but high-humidity conditions, pigs tend to reduce movement and increase prone lying and lateral lying, indicating combined effects of cold stress and moisture discomfort. Notably, during periods of abnormally high CO_2 concentration, pig activity is markedly suppressed, with a pronounced increase in prone lying reflecting abnormal behavioral responses. In contrast to the weak negative correlation of CO_2 observed in Figure 14, its inhibitory effects become more prominent during abnormal fluctuations in long-term observations, suggesting that degraded air quality further exacerbates behavioral inhibition. Overall, abnormal fluctuations in temperature, humidity, and CO_2 concentration are closely associated with distinct behavioral responses, with changes in standing, dog-sitting, lateral lying, and prone lying reflecting environmental stress conditions in group-housed pigs. These findings collectively highlight the critical role of thermal, humidity, and air quality conditions in influencing daily behavioral rhythms and provide a quantitative basis for welfare assessment and early health warning in group-housed pigs.

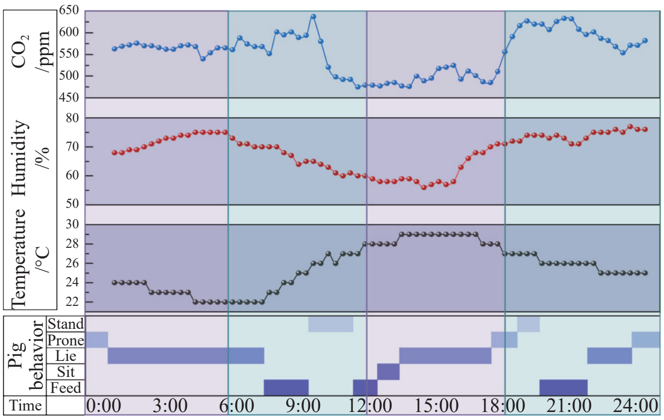


Figure 15 Correlation graph between pigsty environment and pig behavior

3.5 Discussion

The experimental results indicate that the PIG-Net–based framework reliably captures behavioral dynamics of group-housed pigs under complex farming conditions, supporting accurate multi-behavior recognition and stable multi-object tracking. Deployed in a pig farm in Tai'an, the system achieved transmission stability and packet success rates exceeding 98%. The PIG-Net model attained an average mAP of 93.5% across four behaviors (standing, dog-sitting, lateral lying, prone lying) and an IDF1 of 90.7% in multi-object tracking, effectively reducing ID switches and missed detections. Based on 24-hour individual tracking, daily proportions of the four behaviors were quantified, providing a continuous dataset for dynamic coupling analysis with pigsty environmental factors. Correlation analysis revealed significant associations ($|r|$=0.28-0.57), with elevated temperature and humidity linked to increased prone and lateral lying and reduced activity, lower temperature and humidity associated with more standing and feeding, and high CO_2 further suppressing activity. These results show that PIG-Net behavioral tracking combined with environmental measurements enables robust dynamic coupling analysis, supporting systematic evaluation of behavior–environment interactions, welfare assessment, and early health warning. However, analysis is limited to a few postural behaviors, and future work should expand to a broader spectrum for more comprehensive evaluation.

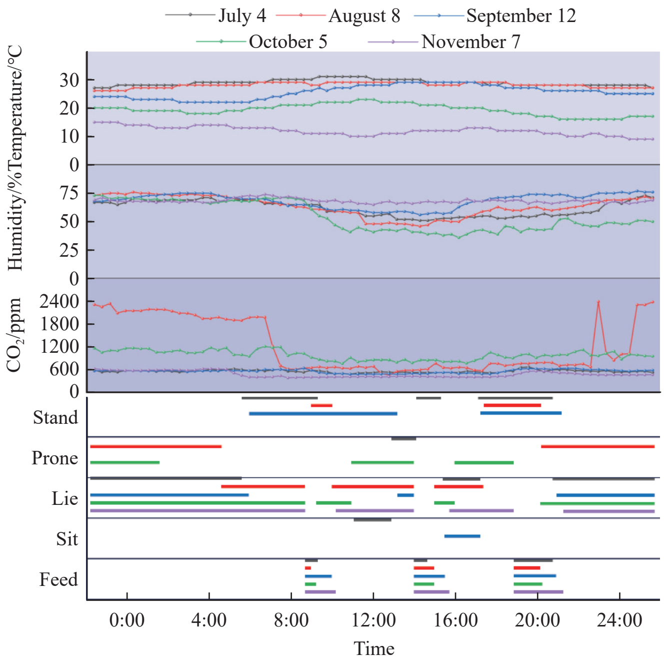


Figure 16 Behavioral responses of group-housed pigs to changes in the pigsty environment

4 Conclusions

In summary, this study proposes a dynamic coupling analysis method for group-housed pig behaviors and pigsty environmental factors based on the PIG-Net model. The proposed method supports the integrated analysis of group-housed pig behaviors and pigsty environmental information, providing technical support for intelligent behavior monitoring and behavior–environment correlation analysis in pig houses. The main conclusions are as follows:

(1) A cloud-edge collaborative system for pig behavior pattern analysis has been developed in this study. After being deployed in a pig farm in Tai'an, this system successfully completed the tasks of pig behavior recognition, tracking, and environmental data collection, achieving transmission stability and packet success rates above 98%.

(2) The PIG-Net model is used for posture recognition and tracking of group-raised pigs, including standing, dog sitting, lateral lying, and prone lying. The experimental results show that the average mAP is 93.5% and IDF1 is 90.7%, effectively mitigating tracking errors caused by occlusion, complex backgrounds, and rapid movements of pigs.

(3) Long-term monitoring combined with Pearson correlation analysis quantified the association between pig behaviors and environmental factors, confirming a significant correlation ($|r|$=0.65-0.76). Temperature, humidity, and CO_2 were identified as the core environmental driving factors. Elevated temperature and humidity inhibited the active behaviors of pigs, whereas cool and dry environments enhanced their activity levels. Under heat and humidity stress, the frequency of prone and recumbent behaviors in pigs increased significantly. Rising CO_2 concentrations further

suppressed pig activity, highlighting the inhibitory effect of microclimate stress.

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