RESEARCH ON MULTI-OBJECT TRACKING OF PIGS BASED ON IMPROVED BYTE TRACK

基于改进 ByteTrack 的多目标生猪跟踪研究

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ABSTRACT

As the pig farming industry evolves towards intelligence and large-scale operations, multi-object tracking technology plays a pivotal role in enhancing farming efficiency and optimizing health management. Addressing the issues of trajectory interruption and jitter caused by frequent occlusion of targets, significant scale variations, rapid motion, and sudden turns in large-scale breeding scenarios, an improved ByteTrack method is presented. This method employs YOLOv8 as the detector and enhanced the ByteTrack framework. By incorporating an Exponential Moving Average (EMA) trajectory smoothing module, it optimizes the trajectory jitter issues encountered by traditional Kalman filtering in fast-moving or sudden turning scenarios, resulting in smoother and more continuous tracking trajectories. Experimental results on a real-world livestock farm video dataset demonstrate that the proposed method achieves improvements across several key evaluation metrics. Specifically, the Multi-Object Tracking Accuracy (MOTA) increased by 1.61%, Identification F1 Score (IDF1) improved by 2.55%, and the Recall rose by 9.68%. The results demonstrate that the proposed method can effectively track pigs in complex farming environments with frequent occlusions, large scale variations, and abrupt motion, providing reliable underlying data support for downstream applications, such as abnormal behavior identification and automated physical activity statistics in intelligent pig farming systems.

摘要

随着养猪业向智能化与规模化发展，多目标跟踪技术对提升养殖效率与优化健康管理具有关键作用。针对规模化养殖场景中目标频繁遮挡、尺度变化显著、快速运动及突然转向导致的轨迹中断与抖动问题，本文提出一种基于改进 ByteTrack 算法的生猪多目标追踪方法，旨在应对规模化养殖场景中目标频繁遮挡、尺度变化显著及轨迹中断等挑战，以提升养殖智能化管理效率。该方法以 YOLOv8 作为目标检测器，并在 ByteTrack 多目标追踪框架基础上，引入指数移动平均（EMA）轨迹平滑模块，有效缓解了传统卡尔曼滤波在目标快速运动或突然转向时出现的轨迹抖动问题，从而获得更为平滑、连续的追踪轨迹。在实际养殖场视频数据集上的实验结果表明，本方法在多项关键评价指标上均有显著提升，其中多目标跟踪准确率（MOTA）提升 1.61%，身份一致性（IDF1）提升 2.55%，召回率提升 9.68%。该方法能够有效应对复杂场景下的目标追踪任务，通过缓解遮挡与尺度变化对追踪精度的影响，能够为后续生猪异常行为识别、运动量自动化统计等实际生产应用提供稳定的底层数据支撑。

INTRODUCTION

The pig farming industry occupies a crucial position in the agricultural economic system, and its development directly affects the stability of meat supply in the market as well as farmers income. With the increasing scale and intensification of pig farming, high labor costs, difficulties in disease prevention, and environmental pollution have become bottlenecks for healthy pig farming (*Reza et al., 2025*). In this context, smart farming has become an important development trend in the pig farming industry (*Trabachini et al., 2025*). Monitoring the health status of pigs is a key aspect of pig production and an important step in achieving intelligent monitoring.

Traditional group pig monitoring mainly relies on manual inspection, which is inefficient, labor-intensive, and unable to provide continuous monitoring. Although sensor-based methods can achieve effective monitoring, they require expensive equipment and may cause stress responses in pigs. In contrast, vision-based multi-object tracking enables continuous and non-contact monitoring by providing identity and location information for each pig, thereby supporting timely abnormal behavior detection and disease prevention.

Monitoring the health status of pigs is a critical component of pig production and a key step in achieving intelligent farming (*Devi et al., 2024*). Traditional manual inspection methods are inefficient, costly, and cannot provide continuous monitoring. Sensor-based approaches are expensive and may induce stress in pigs, negatively impacting their health (*Pandey et al., 2021*). Utilizing multi-object tracking technology, farm staff can monitor pigs' locations, movements, and behavior patterns continuously and without contact, enabling timely detection of diseases, stress, and other abnormalities, and allowing for prompt intervention, thereby effectively preventing disease spread (*Jaoukaew et al., 2024*).

In recent years, methods for multi-object tracking of pigs have shifted from approaches based on handcrafted features to those based on deep learning. Deep learning-based multi-object tracking methods for pigs can be broadly categorized into key-point recognition-based methods, image segmentation-based methods, and object detection-based methods (*Lu et al., 2024*). Key-point recognition methods track targets by detecting their key skeletal points (such as the snout, base of the tail, and four hooves in pigs) (*Psota et al., 2020*). These methods can estimate target poses or behaviors during tracking but rely heavily on key-point visibility, making them unsuitable for densely populated or highly obstructed environments (*Yin et al., 2025*). Methods based on image segmentation precisely extract the target from the background through pixel-level segmentation and then track the mask (*Compte et al., 2025*). However, pixel-level processing is very computationally intensive (*Liang et al., 2025*). The object detection-based approach is currently the mainstream method. It first obtains the bounding boxes of objects through a detector and then matches these boxes between frames to acquire object identities and trajectories (*Li et al., 2025*).

To address challenges in pig farming scenarios, including frequent occlusions, large target scale variations, and abrupt target motion, this paper proposes an improved ByteTrack-based multi-pig tracking framework for achieving more stable and continuous trajectory association in complex breeding environments. The main contributions of this paper are as follows:

(1) YOLOv8 is adopted as the object detector to improve bounding box regression accuracy and enhance detection robustness under complex backgrounds, scale variations, and mutual occlusions;

(2) An Exponential Moving Average (EMA)-based trajectory smoothing module is introduced to improve the ByteTrack framework. By computing a weighted average of historical trajectory positions, this module compensates for the limitations of Kalman filtering during abrupt changes in the target motion state, thereby significantly reducing tracking-box jitter and ensuring the continuity of target trajectories. This makes it particularly suitable for practical applications in complex dynamic scenarios.

(3) A real-world multi-pig tracking dataset covering multiple scenes and camera viewpoints is constructed, and extensive experiments are conducted to validate the effectiveness of the proposed method.

MATERIALS AND METHODS

Dataset construction

In order to ensure the diversity of data scenarios, videos were collected from different farms, with some videos coming from a farm in Taiyuan, Shanxi (Pig Farm 1), some from a farm in Yuncheng, Shanxi (Pig Farm 2), and some from publicly available online datasets. Figure 1 shows samples from the dataset.

As shown in Figure 1, (a) and (c) are taken from an oblique angle, capturing a more comprehensive view of the pigs' bodies, with the main challenge being mutual occlusion. The individuals in (c) have a very high similarity, making identity recognition difficult. (b) is taken from a side view, which is severely obstructed by the pen bars and is also more prone to mutual occlusion. (d) is taken from a top-down view, which reduces occlusion but limits the coverage area and the information that can be collected about the pigs.

In order to train a multi-object tracking model for pigs, long videos were divided into clips ranging from 150 to 600 frames, and the collected videos were annotated in the MOT format. A total of 28 videos were annotated, with 16 used as the training set, containing 4,980 frames, and 12 used as the test set, containing 4,050 frames. The detailed information of the videos is shown in Figure 2. The entire dataset includes a total of 9,030 frames, 304 IDs, and 88,067 annotated objects.

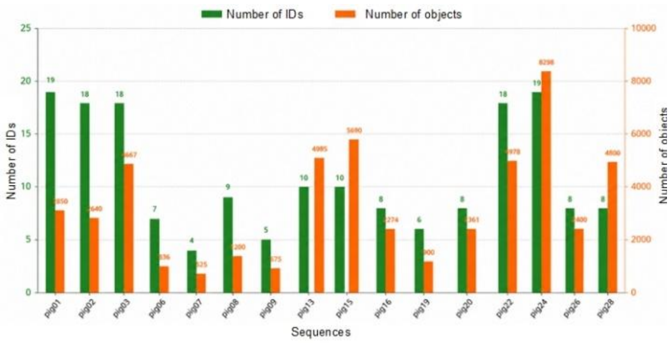
(a) Oblique top view

(b) Side view

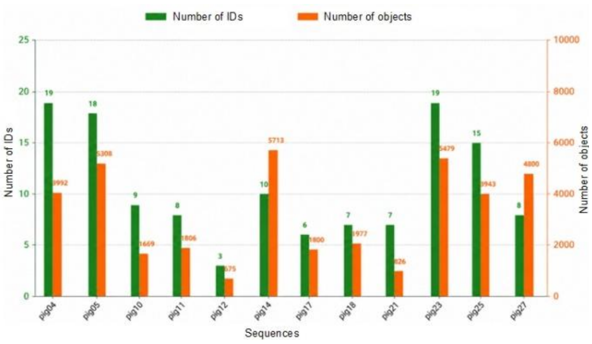
(c) Oblique top view

(d) Side view

Fig. 1 - Samples in the dataset



(a) Training set



(b) Test set

Fig. 2 – Dataset description

Overall architecture

Many online tracking methods rely on Kalman filtering for trajectory prediction (*Stanojevic et al., 2024*). Although Kalman filtering can predict the positions of targets, its predictions are susceptible to noise, resulting in unsmooth trajectories. This is manifested as jumps or jitters in the tracking boxes, which in turn affect the stability of tracking. The workflow of the improved ByteTrack method is shown in Figure 3.

In pig farming scenarios, the movement trajectories of pigs are usually irregular, often accompanied by rapid movements, sudden turns, or body tremors. Based on this, this study introduces the Exponential Moving Average (EMA) algorithm (*Haynes et al., 2012*), which smooths prediction results by performing a weighted average on historical trajectory positions. Unlike Kalman filtering, which assumes relatively smooth linear motion, EMA smoothing is more tolerant to abrupt short-term motion fluctuations commonly observed in pig movement behaviors. This characteristic makes EMA particularly suitable for livestock tracking scenarios with frequent irregular motion patterns.

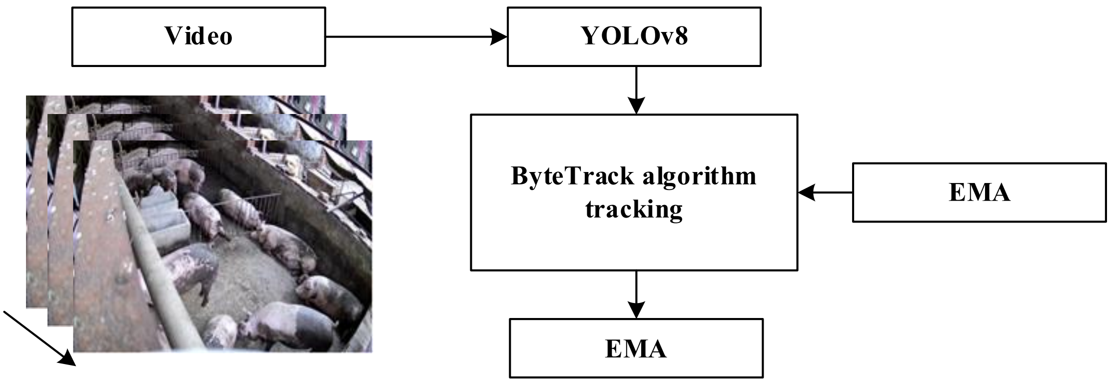


Fig. 3 - Overall architecture of the improved ByteTrack multi-object tracking method

Furthermore, the performance of ByteTrack strongly depends on the stability of object detections, since its association process relies on confidence scores and IoU similarity across consecutive frames. In pig farming scenarios, frequent occlusions, abrupt motion, and similar appearances often lead to unstable detections when conventional detectors are used.

To address these challenges, YOLOv8 is adopted for its stronger feature extraction and localization capability, especially for small-scale and partially occluded targets. Meanwhile, the EMA-based trajectory smoothing module further reduces trajectory jitter caused by sudden motion and detector noise.

ByteTrack Tracking Method

ByteTrack is a lightweight and efficient multi-object tracking algorithm that does not require the integration of a Re-ID module or depend on additional training processes (*Zhang et al., 2022*). When an object undergoes significant occlusion, the confidence of the detection boxes generated by the detection algorithm typically decreases. The most notable improvement of this system is the reasonable reuse of low-confidence detection boxes, which effectively suppresses object loss in occlusion scenarios.

The tracking process of the ByteTrack is shown in Figure 4.

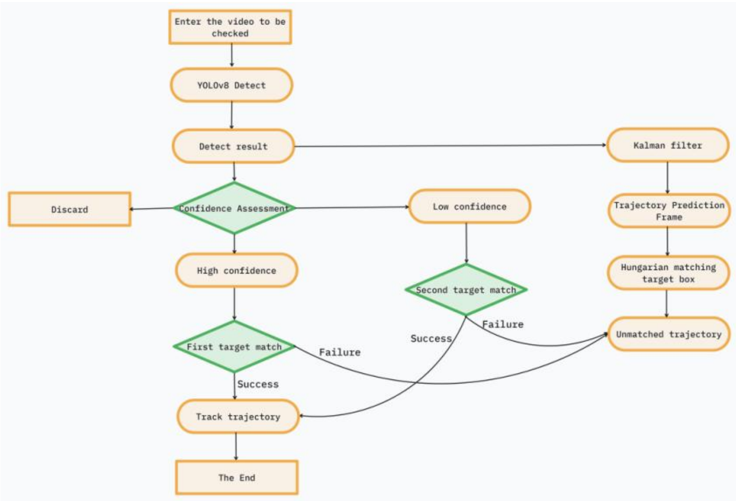


Fig. 4 – Flowchart of ByteTrack

Specifically, the system first divides the detection boxes based on a confidence threshold. In the initial matching stage, the trajectory boxes predicted by the Kalman filter are associated with high-confidence detection boxes through the IoU matrix and the Hungarian algorithm; subsequently, the remaining unmatched trajectories are matched with low-confidence detection boxes in a secondary matching stage. Ultimately, only unmatched detection boxes are discarded, while successfully matched targets are used to update trajectories or initialize new trajectories.

YOLOv8 Detection Method

YOLOv8 is a mature detector widely used in multiple real-world scenarios. These successful applications fully validate YOLOv8's strong adaptability and high performance in various contexts, providing a reliable technical foundation for the pig detection tasks in this study (*Sohan et al., 2024*). The network architecture of YOLOv8 is shown in Figure 5.

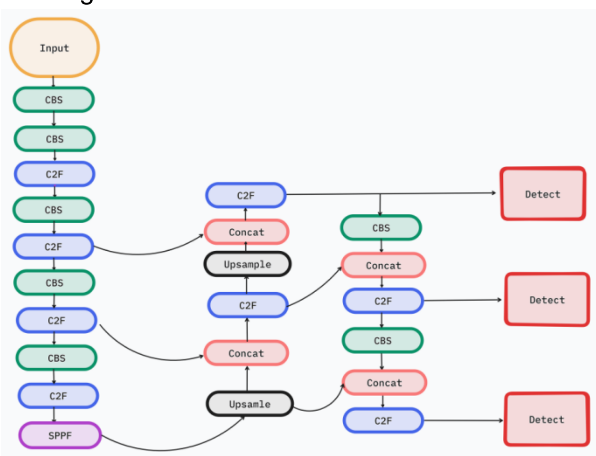


Fig. 5 - YOLOv8 network structure diagram

In Figure 5, the overall architecture of the YOLOv8 model mainly consists of four parts: Input, Backbone, Neck, and Head.

The Input end is responsible for performing data augmentation on the input images to improve the model's generalization ability. The Backbone is used to extract multi-level features from the images and mainly consists of modules such as CBS (*Conv BN SiLU*), C2f (lightweight residual module), and SPPF (spatial pyramid pooling). Through multiple downsampling and feature refinement steps, the Backbone gradually compresses the feature map size while enhancing semantic information.

The Neck section is designed to integrate feature information at different scales to enhance detection performance. This section draws on the design concepts of FPN and PANet, effectively combining shallow and deep features, significantly improving the detection of small targets.

The Head outputs multi-scale feature maps and generates feature maps of three different sizes. Each scale network outputs the target's bounding box, confidence score, and class label.

Evaluation Method

The model evaluation metrics include: $MOTA$, $IDF1$, IDP, MT, ML, IDS, FP(False Positives), FN(False Negatives), precision, and recall (*Dendorfer et al., 2020*).

MOTA is as shown in formula (1):

$$MOTA = 1 - \frac{\sum_t (FN_t + FP_t + IDSW_t)}{\sum_t GT_t} \tag{1}$$

It measures the overall accuracy of the entire tracking system, taking into account missed detections, false positives, and ID switches. IDS is the number of times a target's identity changes. GT is the total number of targets in the ground truth. FP is the false detected targets, and FN is the missed detections.

$IDF1$ is as shown in formula (2):

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

$IDF1$ is the harmonic mean of ID Precision and $ID\ Recall$, used to measure the consistency of identity preservation. $IDTP$ is the correctly predicted identities, $IDFP$ is the incorrectly assigned identities, and $IDFN$ is the missed identities that should have been detected.

The precision and recall is calculated as formula (3) and (4):

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

FN (False Negatives) refers to missed detections, meaning that the target in the ground truth was not detected. TP (True Positive) means the model successfully detected a target that actually exists.

RESULTS AND DISCUSSION

Experimental Setup

This experiment was conducted on a hardware platform equipped with an Intel® Core™ i5-11260H processor, 15.7GB of memory, and an NVIDIA GeForce RTX 3050 GPU, with Windows 11 as the operating system. The algorithm was implemented based on Python 3.10 and the PyTorch 2.6.0 framework, and accelerated using CUDA 11.8. The detection model is based on the YOLO architecture and was trained using YOLOv8s, with the training process consisting of 50 epochs.

During the model training phase, the batch size was set to 16, the initial learning rate was set to 0.001, and the weight decay coefficient was 0.0005. The loss function weight allocation was as follows: BoxLoss was 0.05, the classification loss weight was 0.3, and DflLoss was 1.5. To further improve the model's accuracy and recall, the experiment introduced a data augmentation strategy.

Model Training Results

As shown in Figure 6, the trends of key metrics during the model training process are displayed. After training converges, the model's accuracy remains above 0.95, and the recall stays above 0.87.

For each video sequence, the frame rate is maintained at 10 FPS, and the total inference time is approximately 5 minutes.

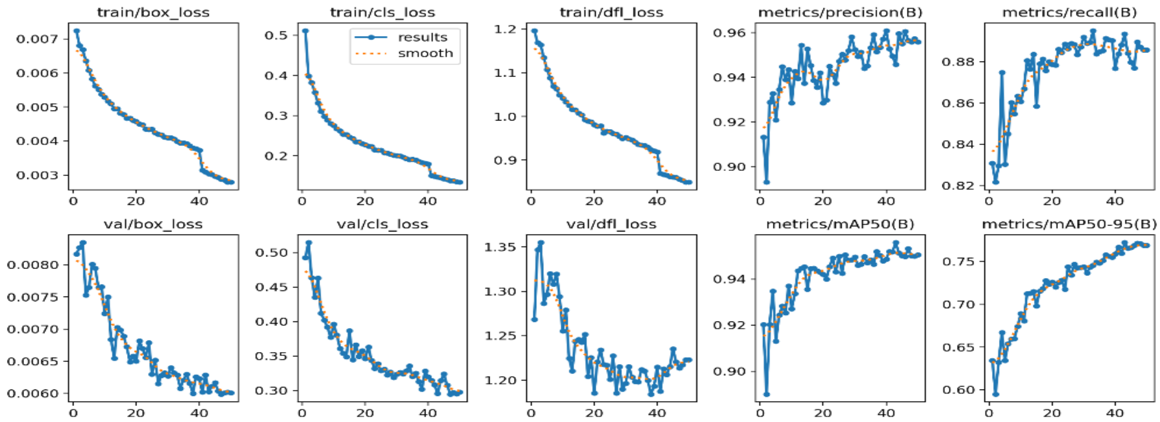


Fig. 6 - Training Results of YOLOv8 Model

Muti-Target Tracking Results Of Live Pigs

The results of multi-pig tracking using the improved ByteTrack algorithm are shown in Table 1.

The improved ByteTrack algorithm performs well in the task of tracking pigs. Although the MOTA metric is relatively low in some specific scenarios (pig12), overall, this improvement is significantly effective.

Table 1

Experimental Results of Multi-object Tracking of Pigs

Video	MOTA	IDF1	IDP	IDR	FP	FN	IDS	precision	recall
pig04	92.84%	92.95%	92.79%	93.11%	145	131	10	96.38%	96.72%
pig05	94.10%	89.66%	89.07%	90.26%	187	116	10	96.52%	97.81%
pig10	72.98%	78.29%	76.50%	80.17%	259	179	13	85.19%	89.28%
pig11	81.34%	67.20%	69.49%	65.06%	104	219	14	93.85%	87.87%
pig12	30.81%	83.52%	72.17%	99.11%	357	105	5	61.49%	84.44%
pig14	84.09%	71.41%	67.63%	75.63%	781	105	23	87.78%	98.16%
pig17	81.00%	91.32%	84.50%	99.33%	328	12	2	84.50%	99.33%
pig18	83.21%	92.05%	91.25%	92.87%	182	147	3	90.95%	92.56%
pig21	79.66%	87.05%	84.34%	89.95%	111	56	1	87.40%	93.22%
pig23	93.63%	83.75%	83.07%	84.45%	210	119	20	96.23%	97.83%
pig25	86.63%	89.52%	84.93%	94.62%	482	32	13	89.03%	99.19%
pig27	99.08%	99.83%	100.00%	99.67%	14	30	0	99.71%	99.38%

Ablation Experiment Results

To evaluate the impact of the improved module on the tracking system, an ablation experiment was conducted on the video pairs in the test set, and the results are shown in Table 2.

Table 2

Ablation Experiment Results

Ablation module	**Evaluation metrics**								
EMA	MOTA	IDF1	IDP	IDR	IDS	FP	FN	precision	recall
×	80.00%	83.00%	87.79%	79.21%	79	1225	4857	94.58%	84.97%
√	81.61%	85.55%	82.98%	88.69%	114	3160	1251	89.09%	94.65%

Figure 7 shows a comparison of the effects before and after adding the EMA module. (a) and (b) are consecutive video frames without using the EMA module, while (c) and (d) show the results of processing the same two video frames after adding the EMA module. As shown in Figure 6, by introducing the EMA trajectory smoothing algorithm, the consistency between the size of the tracking box and the actual size of the pig's body has been significantly improved.

Comparative Experiment

To verify the effectiveness of the improved ByteTrack algorithm, the experiment compared it with two multi-object tracking algorithms, OCSORT and DeepSORT (*Wojke et al., 2017; Cao et al., 2023*). All three algorithms follow the Tracking-by-Detection paradigm, which first uses an object detector to obtain targets in each frame and then matches the detected boxes with existing trajectories through an association strategy. To ensure a fair comparison, all three used YOLOv8s as the base detection model and conducted multi-object tracking tests on the same video sequences. Table 4 shows the results of the comparative experiment.

(a) Frame 1 without EMA module added (b) Frame 2 without EMA module added (c) Add EMA module frame 1 (d) Add EMA module to frame 2

Fig. 7 - Comparison of effects with or without the EMA module

Table 3

Comparison of Experimental Results

Algorithm Name	**Evaluation metrics**								
	MOTA	IDF1	IDP	IDR	IDS	FP	FN	precision	recall
DeepSORT	81.10%	85.55%	82..98%	88.69%	114	263	104	89.09%	94.65%
OCSORT	84.10%	85.52%	89.25%	81.89%	149	374	3651	96.90%	87.59%
Improved ByteTrack	81.61%	85.55%	82.98%	88.69%	114	3160	1251	89.09%	94.65%

As shown in Table 3, among the three trackers, DeepSORT performed the worst overall. This is because in complex scenarios, DeepSORT is prone to higher ID switches and missed detections. OC-SORT has relatively high multi-object tracking accuracy, but it also has a high false detection rate, indicating that it often loses track, resulting in poor trajectory continuity. In contrast, the improved ByteTrack algorithm performs well overall, although its accuracy and stability are slightly inferior to OC-SORT. It can be seen that the improved ByteTrack achieves the best overall performance.

Practical Application Discussion

The data from Pig Farm 1 were collected in Taiyuan, Shanxi Province, from April 19 to April 30, 2019. The pigsty consisted of 10 pens (6 m × 5 m × 1.2 m), each housing 5–6 sows. A Hikvision DS-2CD3T86FWDV2-I3S high-definition network camera was installed on the side wall and ceiling (approximately 2 m height) of each pen for video collection.

Multi-object tracking technology enables continuous and non-contact monitoring of pigs by providing stable identity and trajectory information for each individual. Based on this advantage, the proposed improved ByteTrack method can continuously analyze pig movement trajectories and behavioral patterns, offering reliable data support for abnormal behavior detection, activity analysis, and livestock health management. In practical deployment, the system requires only standard HD cameras and GPU-based edge computing devices. By integrating YOLOv8 with the ByteTrack+EMA framework, the system enables real-time pig tracking and trajectory smoothing while remaining compatible with existing farm management systems.

CONCLUSIONS

This study focuses on the challenges in multi-object tracking of pigs, such as variable target scales, mutual occlusion, and complex scenes, and proposes a pig multi-object tracking method based on an improved ByteTrack. By introducing the EMA trajectory smoothing algorithm, the method performs weighted averaging of the targets' historical position information, effectively suppressing the jitter of detection boxes.

Experimental results show that the proposed improved method achieves significant performance gains in real-world applications. Compared with the baseline model ByteTrack, MOTA increased by 1.61%, IDF1 increased by 2.55%, Recall improved by 9.68%, and the FN was greatly reduced. The results indicate that the improved ByteTrack performs stably in complex scenarios with high pig density, frequent occlusions, and highly similar appearances, demonstrating strong practical application potential.

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