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Performance Analysis of Algorithms Applying YOLOv8 and OC-SORT for Livestock Behavior Analysis

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Abstract

This research develops a smart livestock monitoring system leveraging artificial intelligence with YOLOv8 and OC-SORT technologies to precisely monitor and analyze cow behavior, enhancing detection and tracking capabilities in complex environments. It delves into cows' movement speed and acceleration to uncover behavior patterns and health status, focusing on estrus-related behaviors for optimal breeding strategies. The study identifies changes in activity, social interactions, and mating behaviors as crucial estrus indicators, contributing significantly to livestock management innovations. By offering methods for visual behavior analysis representation, it simplifies the interpretation of findings, advancing livestock monitoring technology. This work not only contributes to smarter livestock management by providing an AI-driven cow behavior tracking model but also opens new avenues for research and efficiency improvements in the field.

Keywords: *Behavior Recognition, OC-SORT, YOLOv8, Object Tracking, Agricultural Applications.*

1. Introduction

Agricultural economics is highly significant for ensuring a stable food supply, promoting balanced development of the country, protecting the environment and ecology, and providing leisure spaces. The demand for beef supply through livestock farming is expected to occupy a significant portion of the future agricultural demand, especially with the increasing need for beef cattle. Moreover, issues related to various livestock diseases have been persistently raised. In South Korea, the breeding of Hanwoo and beef cattle accounted for 31.9% of livestock production in 2019, ranking second after pig farming at 44.6%. However, the continuous rise in international grain prices and labor costs due to population decline has led This study proposes a cow behavior recognition system based on YOLOv8 and OC-SORT [1], which exhibits high

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accuracy and real-time performance for building an animal behavior recognition and tracking system. This system leverages the improved object recognition accuracy of YOLOv8 and the OC-SORT technology, enabling stable real-time tracking in complex environments and occlusion situations, thus providing a superior real-time animal behavior monitoring solution compared to existing systems. to increased production costs for beef, milk, and dairy products, resulting in stagnant income levels. Real-time monitoring of cow behaviors can not only diagnose their health status but also provide data for rational fodder supply and enhance the welfare level of cows [2-4]. Traditional methods of monitoring cow behaviors based on human observation require high labor costs and are prone to errors due to subjective factors of the workers. Although methods based on contact sensors are widely used in cow behavior recognition, they can induce stress responses and potentially harm cow welfare. Furthermore, sensors attached to cows can generate noise data due to factors such as shaking and collisions, affecting the accuracy of behavior detection. In contrast, computer vision technology offers the benefits of automation and non-contact in cow behavior recognition and monitoring [5-7]. This study proposes a cow behavior recognition system based on YOLOv8 and OC-SORT, which exhibits high accuracy and real-time performance for building an animal behavior recognition and tracking system. This system leverages the improved object recognition accuracy of YOLOv8 and the OC-SORT technology, enabling stable real-time tracking in complex environments and occlusion situations, thus providing a superior real-time animal behavior monitoring solution compared to existing systems.

2. Theoretical Basis

2.1 OC-SORT Object Tracking Algorithm

OC-SORT is an advanced algorithm aimed at enhancing object tracking accuracy through an observation-centric method, diverging from the traditional estimation-focused SORT technique. This method prioritizes observed data to address challenges like noise, occlusions, and nonlinear motion more effectively. By integrating object movement into the association phase, OC-SORT reduces tracking failures, employing an Observation-Centric Online Smoothing (OOS) strategy for more reliable tracking by correcting errors from untracked intervals. Additionally, it introduces an Observation-Centric Momentum (OCM) term to improve the identification and reacquisition of lost objects, boosting performance in complex scenarios. OC-SORT's process efficiently manages difficulties such as noise and occlusions, making it ideal for real-time uses, including AI-based smart livestock monitoring systems, by ensuring accurate and stable tracking of animals' movements.

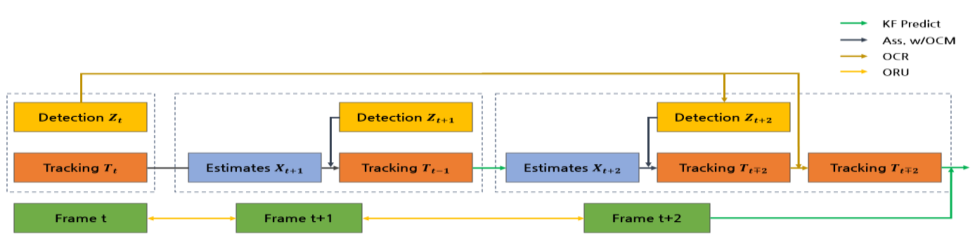

Figure 1. OC-SORT traces the process of the algorithm

3. Materials and methods

This study introduces a method combining artificial intelligence and computer vision to study cow behaviors in a barn, using RGB video frames from AI-Hub. It employs deep learning-based object detection and tracking to accurately monitor cows' movements, clustering, and mounting activities. Data is stored in a

MySQL database and accessible through a PySide6-developed visualization tool, supporting distributed processing. The system operates round-the-clock, analyzing cows' behaviors and social interactions, aiding in understanding their habits and health. This insight offers valuable support for farm managers in decision-making.

3.1 Data Collection

In this study, the focus on data diversity is a key factor in significantly enhancing the generalization ability and accuracy of the algorithms. To evaluate and verify the performance of the YOLOv8 and OC-SORT algorithms in real-world, diverse, and complex scenarios, the research team utilizes image data of cows collected from various regions within South Korea (Gangwon-do, Chungcheong-do, Gyeonggi-do, Gyeongsang-do). This data, captured across different growth stages of cows and various times, provides ideal conditions for assessing the robustness and adaptability of the algorithms. The diversity of the data enables the algorithms to better understand and respond to the various changes and conditions that can occur in real farm environments, thereby enhancing the effectiveness of the algorithms' application in real-world scenarios. This allows the algorithms to effectively recognize and track the constantly changing lighting conditions, various backgrounds, and diverse behavioral patterns of cows.

Figure 2. Data set example

3.2 Data Annotation

The dataset we collected was designed with 26 types of behaviors. We reclassified these 26 behaviors into 4 static behaviors to maximize data availability and to allow for the customization of analysis based on specific experimental needs. This process of reclassification lays the groundwork for a more detailed understanding and analysis of the data according to research objectives. The classification of actions is shown in Table 1.

Table 1. The classification of actions

Static action	Behavior description
stand	The bottom of all four hooves is in contact with the ground with all four legs fully extended and holding the body steady
sit	The condition in which the four legs and lower abdomen are completely in contact with the ground while the front knee is stretched or bent
lower	Head is positioned lower than head is positioned while standing down
mounting	the act of a rutting cow climbing on the rutting cow's hip

3.3 Data Preprocessing

To tackle the factors in complex barn environments that may affect camera recognition, such as manure and flies, we have implemented a range of image enhancement techniques aimed at increasing robustness and recognition accuracy. The process of image enhancement is depicted in Figure 3.

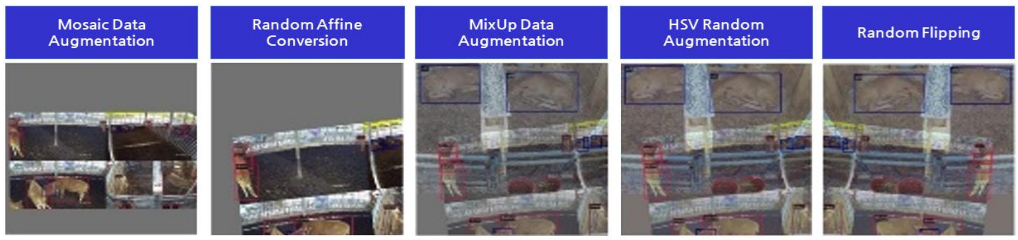

Figure 3. image annotation process used for detecting Hanwoo (Korean cattle)

4. Experiment Results

4.1 Model Training and evaluation environment

The experiment was conducted on a Windows 11 system, utilizing an 11th Generation Intel(R) Core(TM) i9-11900K CPU with a base frequency of 3.50GHz, 8 cores and 16 threads, with a maximum frequency of up to 4.69GHz. The Graphics Processing Unit (GPU) is a GeForce RTX 3090, equipped with 24GB of video memory. The system's memory capacity is 64GB. The deep learning framework used is PyTorch 1.13.1, which was employed for the design, training, validation, and testing of the network structure. The specific environmental settings of the experiment are shown in Table 2.

Table 2. The specific environmental settings of the experiment

Division	Specification
Operation System(OS)	Windows 11
Central Processing Unit(CPU)	Intel i9-11900K
Graphics Processing Unit(GPU)	NVIDIA GeForce RTX 3090
Memory	64GB
Programming Language	Python 3.8
Deep Learning Framework	Pytorch 1.13.1

4.2 Experimental data structure

In this study, we collected a total of 1017 images depicting the behavior of cattle. The dataset was divided into training, validation, and test sets in an 8:1:1 ratio, facilitating the final evaluation of the model's performance. The specific composition of the dataset is presented in Table 3.

Table 3. Data set specific composition

Category	Image count	Label count
Training data	817	3826
Valid data	100	537
Test data	100	680

4.3 Object detection performance Evaluation

In this study, we compared the performance of three object detection models: YOLOv8, YOLOv7, and RTMDet. To assess the performance of these models, we primarily used mean Average Precision (mAP) and recall as key metrics, while also considering the number of parameters and computational requirements of each model. The results of the object detection model comparison are illustrated in Figure 4.

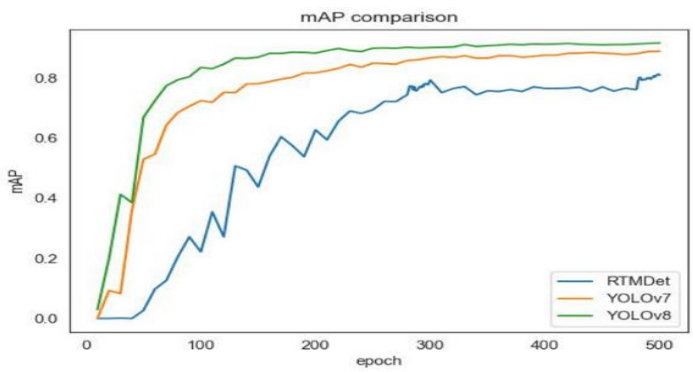

Figure 4. image annotation process used for detecting Hanwoo (Korean cattle)

The comparison results for mean Average Precision (mAP), Recall, Floating Point Operations (FLOPs), and the number of Parameters are presented in Table 4.

Table 4. Performance Comparison of Object Detection models

Algorithms	Parameters (M)	FLOPs (GFLOPs)	mAP (%)	Recall (%)
RTMDet	52.26	79.958	81.0	86.6
YOLOv7	70.835	94.25	89.0	91.2
YOLOv8	43.63	82.56	91.8	93.5

In this study, we conducted an in-depth analysis of the feature maps generated by the three output layers in the main networks of the RTMDet [8], YOLOv7 [9], and YOLOv8 algorithms to understand the features these algorithms focus on while processing images.

4.4 Object Tracking Performance Evaluation

To evaluate the performance of our proposed method (YOLOv8+OC-SORT) in multi-object tracking of cattle, we utilized YOLOv8 as the detector and compared it on the test set with BotSORT and ByteTrack. The comparison results of the object tracking algorithms are shown in Table 5.

Table 5. Comparison Of Object Tracking Algorithms

Algorithms	MOTA	MOTP	FPS
YOLOv8+OC-SORT	79.0	86.2	50
YOLOv8+BotSort	79.8	85.8	12
YOLOv8+ByteTrack	75.0	83.2	54

4.5 Performance evaluation of behavior analysis

To validate the performance of behavior analysis, we conducted tests on a segment of test video, with an example shown in Figure 5.

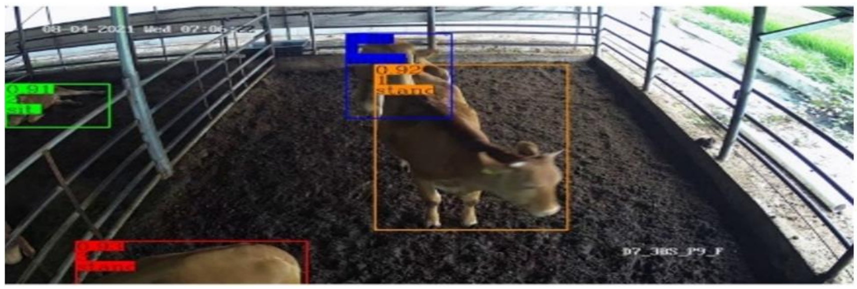

Figure 5. Test sample graph

After obtaining the position information of the cattle, we can further analyze the location data to study the cattle's movement and behavioral characteristics. Firstly, it's necessary to organize the position information of the cattle obtained from OC-SORT. In each frame, the cattle's unique ID, bounding box coordinates, and timestamp can be stored in a structured data table. This step helps to simplify subsequent data processing and analysis work. Based on these location data, we can calculate the movement distance, serving as motion characteristic data to describe cattle movement and behavior.

Table 6. Average European distance table

Cow No	No. 0 cow	No. 1 cow	No. 2 cow	No. 3 cow
No. 0 cow	0	225.3	466.6	318.7
No. 1 cow	225.3	0	554.2	337.2
No. 2 cow	466.6	554.2	0	591.1
No. 3 cow	318.7	337.2	591.1	0

In our developed cattle behavior tracking system, a two-stage strategy is employed to identify mounting behaviors. Initially, the YOLOv8 model detects the bounding boxes and behaviors of cattle in each frame. Once a behavior is recognized as a potential mounting action, it is determined whether the behavior occurs based on whether the intersection area of the bounding boxes of two cattle exceeds 30% in five consecutive frames. This determination is based on the relative positions and overlap degree of the cattle. The process of judging mounting behaviors is illustrated in Figure 6.

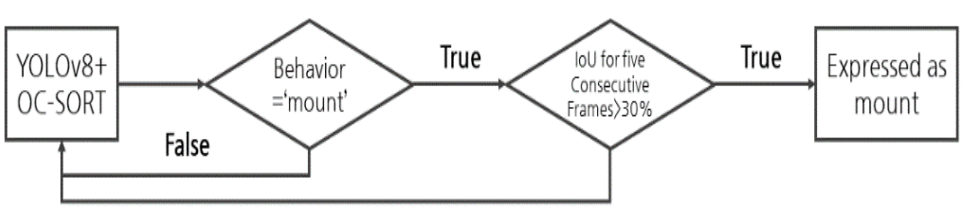

Figure 6. Mounting behaivor detection process

5. CONCLUSION

This study aimed to develop a cattle behavior recognition system based on YOLOv8 and OC-SORT to provide accurate behavior recognition and assist in the management of Hanwoo farms. We compared three algorithms: YOLOv8, YOLOv7, and RTMDet, finding that YOLOv8 demonstrated significant advantages in accuracy, recall, and other metrics, as well as outstanding performance in terms of computational parameters and workload. By applying the OC-SORT algorithm, we were able to maintain high tracking accuracy and stability in complex environments and occlusion scenarios, achieving real-time tracking of cattle. Moreover, by identifying cattle estrus behavior, the possibility of early detection of estrus states to improve the breeding rate and subsequently enhance beef production efficiency was validated. In the future, we plan to continue researching and optimizing this system and to introduce more advanced algorithms into cattle behavior recognition tasks. Through these efforts, we hope to provide more accurate and effective solutions for Hanwoo farms.

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