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Leveraging YOLOv8 and transfer learning for real-time classification of horned sheep behavior: a computer vision approach to precision livestock

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ABSTRACT

Real-time monitoring of livestock behavior is essential for improving animal welfare and optimizing farm productivity. Traditional manual observation is often inefficient, error-prone, and labour-intensive. This study proposes a computer vision-based system for real-time classification of horned sheep behaviours, specifically wake, lay, and sleep, using transfer learning with the YOLOv8 segmentation model. The system is designed for top-view camera setups in one-sheep-per-pen farm structures, enhancing visibility and minimizing occlusion. A dataset of over 12,000 annotated images was collected and augmented to train the model effectively. The proposed system demonstrates a classification accuracy exceeding 90% across all behavior classes, with an average detection latency below one second. Experimental results validate the model's robustness under varied lighting and environmental conditions. This approach enables efficient and scalable behaviour monitoring without requiring additional sensors, offering a practical solution for intelligent farm management and early detection of health-related anomalies.

Keywords: Computer vision, Precision livestock farming, Real-time monitoring, Sheep behaviour recognition, Transfer learning.

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1. INTRODUCTION

The detection of animal behavior, particularly in livestock such as sheep, plays a crucial role in modern farm management by improving animal welfare, productivity, and early disease detection. Recent advances in computer vision and artificial intelligence (AI) have opened new possibilities for automating this process, enabling farmers to obtain accurate, real-time insights without relying on labor-intensive manual observation (Anitha et al., 2020). These technologies also support early detection of behavioral anomalies, facilitating preventive interventions that enhance herd health and farm efficiency.

Deep learning, especially object detection models like YOLO (You Only Look Once), has become one of the most effective methods for visual behavior analysis. YOLOv8 offers a promising balance between detection accuracy (Fotouhi et al., 2024) and computational speed, making it suitable for real-time livestock monitoring applications (Wang et al., 2024a). Observing sheep behavior, such as sleeping, lying down, or being awake, is particularly essential, as these postures reflect physiological and psychological well-being (Zhang et al., 2023a; Carhuas et al., 2025). For example, abnormal lying or inactivity patterns may indicate stress, discomfort, or illness (Wl Allali et al., 2022).

A top-view monitoring approach using fixed cameras is a promising solution to improve visibility and reduce occlusion when observing individual animals (Alon et al., 2023). However, accurate posture classification in horned sheep remains challenging due to shape variations lighting inconsistencies, and the dynamic nature of farm environments (Wang et al., 2024b). Moreover, most existing works either rely on wearable sensors or focus on general sheep behavior without considering the specific risks associated with horned animals in confined spaces (Cominotte et al., 2020).

Despite its potential, implementing top-view position estimation of sheep presents numerous technical challenges. One of the most significant challenges is distinguishing between different postures of a single sheep while accounting for shape variations, lighting changes, and variations in camera angles (Yu et al., 2022). Additionally, YOLOv8 must compensate for external factors such as rapid sheep movements, frequent position changes, and occlusions when multiple sheep are present in an image. Achieving high detection accuracy is critical to ensuring the system operates effectively and reliably (Wang et al., 2024c).

Beyond technical and camera-related challenges, environmental factors such as camera resolution, background conditions, and lighting must also be considered to obtain sharp and reliable images. Lighting variations can significantly impact image quality, thereby affecting the model's accuracy in detecting sheep positions. To mitigate these issues, model training must incorporate diverse environmental conditions, ensuring YOLOv8 adapts effectively to various scenarios (Zhang et al., 2023b).

Despite the increasing adoption of vision-based livestock monitoring systems, limited studies have addressed the specific challenges posed by horned sheep, especially in confined, single-pen environments. Most existing works either focus on general sheep behavior, ignore posture-specific classification, or rely heavily on wearable sensors that may be intrusive and costly. These gaps hinder the deployment of practical, non-invasive, and real-time behavior monitoring systems tailored to horned sheep. This study is motivated by the need to develop a robust, scalable solution that enables precise behavior classification (wake, lay, sleep) using a top-view, sensor-free setup powered by transfer learning on YOLOv8.

Advancements in deep learning and computer vision have also been explored in fields beyond livestock behavior, such as medical imaging. For instance, the application of deep residual-dense networks combined with bidirectional recurrent neural networks (RNNs) has demonstrated significant potential in improving classification accuracy for tasks such as the atrial fibrillation detection (Laghari et al., 2023). Similarly, the integration of machine learning in medical image analysis, particularly in handling high-dimensional data, has helped overcome challenges like image fusion and dimensionality reduction, further optimizing diagnostic performance (Laghari et al., 2024). These innovations in handling complex data are directly applicable to livestock behavior monitoring, where sim challenges, such as occlusion, lighting variations, and complex environmental conditions, are present. By leveraging techniques from these studies, such as deep learning-based feature extraction and transfer learning, the accuracy and efficiency of real-time livestock behavior recognition can be significantly enhanced, ensuring robust performance in diverse farming environments.

Furthermore, quality of experience (QoE) models, which are widely used in VR/AR applications for healthcare offer valuable insights into optimizing the user experience in livestock behavior monitoring systems (Laghari et al., 2024). By considering factors such as network performance, device capabilities, and environmental conditions, these models can ensure that farmers receive accurate and timely information, enhancing decision-making and farm efficiency.

Recent research, including work in Llght YOLOv8n for Liaoning Cashmere goat behavior recognition, has explored optimized YOLOv8 architectures to enhance efficiency in livestock behavior tracking (Chen et al., 2023). These studies propose lightweight convolutional and attention mechanisms to improve accuracy while maintaining computational efficiency. However, real-time applications in specific farm settings, such as one-goat-per-pen infrastructure, still pose challenges for model adaptability. Variations in lighting, occlusions, and discrepancies in movement between sheep and pens continue to present significant obstacles to detection accuracy (Duong-Trung and Duong-Trung, 2024).

The integration of machine learning in agriculture has been widely studied, with research emphasizing its role in optimizing livestock management, improving yield prediction, and enhancing decision-making processes (Boğa and Karabıyık, 2025). These advancements highlight the growing importance of AI-driven solutions in modern farming, reinforcing the need for automated livestock behavior monitoring (Benos et al., 2021). Furthermore, researchers have employed pre-trained convolutional neural networks (CNNs), such as VGG16 and ResNet50, demonstrating that fine-tuning these models significantly enhances accuracy and efficiency.

Another study on intelligent classifiers for sheep and goat identification applied deep learning techniques, utilizing YOLOv8 and transfer learning to improve classification accuracy. These studies demonstrate the versatility of transfer learning in livestock monitoring, reinforcing its effectiveness in enhancing recognition accuracy and computational efficiency (Noor et al., 2020; Yadav et al., 2024). The findings indicate that leveraging pre-trained models reduces the need for extensive labeled datasets, improves generalization, and accelerates training processes. Utilizing deep learning models with feature extraction and multi-scale prediction enables accurate recognition of animal behaviors while minimizing manual annotation efforts (Deng et al., 2021; Yu et al., 2023). This approach aligns with the objectives of this study, which applies transfer learning via Ultralytics' YOLOv8 to classify sheep behaviors efficiently.

To address these challenges, this study proposes a real-time horned sheep behavior recognition system using transfer learning with YOLOv8. The system classifies behaviors into three categories: wake, lay, and sleep, using video data from top-mounted cameras in a one-sheep-per-pen configuration. The main contributions include:

- Designing a top-view monitoring system tailored for horned sheep in individual pens.
- Leveraging YOLOv8-based segmentation with transfer learning to optimize classification performance.
- Developing a scalable, low-latency system for real-time livestock behavior analysis without additional sensors

The remainder of this paper is organized as follows: Section 2 reviews related work in literature review. Section 3 describes the materials and methods. Section 4 presents the result and also discusses the findings and potential improvements. Section 5 concludes the study and outlines future work.

2. LITERATURE REVIEW

Recent developments in computer vision and deep learning have significantly transformed livestock monitoring. Computer vision-based systems are rapidly evolving with architectures that enable cameras and machine learning algorithms to automatically collect, process, and analyze animal behavior data (Duong-Trung and Duong-Trung, 2024; Gong et al., 2024). Image-based systems enable the automatic analysis of animal behavior, reducing the need for manual observation and improving response time to behavioral anomalies. These systems utilize object detection models to monitor postures and activity levels of farm animals, providing insights into health, welfare, and productivity. Compared to traditional sensor-based methods, vision-based techniques offer non-invasive, scalable, and cost-effective solutions.

Advancements in deep learning, such as Mask RCNN and sparse regularized autoencoders (GSRA-KL), have greatly enhanced both medical image classification and gene mutation prediction. Mask RCNN, combined with an attention mechanism, has been effective for brain CT image classification, improving feature extraction and edge segmentation by focusing on relevant image areas (Yin et al., 2024). However, its high computational cost can limit its applicability in real-time systems like livestock behavior monitoring. On the other hand, GSRA-KL, which incorporates KL divergence for data augmentation, excels in handling small datasets and class imbalance, making it ideal for scenarios with limited data. While GSRA-KL provides efficient data augmentation, it does require careful tuning and computational resources for training (Munir et al., 2025).

YOLO is among the most widely adopted models for real-time object detection (Zhao et al., 2023; Gong et al., 2024). In this project, YOLOv8 is employed to classify sheep behaviors such as standing, sitting, and sleeping. This technology enables the system to operate efficiently without requiring additional sensors, unlike traditional methods that rely on specialized hardware.

Deep learning, particularly YOLO and CNN, has proven effective in analyzing animal behavior. Various studies indicate that this approach enhances the efficiency of livestock monitoring. For instance, Gonzalez-Baldizon et al. (2022) utilized YOLOv4 to detect sheep behavior based on RGB images captured from fixed cameras, achieving an accuracy of 99.85%. However, this study did not consider individual monitoring within a single pen. Jiang et al. (2020) applied YOLOv4 to detect goat behavior with 97% accuracy but did not consider the impact of horned goats on detection and analysis (González-Baldizón et al., 2022; Jiang et al., 2020). Hu et al. (2023) developed an improved YOLOv5 model with an attention module to recognize sheep behavior in grazing environments. While this study improved sheep behavior detection accuracy, it faced challenges such as varying lighting conditions and different camera angles. Additionally, Hu et al. (2023) emphasized the importance of model enhancements to cope with unpredictable environmental conditions, which is also a concern in this project.

Furthermore, recent studies on livestock behavior recognition using YOLO-based models highlight the effectiveness of deep learning in real-time monitoring. Mu et al. (2024) proposed the CBR-YOLO model, an optimized version of YOLOv8 designed to improve cattle behavior recognition under various weather conditions while maintaining efficiency on edge devices. Similarly, Saifudin et al. (2024) implemented YOLOv8 to classify cow behaviors such as lying, standing, eating, and ruminating, achieving a mean average precision (mAP) of 0.778. However, this study also identified occlusion as a key limitation, affecting detection accuracy in crowded environments. These findings reinforce the potential of YOLOv8 for behavior classification in livestock farming, demonstrating its advantages over wearable sensor-based approaches in terms of cost-effectiveness and animal welfare. By leveraging these insights, this project aims to further refine YOLOv8-based behavior recognition for sheep, ensuring accurate classification across different environmental conditions (Mu et al., 2024; Saifudin et al., 2024).

YOLOv8, being a cutting-edge object detection algorithm, has proven to have a high level of usability in a variety of industries, including agricultural and cattle tracking. In fruit classification, for example, Simanjuntak et al. (2024) examined the use of lightweight YOLOv8 models (YOLOv8n, YOLOv8s, and YOLOv8m) in fruit maturity determination, with 100% accuracy in training, and a minimum loss of 0.003 attained with YOLOv8s, proving its effectiveness in fruit maturity determination automation. YOLOv8 has even been utilized in cattle tracking, for cattle feeding behavior detection. Comparison between YOLOv8 and YOLOv10 showed that both models, having detected cattle feeding behavior such as biting and chewing with an accuracy level of about 98%, performed with YOLOv10 having a faster convergence and generalization (Guarnido-Lopez et al., 2024).

These studies serve to illustrate YOLOv8's effectiveness and adaptability in enhancing automation in a variety of industries, paving the way for efficient and effective real-time tracking solutions.

While YOLO-based systems show promising results, several challenges remain unaddressed, particularly for horned sheep. Most prior works do not consider the specific risks associated with horned animals housed individually. Environmental variations such as lighting changes, camera angle distortion, and animal occlusion can impair classification accuracy. Additionally, crowding in shared pens complicates individual behavior recognition, which is critical when tracking posture-related health conditions. Wearable sensor alternatives can be intrusive and costly to scale.

Meanwhile, transfer learning has emerged as a powerful tool in computer vision, enabling models to adapt from general tasks to domain-specific problems with limited labeled data. Studies leveraging pre-trained CNNs like ResNet50 and VGG16 report improved accuracy in behavior classification. For instance, Noor et al. (2020) demonstrated effective facial expression analysis in sheep using deep transfer learning. Similarly, Yadav et al. (2024) developed intelligent classifiers for sheep and goat identification with enhanced recognition capabilities. These approaches highlight the potential of transfer learning to generalize across diverse behavioral datasets and reduce annotation effort.

Advancements in video streaming technologies have significantly improved the efficiency of transmitting and processing high-quality video data in real-time, making it essential for applications like livestock behavior monitoring. These developments, particularly in video compression algorithms and adaptive streaming protocols such as H.265 and VP9, enable seamless transmission of video data even in bandwidth-limited environments, which is crucial for large-scale livestock monitoring systems (Laghari et al., 2023). The use of high-resolution formats such as 4 K and 8 K further enhances the ability to monitor livestock behavior with greater accuracy, providing clearer video streams that improve the detection of animal movements and postures. One of the key advantages of video streaming over traditional sensor-based methods is its non-invasive and scalable nature, which allows for continuous and real-time monitoring of animals without the need for additional specialized hardware. However, video streaming systems face challenges such as high computational requirements for processing large video datasets in real-time, which may limit their deployment in resource-constrained environments like small farms. In comparison, sensor-based systems may be less computationally demanding but can be costlier to scale and less flexible in terms of coverage. Additionally, while video streaming offers superior image quality, it may struggle with latency and processing time when high-definition formats are used, making it less suitable for scenarios requiring immediate feedback. The evaluation of such systems highlights the importance of runtime optimization in streaming action anticipation scenarios, where computational resources are constrained, and real-time performance is crucial (Furnari and Farinella, 2023).

Despite advancements, limited research has addressed behavior detection in horned sheep using real-time top-view imaging. Most existing methods either rely on side views, focus on non-horned species, or neglect individual-pen scenarios. To fill this gap, our study introduces a YOLOv8-based segmentation model fine-tuned through transfer learning, optimized for classifying three key behaviors: wake, lay, and sleep. This approach is tailored for top-down observation in a one-sheep-per-pen layout, offering a novel solution for behavior monitoring in modern livestock farming.

Table 1 highlights the comparative advantage of the proposed system over prior studies. Unlike previous work that primarily utilized side-view imagery or focused on non-horned species, our system uniquely targets horned sheep using top-down camera setup. Furthermore, it also supports real-time, sensor-free behavior classification of three critical postures, enabling robust deployment in practical smart-farm settings.

Table 1. Comparison of vision-based behavior recognition systems in livestock with emphasis on horned sheep monitoring

Author	Species	Behavior classes	Camera view	Real time	Sensor free	Horned sheep focus	Accuracy/ mAP
Gonzalez-Baldizon et al. (2022)	Sheep	Standing, sitting	Side-view	No	Yes	No	Precision 99%
Jiang et al. (2020)	Goat	General postures	Side-view	No	No	No	Accuracy 97%
Hu et al. (2023)	Sheep (grazing)	Outdoor behavior	Side-view	No	Yes	No	–
Mu et al. (2024)	Cattle	Grazing behaviors	Varies	Yes	Yes	No	–
Saifudin et al. (2024)	Cow	Lying, eating, etc.	Side-view	Yes	Yes	No	mAP = 0.78
Noor et al. (2020)	Sheep	Facial expression	Close-up face	No	No	No	–

3. MATERIALS AND METHODS

This section presents the overall methodology for developing a real-time sheep behavior recognition system using computer vision and deep learning. The process begins with data collection through a top-mounted camera that captures video footage of individually housed horned sheep. The recorded videos are segmented into frames, annotated using Roboflow, and augmented to increase dataset variability. The annotated dataset is then used to train a YOLOv8 segmentation model through transfer learning. Following training, the best-performing model is deployed into a real-time inference system that classifies sheep behavior into three categories: wake, lay, and sleep. The complete pipeline includes data preprocessing, model training, system architecture design, and live behavior visualization using OpenCV.

3.1 Animal Behavior

Livestock behavior is a key indicator of animal health and welfare, often reflecting both physiological and psychological conditions. In sheep, common behaviors such as standing, lying, and sleeping provide crucial insights into physical well-being, energy levels, and potential health issues. Deviations from normal behavior patterns, such as prolonged inactivity, excessive lying, or irregular posture, may signal stress, metabolic disorders, or illness (Zhang et al., 2024). Additionally, sleeping, waking, and resting patterns play a vital role in sheep health, as disruptions in these behaviors can indicate stress, discomfort, or underlying health issues.

In this project, each sheep is housed individually in a separate pen due to the presence of horns, which increases the risk of injuries related to abnormal health conditions when housed in groups (Xu et al., 2023). Health issues in sheep can manifest through changes in posture, prolonged inactivity, or irregular movement patterns, which may indicate digestive problems, metabolic disorders, or other physiological stressors. Monitoring sheep behavior, particularly rumination duration and movement patterns, is crucial, as studies have shown that sheep with compromised health exhibit reduced and inconsistent rumination activity (Yu et al., 2024).

Furthermore, in this study, behavior classification is focused on three primary states: wake, lay, and sleep. The Wake class represents active or standing sheep, typically associated with alertness and feeding. The Lay class denotes resting postures with the sheep lying down but not fully asleep, while the Sleep class captures curled postures indicating minimal movement and deep rest. These classifications are critical for early detection of anomalies related to stress, fatigue, or injury. Horned sheep pose additional challenges in group housing due to the risk of injury during aggressive interactions. For this reason, each animal in the study is housed individually in a dedicated pen, allowing for clearer observation and minimizing occlusion in top-down imaging. By focusing on these three behavioral states in a controlled environment, the model can be optimized to detect health-related behavioral deviations with higher precision and reliability.

3.2 Transfer Learning

Transfer learning is an effective deep learning technique that enables a model pre-trained on large-scale datasets to be fine-tuned for specific tasks with limited data. This approach is particularly advantageous in agricultural domains, where labeled datasets are often scarce and costly to obtain. In the context of sheep behavior recognition, transfer learning allows the model to reuse learned features such as body contours, postures, and motion patterns, significantly improving accuracy while reducing training time.

This study utilizes the YOLOv8 segmentation model provided by the Ultralytics framework, leveraging its pre-trained weights for object detection and instance segmentation on a sheep behavior dataset to improve classification performance. Instead of training the model from scratch, the fine-tune on a custom-labeled sheep behavior dataset using top-view camera footage. The training process was conducted over 100 epochs, enabling the model to gradually adapt to domain-specific features while minimizing overfitting.

Ultralytics is a deep learning framework and Python library that provides an accessible and efficient interface for implementing the YOLO family of object detection models, including YOLOv8. It offers comprehensive tools for model training, validation, and deployment, supporting various vision tasks such as object detection, image classification, and instance segmentation. Through its modular and user-friendly design, Ultralytics enables rapid prototyping, real-time inference, and seamless integration with custom datasets. This framework has been widely applied in animal species recognition and livestock monitoring, demonstrating increased detection efficiency and robustness (Zhu, 2024; Dwivedi et al., 2025). By reusing learned features through transfer learning, the model generalizes better to sheep postures and movements, enabling real-time behavior recognition for automated livestock management.

3.3 Proposed System

This study proposes an automated behavior recognition system designed to classify the posture of horned sheep in real time using a computer vision-based approach. The system leverages a top-down camera perspective combined with the YOLOv8 segmentation model to detect and classify sheep behavior into three distinct categories: wake, lay, and sleep. By integrating deep learning with real-time video processing, the system enables efficient, non-invasive monitoring in a one-sheep-per-pen configuration. The overall architecture is optimized for low-latency processing and high detection accuracy, making it suitable for implementation in modern smart farming environments.

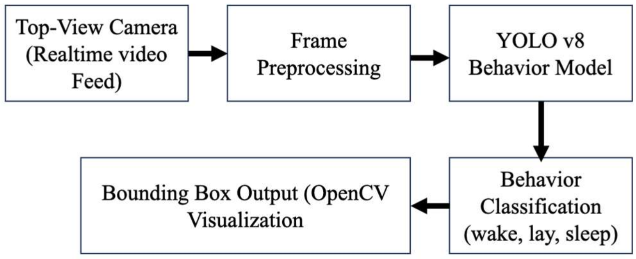


Fig. 1. The proposed system

As shown in Fig.1, the system receives input from a top-mounted HD camera placed above the sheep pens. The video feed is streamed directly to a processing unit running a Python-based application that integrates the YOLOv8 model using the Ultralytics framework. After behavior classification, the system generates an Output Bounding Box Frame, which visually represents the detected posture of each sheep. The model performs instance segmentation to identify individual sheep and classify their behavioral states. This structured approach ensures an automated and efficient method for sheep monitoring, leveraging deep-learning-based object detection to enhance livestock management and welfare analysis.

Each detection is visualized in real time using OpenCV, with bounding boxes and class labels overlaid on the video output. The YOLOv8 model is configured with an input resolution of 1280 × 720 pixels and a confidence threshold of 0.5 for behavior classification. The top-down perspective minimizes occlusion and maximizes the visibility of full-body postures.

In the meantime, Fig. 2 illustrates the structure diagram of the training pipeline. Training pipeline of the sheep behavior classification model using transfer learning. The process begins with top-view video capture, followed by frame extraction and annotation. Augmentation techniques are applied to expand dataset variability before splitting into training, validation, and test sets. A YOLOv8 segmentation model is fine-tuned using transfer learning for 25 epochs. The trained model is evaluated using standard performance metrics including mean average precision (mAP), precision, and recall.

Fig. 3, illustrates the flowchart of the system designed for real-time classification of sheep behavior into Lay, Sleep, or Wake using a YOLOv8-based model. The process begins with system initialization, where video capture from a top-mounted camera is established. Once the video stream is active, the pre-trained YOLOv8 behavior model is a loaded

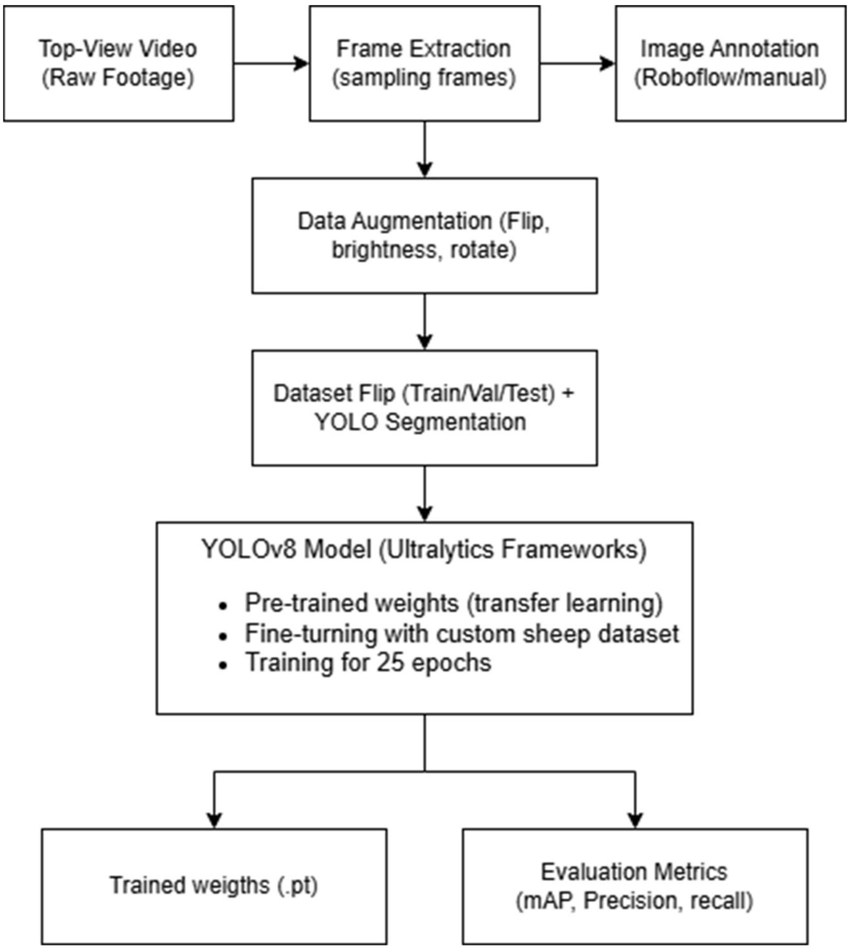


Fig. 2. Pipeline diagram

into memory. The system continuously attempts to capture video frames. If frame capture fails, the program terminates safely. Upon successful frame acquisition, the captured image is resized to match the input dimensions required by the YOLOv8 model (e.g., 1280 × 720 pixels), ensuring compatibility and performance efficiency.

Next, the resized frame undergoes inference using the YOLOv8 model. The model detects the presence of sheep and classifies their behavior into one of three predefined categories: wake, lay, or sleep. Following inference, the detected behaviors are further processed and labeled appropriately. The system then draws bounding boxes around each sheep with their corresponding behavior label using OpenCV, allowing users to visually interpret the behavior classification in real time. The processed frame is displayed as output on the screen for continuous monitoring. The system remains in this loop until it is manually exited by the user, or an error occurs, at which point the program terminates.

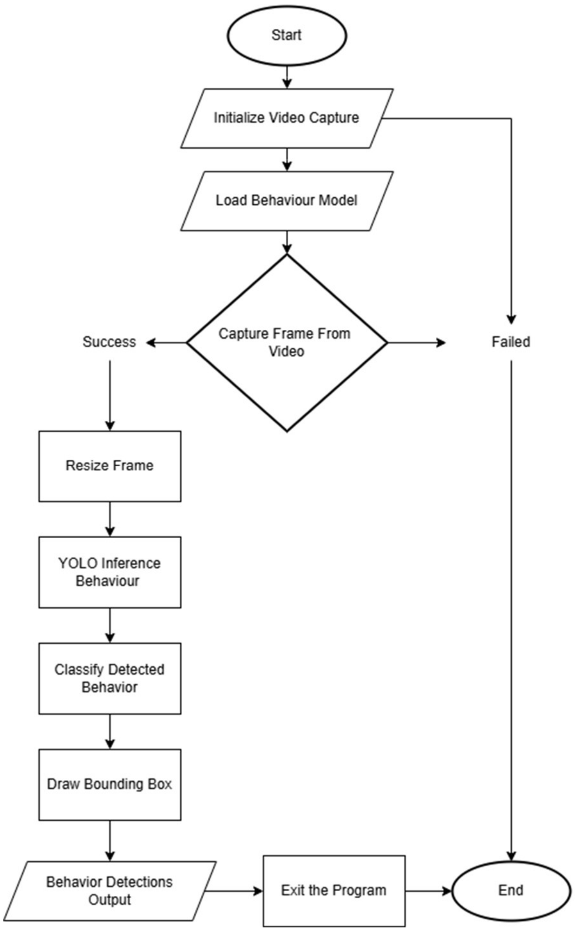


Fig. 3. Flowchart System

3.4 System Implementation

The real-time sheep behavior classification system was implemented using an edge computing device as the primary processing unit. This system was designed to classify sheep behaviors, including standing, sitting, and sleeping, in a controlled barn environment through computer vision and deep learning techniques. The objective was to automate livestock monitoring without requiring additional sensors, reducing costs, minimizing disturbances to the animals, and ensuring high accuracy and efficiency.

The data collection process began with a Logitech C615 HD webcam strategically positioned in the barn, continuously capturing video footage of the sheep. The camera supports a resolution of 1920 × 1080 pixels (Full HD) and operates at up to 30 frames per sec (fps), providing sufficient clarity and temporal resolution for behavior recognition tasks. To facilitate remote monitoring, a remote access solution was employed, allowing video capture without direct human presence.

Fig. 4 shows the implementation of camera position on the system. The illustration depicts the physical setup of the real-time monitoring system designed for behavior detection in horned sheep. Each sheep is housed individually in a dedicated pen to prevent aggressive interactions and ensure unobstructed observation. A fixed overhead camera is mounted above the pens, capturing a top-down view of the enclosures. This top-view configuration is chosen to maximize visibility of the animals' full-body posture while minimizing occlusion caused by pen walls or other sheep. The camera continuously streams video footage, which is fed into a YOLOv8-based behavior classification model. This configuration enables accurate and non-intrusive identification of behavioral states, such as wake, lay, and sleep, in a controlled farm environment, allowing for scalable and sensor-free livestock monitoring.

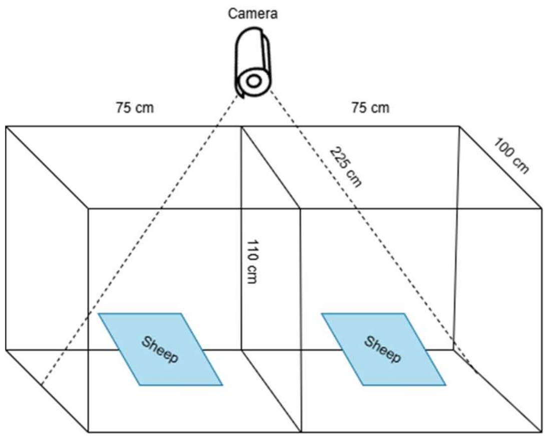


Fig. 4. Camera position

3.5 Training method

The training process, begins by creating a dedicated workspace in Roboflow, where a custom sheep behavior dataset is developed. Video frames are extracted and annotated to label sheep behaviors with polygon masks using the YOLOv8 segmentation format. The annotated dataset consists of 5,410 images, distributed across three classes: 1,826 for wake, 2,579 for lay, and 1,363 for sleep, all captured from a top-view perspective to ensure unobstructed posture analysis.

To improve generalization and model robustness, preprocessing steps include auto-orientation and resizing to 1280 × 720 pixels. Data augmentation techniques are applied to each image, producing three additional variants per frame using horizontal and vertical flipping, random rotation (−15° to +15°), grayscale conversion (25% of images), brightness adjustment (−25% to +25%), and exposure modification (−20% to +20%). This expands the dataset to 12,984 images where each annotation includes both class labels and corresponding object masks represented as polygon coordinates.

The dataset is versioned and exported in YOLOv8-compatible format, with annotations structured into separate directories for training, validation, and testing. This structured dataset is then used to train a YOLOv8 segmentation model using the Ultralytics framework. Upon completion, the model generates a best.pt weights file containing the optimized parameters for real-time behavior inference.

To achieve this, the model utilizes a transfer learning approach, where pre-trained weights from a similar task or model are fine-tuned using the specific dataset. The pseudocode for this process is as seen in Fig. 5.

```
BEGIN

    FUNCTION transfer_learning_train:

        # Step 1: Load the pre-trained YOLOv8 model
        # Load pre-trained model weights as a starting point
        LOAD pre_trained_model FROM "path/to/pretrained_model.pt"

        # Step 2: Fine-tune the model with the specific dataset
        # Use the dataset to fine-tune the model through transfer
learning
        CALL pre_trained_model. train WITH PARAMETERS:
            - data: "path/to/dataset"
            - epochs: 25
            - imgsz: 800
            - plots: TRUE
            - device: 'cuda'

        # Step 3: Save the optimized model weights
        # Save the model's optimized weights after fine-tuning
        SAVE fine_tuned_model_weights AS "best.pt"

        # Step 4: Return the results from the fine-tuning process
        RETURN the training results including performance metrics
and optimized weights

    END FUNCTION

    # Main Program Execution
    # Call the transfer learning training function to start the
fine-tuning process
    CALL transfer_learning_train

END
```

Fig. 5. Pseudocode of pre-trained weights

This pseudocode outlines the core process of loading a pre-trained YOLOv8 model, fine-tuning it with the specific dataset, and saving the final weights for deployment. The fine-tuning process utilizes the transfer learning methodology to adapt the model to the new task while leveraging the knowledge gained from the original dataset.

3.6 Experimental Scenario

The proposed system was tested in a controlled farm environment where horned sheep were housed individually in standardized enclosures. A single top-view camera was installed above each pen to capture continuous video footage under natural lighting conditions. The camera was positioned at a fixed height to maintain a consistent field of view across all pens. The system was evaluated on its ability to classify three behavioral states—wake, lay, and sleep—in real-time, based on live video input from the installed camera.

To validate performance, the trained YOLOv8 model was deployed on a workstation equipped with an NVIDIA GPU. Real-time inference was conducted by feeding live video into the system while sheep exhibited natural behaviors over extended observation periods (minimum 30 mins per session). The predictions from the model were recorded and compared against manually annotated ground truth labels to assess detection accuracy, classification consistency, and latency. Additional testing was performed under varying lighting intensities (morning, afternoon, and evening) to evaluate model robustness. The system's usability was also observed from a practical perspective, including ease of deployment, interface readability, and visual feedback clarity using OpenCV.

4. RESULTS AND DISCUSSION

This section presents the outcomes of the project, including the training and output results.

4.1 Training Results

The training process was conducted using a segmentation model with three classes: lay, sleep, and wake, aiming to detect sheep behavior in a barn setting. The performance evaluation is based on two key metrics: the precision-recall (PR) curve and the confusion matrix.

The relationship between precision and recall is mathematically defined. Precision is calculated using the formula:

$$Precision = \frac{TP}{FP + TP} \quad (1)$$

where TP represents true positives, or correctly detected sheep behaviors, and FP denotes false positives, where other behaviors were incorrectly classified. Recall is defined as:

$$Recall = \frac{TP}{TP +} \quad (2)$$

where FN represents false negatives, or actual behavior instances that were not detected by the model.

Fig. 6 depicted the confusion matrix. The confusion matrix provides an evaluation of the trained YOLOv8 model in classifying sheep behaviors into lay, sleep, and wake. The horizontal axis represents the true labels, referring to the actual behavior of the sheep as annotated in the dataset, while the vertical axis represents the predicted labels assigned by the model. Each cell in the matrix indicates the number of behavior instances classified into each category.

The model correctly classifies 622 instances of Lay, with 10 misclassified as sleep and 1 as wake. Sleep behavior is accurately identified in 297 cases, with 4 misclassified as Lay and 11 unrecognized. Wake behavior is correctly detected in 477 instances, with 12 misclassified as lay or sleep. Instances categorized as Background are not included in this analysis, as they fall outside the scope of behavior classification and do not represent the target detection classes. These entries typically reflect detection errors at the object level rather than within behavior recognition, and thus are excluded to maintain focus on behavioral performance.

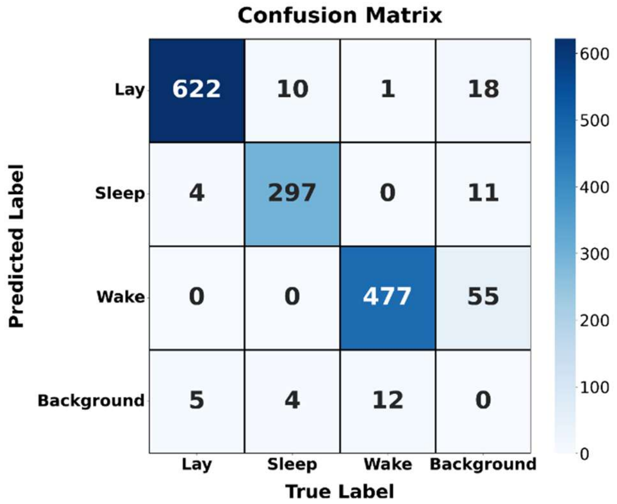


Fig. 6. Confusion matrix

The matrix helps assess how well the model distinguishes among the three defined behaviors. A high count along the diagonal represents strong agreement between predictions and ground truth, while off-diagonal values highlight confusion between similar postures. The results confirm the model's ability to provide accurate behavior classification, supporting structured and automated sheep monitoring in real time.

Meanwhile, the precision-recall (PR) curve illustrates in Fig. 7 the YOLOv8 model's performance in classifying sheep behaviors, with each colored line representing a specific behavior class: lay, sleep, and wake.

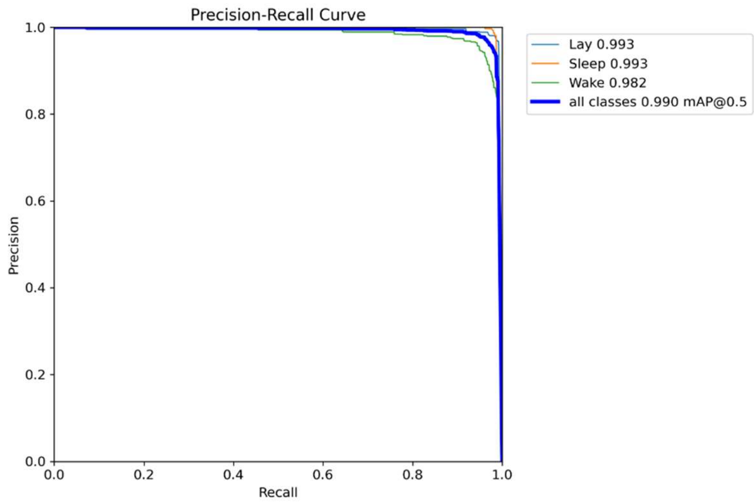


Fig. 7. Precision-Recall Curve

The curves remain close to precision = 1.0 across most recall values, indicating that the model maintains high classification accuracy while minimizing false positives. The steep drop-off near recall = 1.0 suggests that as recall increases, more false positives occur due to a lower detection threshold.

The blue line represents the overall PR curve for all classes, showing an mAP@0.5 of 0.990, which indicates strong generalization across all behaviors. Meanwhile, the individual class curves, with sleep achieving the highest precision (0.995), followed by lay (0.993) and wake (0.982), highlight the model's ability to differentiate between behaviors with minimal overlap. The slight variation in the curves suggests that Wake has a marginally higher misclassification rate compared to lay and sleep.

Overall, the curve distribution confirms that the model effectively balances precision and recall, ensuring robust classification performance across different behavior states. Further optimizations, such as confidence threshold adjustments or dataset refinements, could help mitigate the slight precision drop at high recall values.

Furthermore, the training results of the YOLOv8 model provide insights into instances and precision, which measure detection accuracy can be seen in Table 2. According to the table, instances represent the total number of labeled behaviors in the dataset, indicating how frequently each class (lay, sleep, wake) appears. A higher instance count improves the model's ability to generalize behavior patterns. Precision reflects the accuracy of predictions, showing the proportion of correctly identified behaviors. The model achieves high precision across all classes, with lay at 0.985, sleep at 0.986, and wake at 0.965, indicating reliable classification with minimal false detections.

Table 2. Training Result

Class	Images	Instances	Precision
All	1086	1432	0.979
Lay	515	631	0.985
Sleep	278	311	0.986
Wake	365	490	0.965

4.2 Performance Results

The system generates output bounding boxes to classify sheep behavior into lay, sleep, or wake. These bounding boxes provide a visual representation of detected behaviors, ensuring clear identification and tracking across video frames. Fig. 8 shows the system while classified the sheep. The system effectively detects and classifies sheep behavior, as demonstrated in the bounding box outputs for the Wake class. The green bounding boxes indicate the model's ability to accurately identify sheep in an active state, with confidence scores of 0.95 while in full body. The detection results show that the model can consistently recognize Wake behavior across different poses and orientations, ensuring reliable classification.

The detected posture follows a fully upright stance, with the sheep's legs extended and body positioned in an alert state. This posture is characteristic of wake behavior, where the sheep is either standing still or engaged in an activity such as feeding or observing its surroundings.

Fig. 8. Detection results of awake sheep

Fig. 9 illustrates the system's ability to detect and classify sheep behavior in the Lay category with high accuracy. The green bounding boxes highlight two sheep identified as being in a resting position, with confidence scores of 0.86 and 0.96, demonstrating the model's effectiveness in distinguishing lay behavior. The bounding boxes are well-aligned with the sheep's bodies, ensuring precise detection even in varied orientations and environmental conditions. However, the confidence score for the sheep on the left is slightly lower (0.86) due to incomplete visibility of its full body, which may reduce the model's ability to extract all relevant features, leading to a slight decrease in classification confidence.

Fig. 9. Detection result of laying sheep

Lay behavior is characterized by the sheep resting with its body positioned close to the ground, either with its legs folded beneath or partially extended. This posture allows the sheep to remain in a stable position while reducing muscle strain. Variations in limb positioning, such as a more compact or slightly stretched posture, can influence detection confidence depending on the degree of visibility within the frame.

Fig. 10 illustrates the system's ability to detect and classify sheep behavior in the Sleep category with high accuracy. The green bounding box highlights a sheep identified as being in a sleeping position, with a confidence score of 0.90, demonstrating the model's effectiveness in distinguishing Sleep behavior from other states.

Fig. 10. Detection result of sleeping sheep

The detected posture follows a curled-up position, where the sheep's legs are tucked beneath its body, and its head is resting close to the body. This posture is characteristic of sleep behavior, indicating a state of rest with minimal movement. the model maintains stable classification even under different lighting conditions, ensuring consistent detection across various scenarios.

Furthermore, to evaluate the robustness and adaptability of the sheep behavior detection system under less-than-ideal conditions, scenario-based testing was conducted. These scenarios simulate realistic challenges that may occur in practical deployment, such as obstructed views and angled camera positioning. Specifically, tests were carried out where objects partially blocked the camera's line of sight or where the camera was positioned at a non-perpendicular angle relative to the sheep. These conditions are critical to assess, as they may affect the system's ability to consistently detect and classify behaviors such as lay, sleep, and wake. this section presents the impact of such scenarios on detection accuracy and inference stability. Fig. 11 and Fig. 12 show the detection scenario with visual obstruction.

Fig. 11. Detection scenario with visual obstruction due to bamboo poles

In real-world deployments, the monitoring environment may not always be ideal, and various physical obstructions could hinder camera visibility. One such scenario was simulated by placing vertical bamboo poles above the enclosure, partially blocking the view of the monitored sheep. This obstruction challenges the object detection system by reducing the visible area of the animals, particularly around their heads and upper bodies. Another experiment scenario is conducting to test the performance of the system is camera positioning as seen in Fig. 13, Fig.14, and Fig. 15.

Fig. 12. Detection scenario with visual obstruction due to bamboo poles

Fig. 13. Tilted camera angle of wake

In this scenario, the camera was intentionally positioned at an inclined angle to simulate non-ideal mounting conditions, which may occur due to improper installation or environmental shifts. This tilt affects the visual geometry of the captured image and potentially influences the model's object detection accuracy. Despite this deviation, the detection system demonstrated robustness in classifying all three activity states—wake, lay, and sleep. As shown in the provided figures, the bounding boxes still accurately enclosed the target object (sheep), and the confidence scores remained relatively high across different poses. the wake state yielded a confidence of 0.88, the lay state reached up to 0.94, and the sleep state was identified with a confidence of 0.87. these results indicate that the model maintains acceptable reliability under moderate camera tilting, which is promising for real-world applications where ideal camera placement is not always achievable.

Fig. 14. Tilted camera angle of lay

Fig. 15. Tilted camera angle of sleep

4.3 Discussion

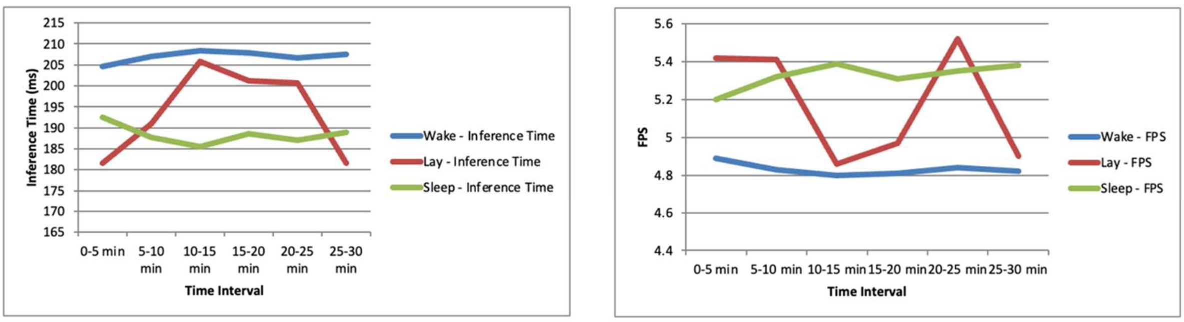
The results of this study demonstrate the effectiveness of the YOLOv8-based model in detecting and classifying sheep behaviors into Lay, Sleep, and Wake with high accuracy. The system successfully identifies behavioral states in real-time, with bounding boxes providing clear visual representations of detected postures. The model's performance is reinforced by high precision scores across all behavior classes, ensuring minimal misclassification while maintaining reliable detection under various environmental conditions.

Compared to previous studies, the proposed YOLOv8-based system demonstrates notable improvements in both detection accuracy and real-time performance. For instance, (Gonzalez-Baldizon et al., 2022) utilized YOLOv4 for sheep behavior classification with a reported precision of 99.85%, yet their system did not incorporate real-time deployment or individual-pen configuration. Similarly, Hu et al. (2023) enhanced YOLOv5 with attention mechanisms for grazing behavior detection, focusing primarily on outdoor settings without emphasis on posture-specific classification.

In contrast, the present study achieves a high mAP@0.5 of 0.990 and precision scores exceeding 0.96 across all behavior classes within an indoor top-view setup, making it more suitable for confined animal monitoring scenarios. Moreover, unlike prior research relying on wearable sensors or multi-animal environments, this study focuses on sensor-free posture classification for individually housed horned sheep—an area that remains underrepresented in the literature. These distinctions highlight the novelty and practicality of the proposed system for farm-scale implementation.

Fig. 16 presents a comparative analysis of the model's real-time performance using two key metrics: average inference time and approximate frames per second (FPS) for each behavior class over six consecutive 5-minute intervals. the top subplot shows that the inference time for the wake class remained stable (~205–208 ms), while the lay class exhibited more fluctuation, peaking at 205.75 ms during the 10–15 minutes interval. the sleep class maintained the most consistent and generally faster inference times, ranging between 185–193 ms.

The bottom subplot illustrates the approximate FPS across the same intervals. As expected, inverse trends are observed—lower inference times correspond to higher FPS values. The Sleep class achieved the highest and most stable FPS (~5.3–5.4), followed by Lay, which peaked at 5.52 FPS, while Wake remained slightly lower (~4.8–4.9 FPS). This comparative evaluation confirms the model's sustained real-time performance and highlights the slight variability in processing efficiency between behavior classes. These metrics support the system's applicability for continuous livestock behavior monitoring under realistic conditions.



(a) (b)

Fig. 16. Comparative analysis: (a) inference time vs (b) FPS overtime

The classification of lay behavior is highly accurate, with the model correctly detecting sheep in a resting position even when orientations vary. however, minor confidence fluctuations were observed in cases where the full body of the sheep was not entirely visible. Similarly, Sleep behavior was well distinguished, characterized by a curled posture with legs tucked beneath the body, confirming the model's ability to recognize resting states effectively. The Wake category also exhibited strong detection performance, with the model consistently identifying standing or active sheep. Despite its robustness, a slight decline in precision was noted in cases where lighting inconsistencies or occlusion affected feature extraction.

This is further supported by the model's mAP@0.5 score of 0.990 and precision scores above 0.96 across all classes, confirming consistent performance in behavior detection. The ability to detect and classify behavior autonomously presents a significant opportunity for reducing labor costs in livestock monitoring, while enabling early detection of abnormal behavioral patterns indicative of health issues.

This system demonstrates the potential of AI-powered livestock monitoring tools for supporting animal welfare and precision farming practices. By replacing or supplementing manual observation with automated detection, farmers can achieve consistent, scalable monitoring while reducing dependency on labor and minimizing disturbance to the animals. The practical deployment of such systems could enable early diagnosis of health issues, behavioral anomalies, or environmental stressors, supporting smarter farm management and improved livestock outcomes.

Despite its strong performance, the model still encounters challenges when exposed to occlusion, motion blur, and inconsistent lighting. These factors may lead to misclassification or reduced confidence scores. Additionally, the model was trained and tested in a controlled environment, which may not fully reflect the complexity of outdoor or group-housed systems. Furthermore, the current system focuses solely on posture-based classification and does not account for other behavioral dimensions, such as movement trajectories, vocalization, or interaction.

Overall, on address the identified limitations, future work will focus on expanding the dataset to include more diverse environments, lighting variations, and sheep breeds. Incorporating temporal information via video sequence modeling or transformer-based architectures could enhance behavior recognition stability. Multi-animal tracking, context-aware inference, and integration with IoT sensors may also improve system versatility. In addition, evaluating the model's performance on embedded systems will be key to ensuring feasibility in remote or resource-limited farm environments.

5. CONCLUSION

This study introduced a real-time, sensor-free sheep behavior classification system utilizing YOLOv8 and transfer learning, designed to detect three primary behaviors: Lay, Sleep, and Wake. The model demonstrated high accuracy and strong generalization capabilities, achieving a mAP@0.5 of 0.990 and precision above 0.96 across all behavior classes. Real-time bounding box outputs provided interpretable and consistent posture monitoring, supporting automated livestock surveillance without additional hardware.

The system reliably classified lay and sleep behaviors, with only minor confidence drops observed under partial occlusion. wake behavior was also detected with high accuracy, though performance declined slightly in conditions involving poor lighting or motion blur. These findings validate the system's effectiveness for precision livestock monitoring.

For future work, improvements will focus on expanding the behavioral dataset to include more diverse postures and environmental conditions, tuning classification thresholds, and optimizing post-processing. Temporal sequence modeling and multi-frame analysis may further enhance robustness. Overall, this research contributes to the development of intelligent farm monitoring systems that support early health intervention and efficient livestock management.

DECLARATION OF COMPETING INTEREST

The authors declare no conflict of interest.

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