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FARM ASSISTANT COUNTS SHEEP

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Abstract: Small livestock farming in our country is mostly based on pasture. The most important advantage of this situation is that it reduces feed expenses and increases our profitability within the farm. However, the most important problem is in the counting of animals when they come from the pasture to the pen and when they go from the pen to the pasture. This situation depends on the shepherd's attention and follow-up. However, finding experienced shepherds in our country is becoming more and more difficult every day. It may be difficult or even impossible for a sheep giving birth in the pasture to follow the herd when the geographical conditions become difficult. Quick counting of sheep and lambs as the animals enter and exit the pen depends on the shepherd's practice and experience. In order for this situation to be more realistic and to prevent personal mistakes, different alternatives should be considered. For this reason, a system has been developed using deep learning techniques to automatically count the animals in the herd when entering the pen. This system will automatically count the animals at the entrance and exit of the farm, and in case of missing animals, the system users will automatically notify the system users via web and mobile applications. With the implementation of this system, it will be possible to determine the losses that will occur on the farm with an early warning system. In our study, animals will be detected with the deep learning-based YoloV8 pre-trained model on images taken from fixed cameras that will be placed at the entrance and exit of the pen. Counting results obtained from the developed system can be used on different devices by providing multi-platform support. By disseminating this practice, losses of sheep and lambs in the pasture can be prevented.

Keywords: Sheep counting, Object detection, Object counting, YoloV8, Object tracking

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1. Introduction

The practice of small livestock farming represents a significant source of income for farmers residing in rural areas. In countries with extensive pastures, such as Türkiye, small ruminants, including sheep and goats, are predominantly fed using natural pastures. This has the dual benefit of reducing feed costs and allowing animals to grow in a more natural environment. However, pasture-based small ruminant farming also presents certain difficulties in terms of herd management. Accurate counting and monitoring of the herd has become even more complicated, especially in herds with many animals (Joshi et al., 2008). At this point, new opportunities provided by technology offer a promising solution to these problems.

The unrestricted movement of animals in pastures can give rise to significant challenges in regions where the geographical conditions are particularly challenging. A sheep may become separated from the herd as a result of predator attacks or other unforeseen circumstances. The occurrence of animals being separated from the herd is only identified following the completion of the count. It is therefore important to conduct a rapid count. Technological techniques have been employed to render the process of animal counting autonomous. While traditional technologies, such as RFID, are employed in the tracking of animals, the advancement of deep learning-based algorithms has the potential to significantly enhance the efficiency of this process (Esen and Onan, 2022; Canga et al., 2022). The implementation of automated animal counting techniques based on image analysis from fixed cameras has the potential to enhance herd management practices, reducing the likelihood of human error (Kavurur, 2023; Özden et al., 2023).

The present study is concerned with the enumeration of sheep. The counting process is performed in two distinct ways. The first counting process is that of a regional count. This process entails the enumeration of sheep within a specified region of the image. The second counting process is the determination of the number of sheep that traverse a specific line. In order to perform these processes, both object recognition and real-time object recognition techniques were employed. In the course of the tests, the Yolo v8 pre-trained model was employed, demonstrating optimal efficiency in the execution of these processes. This study hypothesizes that the YOLOv8-based system will outperform traditional counting methods in terms of accuracy and efficiency.

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2. Materials and Methods

The objective of this study is to enumerate sheep within a specified area and at designated transition points. The system is based on deep learning and object detection algorithms, with training conducted using various versions of the YOLOv8 model. Furthermore, object tracking algorithms have been employed to monitor the movements of sheep and enhance the precision of counting operations. This section will provide a comprehensive overview of the utilized dataset, deep learning models, object tracking methodologies, and evaluation metrics. The experimental studies and the specifics of the techniques utilized to assess the accuracy and performance of the developed system will be presented subsequently.

2.1. Dataset

In this study, a single-class sheep dataset was employed. The YoloV8 pre-trained model is capable of detecting sheep autonomously. It is crucial to capture images of sheep from diverse angles to enhance the efficacy of object detection algorithms (Lin et al., 2014). To this end, the model was augmented with the RoboFlow sheep detection dataset, encompassing images captured from varying angles. The RoboFlow Sheep Detection dataset comprises 200 training, 200 validation, and 175 test images. Figure 1 shows sample images for the dataset.

2.2. Models Used and Object Detection

In order to facilitate the counting process, it is necessary to employ a model that is capable of performing real-time object detection. Accordingly, the YOLO (You Only Look Once) architectural approach is employed in the present study. YOLO is an algorithm that provides high-speed and real-time object detection (Redmon et al., 2016). YOLOv8 has advanced feature extraction layers and an optimised architecture (Bochkovskiy et al., 2020). YOLOv8 models have nano (n), small (s), medium (m), and large (x) architectures and are optimised for different difficulty levels. The decision to select a model was made by comparing these four versions of YOLOv8 (Dandıl et al., 2024). The sheep sample detected with yolov8 is shown in Figure 2.

Figure 1. Sample images of the dataset.

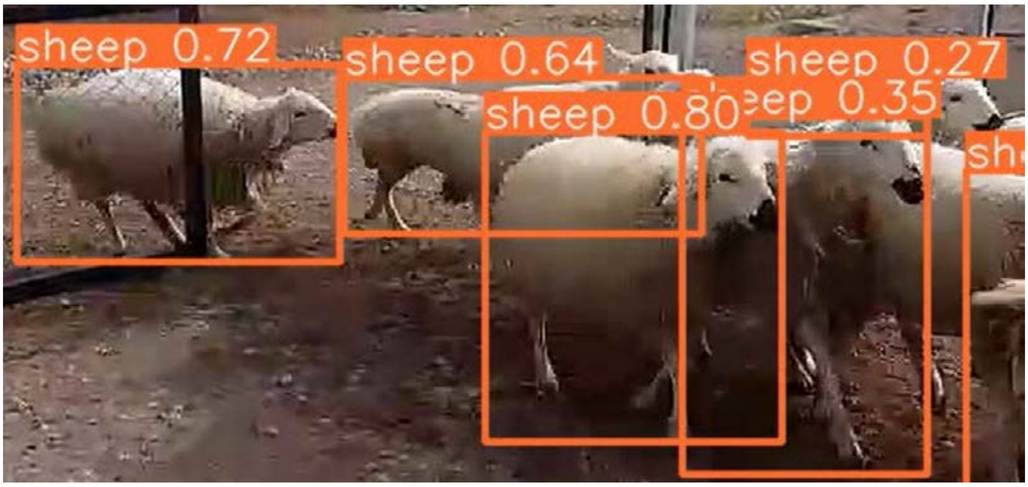

Figure 2. Sheep sample detected with yolov8.

In the training of the models, the AdamW optimiser, a robust optimisation method, was employed. AdamW is a variant of the Adam optimisation algorithm. It prevents overfitting of the model by adding L2 regularisation (Kingma and Ba, 2014). During the training phase, the batch size was set to 8, the epoch number to 50, and the image size to 640. The application of data augmentation techniques, including horizontal flipping and colour alteration, served to enhance the diversity of the dataset and reinforce the model's capacity for generalization (Lin et al., 2014).

2.3. Object Tracking

Object tracking is a crucial aspect in the monitoring of sheep movements, thereby enhancing the precision of counting operations. In the present study, two distinct object tracking algorithms were employed. The ByteTrack and BoTSort algorithms.

The ByteTrack algorithm is a modern approach to object detection and tracking that has demonstrated particular efficacy in multi-object tracking tasks (Zhang et al., 2022). The ByteTrack algorithm enables the tracking of detected objects based on their positions in previous frames.

BoTSort is an algorithm that offers a balance of high accuracy and speed and can be integrated with modern object detection architectures such as YOLOv8 (Wang et al., 2023). A comparison of the performance of the two algorithms revealed no significant difference. The decision was taken to use BoTSort. Tracking the movements of a sheep between frames is shown in Figure 3.

2.4. Sheep Counting Types

The system is capable of performing two distinct counting operations. Regional counting is employed to ascertain the number of sheep within a specified area. This operation is primarily based on the counting of sheep from a single image subsequent to their ingress into the pens.

The process of counting passing sheep is the determination of the number of sheep entering and exiting through a specified boundary line (e.g., a gate) in real time. Counting passing sheep is of paramount importance for the monitoring of animal movements in a farm environment. Therefore, real-time sheep tracking can be employed in conjunction with a multitude of operations other than this counting.

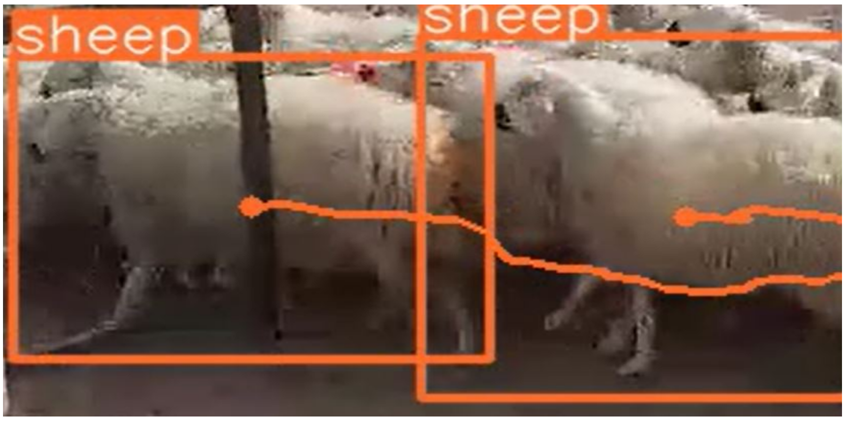

Figure 3. Tracking the movements of a sheep between frames.

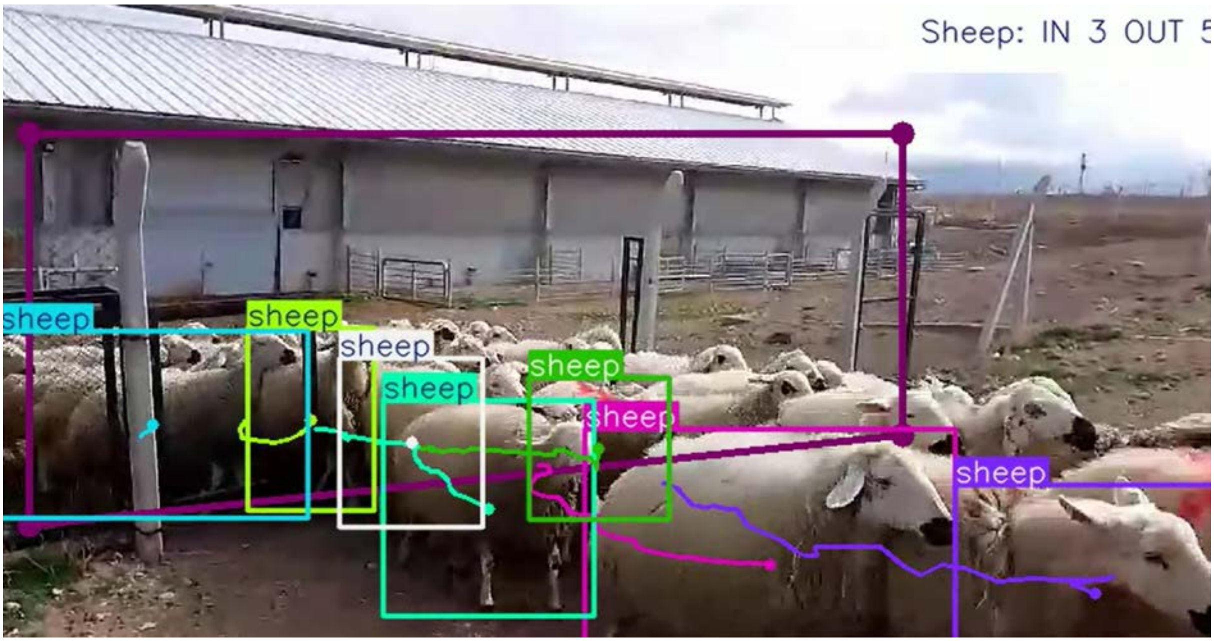

Figure 4. Regional counting process example image.

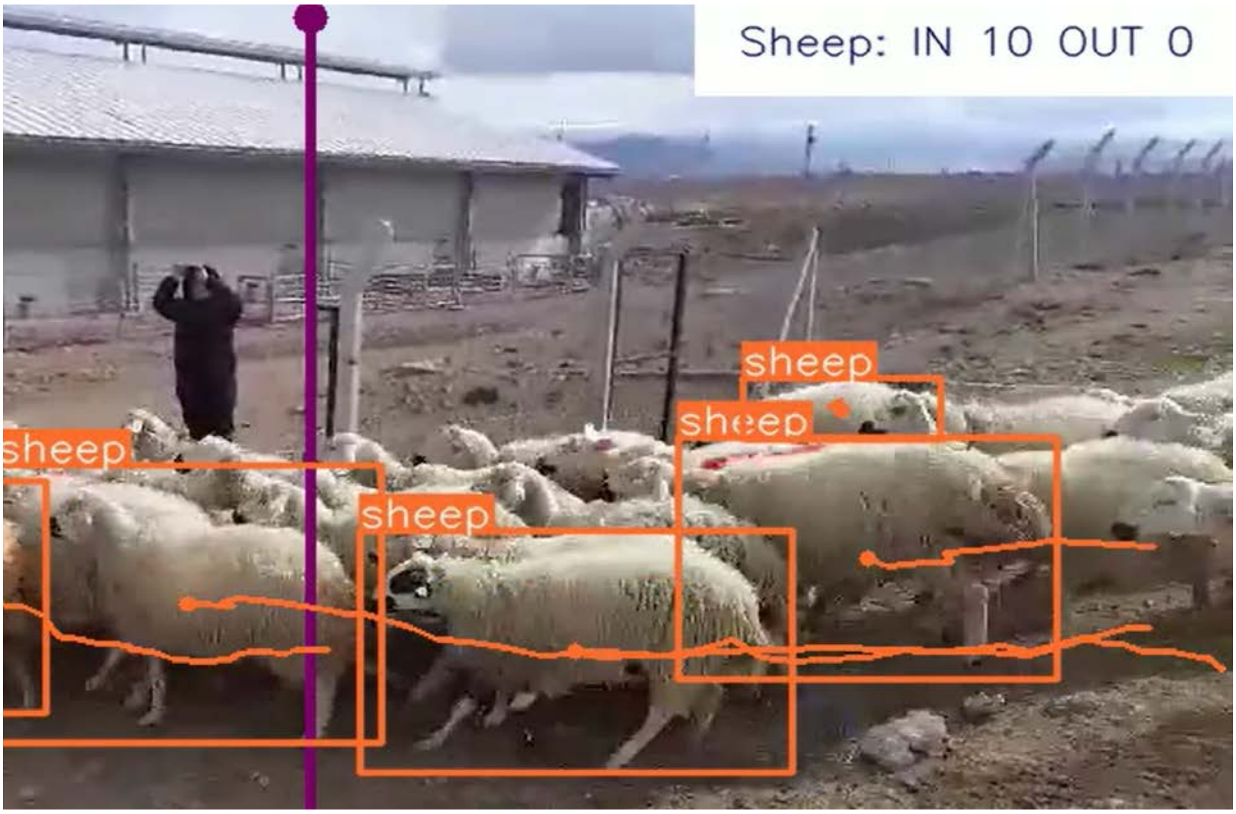

Figure 5. The process of counting passing sheep image.

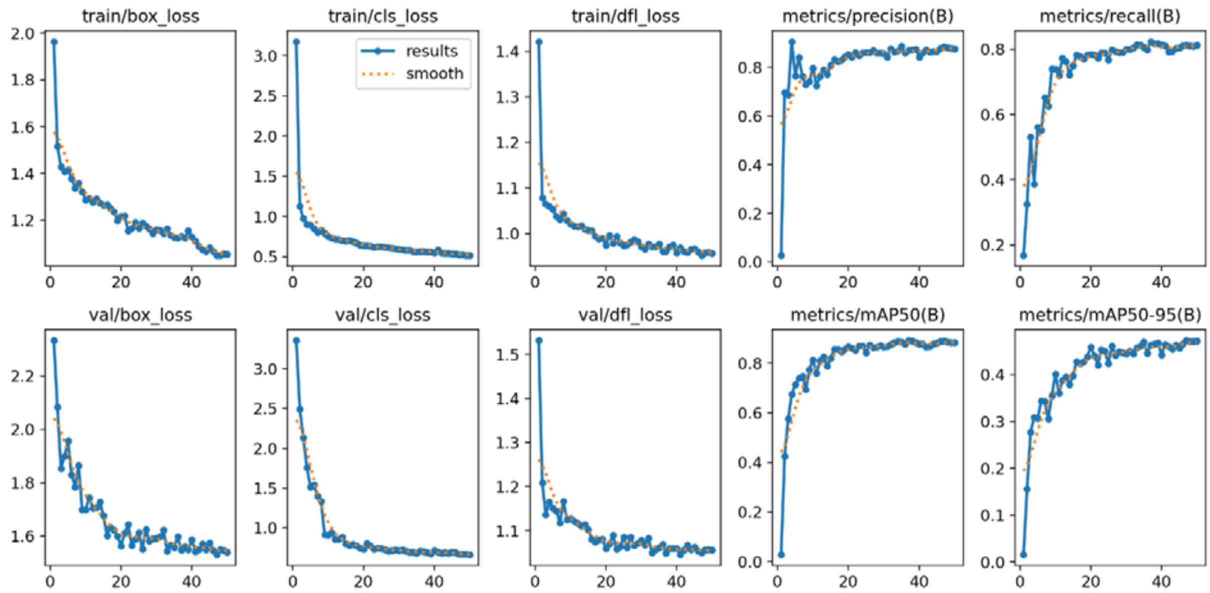

Figure 6. The training results for Yolov8n.

2.5. Evaluation Metrics

In order to evaluate the performance of the models, mean Average Precision (mAP) and training/validation losses were taken into account. In particular, mAP50 and mAP50-95 are the two main metrics used to measure the object detection performance of the models (Padilla et al., 2020). While mAP50 measures whether the detected objects are correctly counted with a 50 percent overlap rate, mAP50-95 takes into account a wider overlap range (from 0.5 to 0.95)(Everingham et al., 2010). In addition, the balance between the accuracy and losses of the model was monitored with the loss values used during training (Yuksel and Tan, 2023).

3. Results

Yolov8 has introduced different versions in response to varying demands, including those related to hardware costs, accuracy, and speed. In our study, four distinct versions of YOLOv8 were evaluated. These were YOLOv8n, YOLOv8s, YOLOv8m, and YOLOv8x. All were trained using the same dataset, and a comparative analysis was conducted.

In the training results for Yolov8n, the highest values were reached as 0.89174 mAP50 and 0.47129 mAP50-95. The training results for Yolov8n are shown in Figure 6.

In the training results for Yolov8s, the highest values were reached as 0.93040 mAP50 and 0.53200 mAP50-95. The training results for Yolov8s are shown in Figure 7.

In the training results for Yolov8m, the highest values were reached as 0.92553 mAP50 and 0.52822 mAP50-95. The training results for Yolov8m are shown in Figure 8.

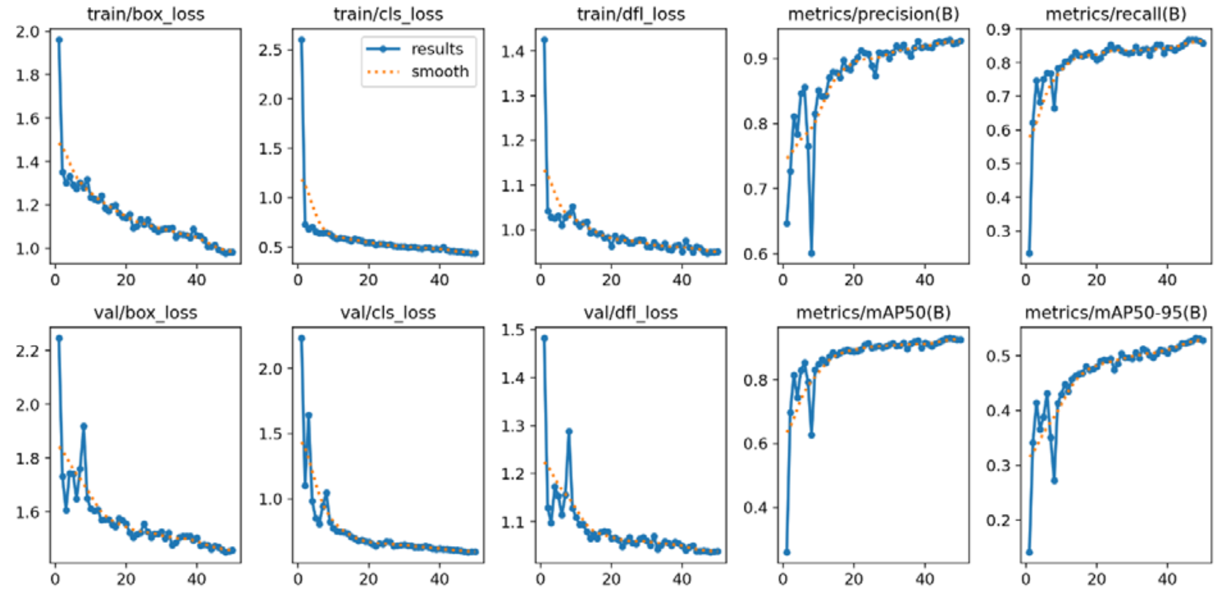

Figure 7. The training results for Yolov8s.

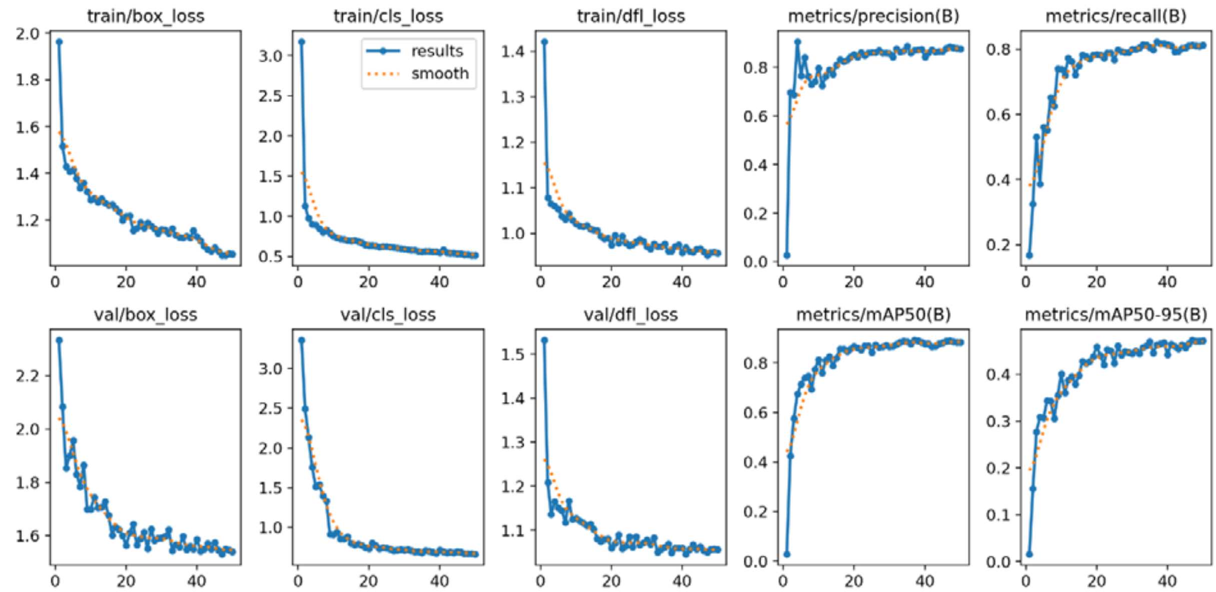

Figure 8. The training results for Yolov8m.

In the training results for Yolov8x, the highest values were reached as 0.92286 mAP50 and 0.53836 mAP50-95. The training results for Yolov8x are shown in Figure 9.

The findings indicate that the YOLOv8 Small model demonstrated the highest accuracy rates in both the mAP50 and mAP50-95 metrics. In particular, the mAP50 value yielded the most successful result, with a value of 0.93040. While the YOLOv8 Extra model attained the highest result of 0.53836 according to the mAP50-95 metric value, the YOLOv8 Small model demonstrated the most balanced and high-performance characteristics in general.

The YOLOv8 Nano, Medium and extra models demonstrated inferior performance in comparison to the mAP50-95 results. In object recognition problems, a mAP50 value of 0.9 indicates a high level of success (Lin et al., 2017). Additionally, mAP50-95 values of 0.6 indicate a high level of success of a model (Huang et al., 2017). The YOLOv8s model is considered successful in generally accepted scales. For this reason, YOLOv8s was used as the object detection model in this study.

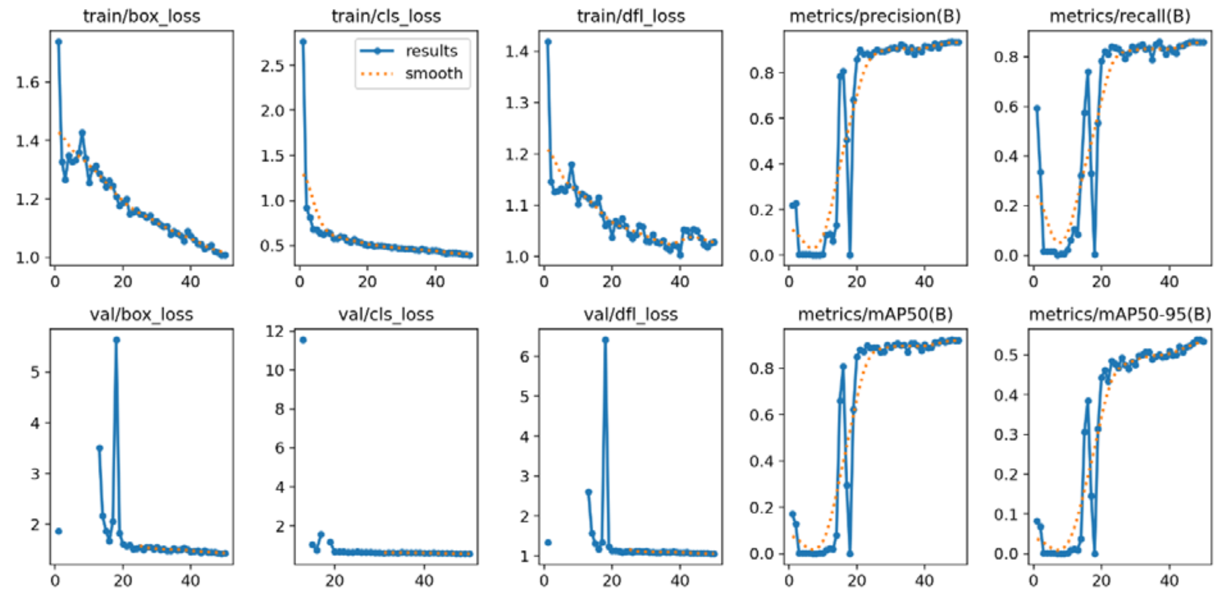

Figure 9. The training results for Yolov8x.

4. Discussion

The objective of this study was to assess the viability of a system based on the YOLOv8 model for the secure monitoring and enumeration of animals in pastures and surrounding enclosures in small livestock farming. In light of the inherent challenges associated with conventional shepherding techniques and the scarcity of available personnel in Türkiye, the integration of automated and digital tracking systems holds immense promise for the advancement of this sector. The four distinct models (n, s, m, x) of the YOLOv8 algorithm utilized in the study were evaluated in terms of their performance, and the most optimal model was selected based on the training process and accuracy rates. Comparative results of the models are shown in Table 1.

Table 1. Comparative results of the models

Model	mAP50	mAP50-95
YOLOv8n	0.89174	0.47129
YOLOv8s	0.93040	0.53200
YOLOv8m	0.92553	0.52822
YOLOv8x	0.92286	0.53836

In order to enhance the efficacy of the model, the AdamW optimisation algorithm and data augmentation techniques were employed. The ByteTrack and BoTSort algorithms were also evaluated for their suitability for object tracking. Following a comparison of their respective performances, the latter was selected as the most appropriate for the task.

The counting and monitoring methods developed in this research make a significant contribution to small livestock enterprises in terms of animal safety and counting accuracy. The capacity to monitor the daily movements of animals diminishes the workload of shepherds and facilitates the secure supervision of animals. Furthermore, the automation of counting processes enhances efficiency in activities such as shepherding and herd management and provides alternative solutions in instances where there is a shortage of qualified personnel in shepherding. In this regard, the functionality of the system offers an operational convenience and security advantage in Türkiye and other regions where livestock sectors are prevalent.

Future work should focus on improving the performance of the system under different weather and lighting conditions. In particular, the effects of adverse weather conditions such as heavy fog, rain, snow and daylight differences on the accuracy of the system can be studied in detail. Methods such as thermal camera data or night vision technologies, which perform better in low light conditions, can be investigated. In addition, extending the data sets to cover such challenging environmental scenarios can help to make the model more robust. Such improvements will allow the system to be used more effectively in real-world applications.

5. Conclusion

The objective of this study was to develop a digital monitoring and counting system that would ensure the safe and accurate counting of sheep in small livestock farming. The system, which was developed based on the YOLOv8 model, demonstrated high accuracy in monitoring small livestock and contributed to automatic counting and security monitoring, which is a crucial requirement in local livestock farming. The integration of object tracking algorithms employed in the study enabled the effective tracking of sheep movements, thereby facilitating the implementation of a monitoring mechanism that enhanced numerical accuracy.

The development of a more accurate and reliable system, based on an improved dataset and model, represents a significant opportunity for countries such as Türkiye, where there is a shortage of personnel in small livestock farming. Such technological solutions have the potential to both facilitate shepherding and provide an effective alternative for ensuring animal safety.

Author Contributions

The percentages of the authors' contributions are presented below. All authors reviewed and approved the final version of the manuscript.

	M.B	M.A.K.
C	50	50
D	30	70
S	50	50
DCP	100	0
DAI	0	100
L	50	50
W	20	80
CR	80	20
SR	80	20
PM	50	50
FA	50	50

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The authors declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no experimental study on animals or humans.

Acknowledgments

This work was previously presented in summary form at VIII. International Congress on Domestic Animal Breeding Genetics and Husbandry, 2024 as a conference abstract. The current paper significantly expands upon the preliminary findings presented in that abstract, incorporating additional data, advanced analysis methods, and comprehensive discussion to provide a more in-depth exploration of the research topic.

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