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Deep Learning in Agriculture: Detection and Analysis of Sugar Beets with YOLOv8

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ABSTRACT In this study, the performance of the YOLOv8 model in detecting sugar beets was evaluated using images obtained from a drone over a sugar beet field. High-resolution drone images were divided into small segments, labeled, and the model was trained using data augmentation techniques. The results obtained during the training and testing phases demonstrated that the model successfully detected sugar beets with high accuracy, precision, recall, and F1 score values. The analysis of label correlograms and result graphs confirmed the model's labeling accuracy and detection capability. These findings indicate that the YOLOv8 model can be an effective tool in agricultural production monitoring and plant health assessment applications. In the future, the model's performance will be more comprehensively evaluated using datasets obtained from different geographical regions and various agricultural products.

KEYWORDS
Sugar beet detection
Drone images
Deep learning
YOLOv8
Agricultural monitoring

INTRODUCTION

Sugar beet is a significant crop worldwide and plays a crucial role in global food security and economy (Yalçınkaya *et al.* 2006). With its high sugar content, sugar beet is a vital component in sugar production, which is a fundamental food item in many households worldwide (Semerci 2016). The crop is cultivated in various parts of the world, including major producers like the United States, France, and Germany. Sugar beet cultivation is a complex process that requires careful planning, precise irrigation, and timely harvesting to ensure optimal yields (Yalçınkaya *et al.* 2006).

Sugar beet is also a significant crop in Turkey, especially in the eastern regions where the climate is more favorable for agriculture (Tursun 2016). The country has a long history of sugar beet production dating back to the early 20th century. Today, Turkey is one of the largest sugar beet producers globally, with a significant portion of its production coming from eastern provinces (Semerci 2016). The country's sugar beet industry is supported by a network of sugar factories, processing plants, and research institutions working together to increase yields, reduce costs, and improve overall efficiency.

Drone technologies offer revolutionary innovations in the agricultural sector and are used in areas such as monitoring plant health, managing irrigation, and increasing crop Drone technologies offer revolutionary innovations in the agricultural sector and are used in areas such as monitoring plant health, managing irrigation, and increasing crop productivity. For instance, aerial photography and multispectral imaging with drones enable farmers to analyze field conditions more quickly and accurately (Zhang and Kovacs 2012). These technologies offer time and cost savings in critical agricultural processes such as disease and pest detection, and unmanned aerial vehicles provide a much more effective solution for surveying large agricultural areas in a short time compared to traditional methods (Tsouros *et al.* 2019). The development of these technologies paves the way for more sustainable and efficient practices in agricultural activities. With the increasing use of unmanned aerial vehicles in agricultural production, studies on the integration and optimization of these technologies are gaining momentum (Bendig *et al.* 2013).

Artificial intelligence and image processing methods are fundamentally transforming data analysis and decision-making processes in the agricultural sector. Specifically, object detection and classification algorithms provide high accuracy in the analysis of agricultural images (Kamilaris and Prenafeta-Boldú 2018). Deep

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learning models such as YOLO (You Only Look Once) offer effective solutions for the automatic identification and monitoring of agricultural products (Redmon *et al.* 2016). These algorithms can be trained on large datasets and provide valuable insights into plant health and productivity (Chlingaryan *et al.* 2018). Additionally, AI-supported image processing techniques are used in the autonomous management of agricultural machinery and precision farming applications. The adoption of AI and image processing technologies in agriculture enhances the optimization and sustainability of production processes (Chlingaryan *et al.* 2018).

The journey from YOLO-v1 to YOLO-v8 showcases the continuous improvement and adaptability of these models. (Hussain 2023) discusses the progression and complementary nature of YOLO models, emphasizing their integration into digital manufacturing and defect detection. (Talaat and ZainEldin 2023) propose an enhanced fire detection approach for smart cities utilizing YOLO-v8, highlighting its efficacy in real-time scenarios. (Terven *et al.* 2023) provide a comprehensive review of YOLO architectures, noting the advancements up to YOLO-v8 and the introduction of YOLO-NAS, which further enhance performance and accuracy in computer vision tasks. Additionally, (Kim *et al.* 2023) demonstrate the application of YOLO-v8 in high-speed drone detection, underlining its capability in rapid and precise object identification. These studies collectively illustrate the versatility and robust performance of YOLO-v8 across diverse applications, marking it as a pivotal development in the field of computer vision.

Modern approaches in sugar beet production involve the integration of new technologies to increase efficiency and ensure environmental sustainability. Advanced agricultural machinery and sensor systems enable more efficient management of sugar beet fields (Hoffmann and Kenter 2018). These systems continuously monitor soil moisture, plant health, and growth rates, providing farmers with real-time data. This allows for the optimization of precision farming practices, fertilization, and irrigation processes, thereby minimizing environmental impacts (Weiss *et al.* 2020).Modern biotechnology methods also play a significant role in the development of disease-resistant and high-yielding sugar beet varieties. These innovative approaches contribute to increased sustainability and economic gains in sugar beet production (Kumar *et al.* 2016).

The use of drone and artificial intelligence technologies in agriculture has the potential to further improve agricultural production processes in the future (Kaya and Goraj 2020). AI algorithms, integrated with big data analytics, can provide decision support systems at every stage of agricultural production processes (Wolfert *et al.* 2017). These technologies will enhance the agricultural sector's ability to adapt to global challenges such as climate change and population growth (Rose *et al.* 2016). Additionally, data-sharing platforms and smart farming networks will facilitate farmers' access to information, contributing to the creation of a collective knowledge base. The widespread adoption of drone and AI technologies in agriculture will enable the development of more sustainable, efficient, and resilient agricultural systems in the future (Eastwood *et al.* 2019).

MATERIALS AND METHODS

Dataset and Resources

The dataset used in this study consists of high-resolution drone images of sugar beet fields obtained from the internet. The images contain sugar beet plants in the green leafy growth stage. To ensure the accuracy and diversity of the images, the dataset, comprising 271 images, was divided into small segments and augmented using various data augmentation techniques. Each image segment was cropped to include sugar beet plants prominently. Subsequently, the images were manually labeled. The labeling process was carried out carefully and meticulously to provide accurate data and enhance the training performance of the model.

The artificial intelligence model was developed following the "Machine Learning Lifecycle" depicted below and in Figure 1.

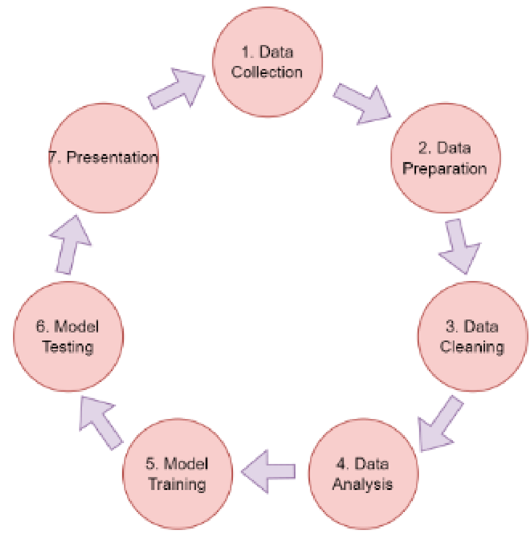

Figure 1 Machine Learning Lifecycle

Artifical Intelligence

With the advancement of technology today, artificial intelligence, a subject that continues to evolve, made its debut during a meeting in 1956, introduced by John McCarthy (Yılmaz *et al.* 2020). Artificial learning entails the ability of a computer or a machine under computer control to make decisions using mechanisms resembling those of living beings that can learn (Özel, M. A. and Baysal, S. S. and Şahin, M. 2021). In short, Artificial learning (AI) aims to replace human intelligence with machine intelligence (Munakata 1998). Artificial learning systems are those that interpret complex data through various methods to make it more understandable and improve themselves based on the experiences they gain (Aksoy *et al.* 2021).

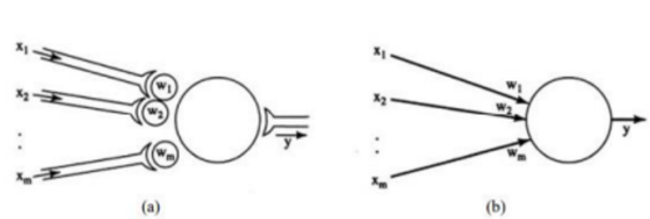

Figure 2 (a) A neuron model preserving the natural neuron image. (b) Another representation of the model (Munakata 1998)

A biological neuron is the fundamental building block of the nervous system. Its main function is to facilitate the transmission of information. It receives, transmits, and responds to stimuli. The artificial neuron shares similarities with it, consisting of structures such as axon, synapse, dendrite, myelin sheath, and nucleus. After defining the neural network architecture, the network enters the training phase. In this stage, the network learns by iteratively adjusting the weights of its connections based on provided examples (Munakata 1998).

Artifical Neural Networks

Artificial neural networks gained recognition through a study conducted by Warren McCulloch and Walter Pitts in 1943. They belong to the subset of artificial intelligence. The mathematical modeling of the neural structure of the human brain, for learning from experiences and remembering methods, is referred to as artificial neural networks. The aim is to model the neuron network of the brain to transfer the learning and decision-making process of the human brain to the computer environment. A neural network (NN) is an abstract computer example of the human brain (Munakata 1998).

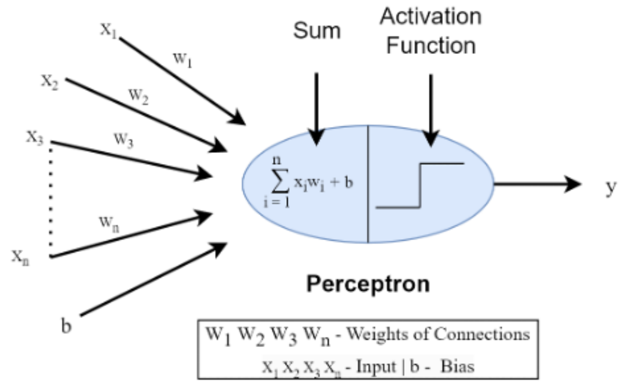

Figure 3 Mathematical model of a neuron (Tan *et al.* 2021)

Artificial neural networks are composed of artificial neurons. They have five basic components: inputs, weights, summation function, activation function, and outputs. Single-layer neural networks consist of input and output layers. These layers are generally used to solve linear problems. There can be one or more neurons in the layers (Yılmaz *et al.* 2020).

Machine Learning

In 1950, Alan Turing anticipated the development of the concept of machine learning and its future impact. Machine learning, a method used in artificial intelligence studies, is considered a subset of artificial intelligence. Deep learning is also a subset of machine learning. The relationship between artificial intelligence, machine learning, and deep learning is shown in Figure 4 (Tan *et al.* 2021).

The manual processing and analysis of very large datasets are not feasible. To address these problems, Machine Learning (ML) methods have been developed. Machine learning is the general term for computer algorithms that model a problem based on the data specific to that problem. The model created with the available dataset and the algorithm used are designed to perform optimally (Atalay and Çelik 2017).

Deep Learning

Following AlexNet's victory in the ImageNet competition in 2012, deep learning models began to be used in subsequent competitions. Deep learning is a subclass of machine learning with one or more hidden layers to gradually extract high-level features from raw data (Kazanç *et al.* 2021).

Deep learning can successfully analyze large datasets and can be applied to any field where data is available (Tan *et al.* 2021). The widespread success of deep learning is attributed to its method of computing outputs. A significant advantage of deep learning compared to traditional techniques is that it does not require an explicit feature extraction stage (Bozkurt 2021).

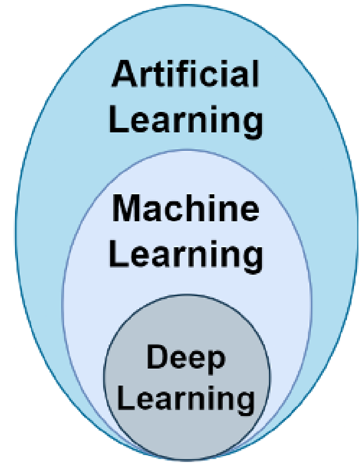

Figure 4 Artificial Intelligence Architecture (Arslan 2021)

Due to advancements in hardware, there has been an increased focus on deep learning studies, which has in turn improved object detection success rates. R-CNN, Faster R-CNN, Single Shot Detector (SSD), and YOLO are some of the deep learning-based object detection methods.

Among these methods, the YOLO algorithm and the DarkNet model offer high processing speed and accuracy. Experiments were conducted for four different versions of the algorithm, and the results were compared. The best results in terms of detection accuracy and speed were achieved with Version-4 algorithm. The success of deep learning methods has been proven in ImageNet classification competitions (Seçkin 2021).

Training and Optimization of YOLOv8 Model

YOLOv8 is a model developed for real-time object detection and offers significant improvements over its previous versions. One of the biggest advantages of YOLOv8 is its ability to provide high accuracy at high speed (Redmon *et al.* 2016). The model has been optimized for sugar beet detection and trained on the dataset prepared for this study. YOLOv8 has the ability to detect objects in a single network without incorporating complex components like region proposal networks (Bochkovskiy *et al.* 2020).

Various data augmentation techniques were used during the model training process. Images were processed with techniques such as rotation, scaling, brightness, and contrast adjustments. These techniques were used to improve the model's generalization ability. The hyperparameters of YOLOv8 were optimized during the training process; these hyperparameters include factors such as learning rate, batch size, and number of epochs. During training, the performance of the model on training and validation sets was monitored, and necessary adjustments were made. The loss function was carefully selected to improve the model's accuracy. The loss function of YOLOv8 focuses on minimizing classification and localization errors.

Additionally, the architecture of the model has been optimized for both speed and accuracy. YOLOv8 can provide fast results even on large datasets with efficient memory usage and computational requirements (Sokolova and Lapalme 2009). The output layers of the model provide class predictions and bounding box coordinates for each object. In this study, the performance of YOLOv8 was evaluated using metrics such as accuracy, error rate, precision, recall, and F1 score. The results showed that the model achieved high accuracy and efficiency in sugar beet detection.

Evaluation Metrics

The performance of the model was evaluated using metrics such as accuracy, loss, precision, recall, F1 score, and mean Average Precision (mAP).

Accuracy Accuracy represents the ratio of correct predictions made by the model to the total predictions. In a classification problem, accuracy is calculated as the ratio of correctly classified examples to the total examples.

TP (True Positives): Correctly predicted positive instances. TN (True Negatives): Correctly predicted negative instances. FP (False Positives): Incorrectly predicted positive instances. FN (False Negatives): Incorrectly predicted negative instances.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Precision Precision is a metric that represents the ratio of correct detections made by the model to the total detections. This metric is particularly important to assess the impact of false positives. A high precision value indicates that the majority of detections made by the model are correct. It measures the accuracy of the positive predictions made by the model and is calculated using the following formula:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

Recall Recall, also known as sensitivity or true positive rate, measures the ratio of correct detections made by the model to the total number of actual objects. This metric is particularly important to assess the impact of missed positives (false negatives). A high recall value indicates that the model successfully detects all available sugar beets. Recall measures how well the model detects all sugar beets and is calculated using the following formula:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

F1 Score F1 score represents the harmonic mean of precision and recall, summarizing the overall performance of the model. This metric balances precision and recall, providing a single value to evaluate the model's performance. It is calculated using the following formula:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

The F1 score is an important metric, especially in imbalanced datasets, because it considers both correct detections and missed detections.

Mean Average Precision (mAP) mAP measures the average accuracy performance of the model across all classes. This metric is obtained by averaging the Average Precision (AP) values calculated for each class. mAP represents the overall detection performance of the model and is calculated using the following formula:

$$mAP = \frac{1}{N} \sum_{i=1}^{N} AP_i \tag{5}$$

Here, N represents the total number of classes, and AP_i represents the Average Precision value calculated for each class. mAP is an important metric when evaluating the overall performance of the model because it considers the performance across all classes.

RESULTS

This study evaluated the performance of the YOLOv8 model for sugar beet detection, and the results were promising. Various data augmentation techniques were employed during the model training to increase the diversity of the dataset and enhance the model's generalization ability. After applying these augmentation techniques, the dataset expanded to 1355 images. The F1 score graph obtained after the training process demonstrates that the model exhibits high performance in terms of accuracy and precision. In the F1 score graph, it is evident that the accuracy improves and errors decrease as the training progresses.

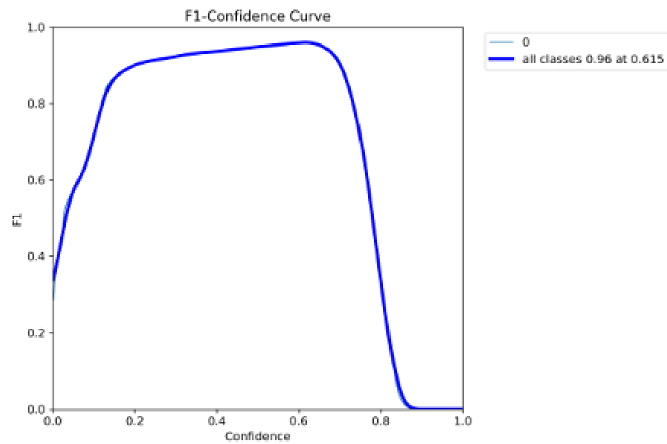

Figure 5 F1 Score Graph

IN-TEXT CITATIONS

A labels correlogram image was used to analyze the correlation between labels and the model's labeling accuracy. This analysis confirms that the model consistently produces accurate labeling. The correlogram shows the relationship between each label and other labels, as well as how accurately the model detects each label. This demonstrates how well the model distinguishes between similar-looking objects and how precise it is.

Additionally, as is seen from in the result graph the sugar beet plants detected by the model are accurately identified, and the bounding boxes are correctly placed.

The images used in the testing process were selected to evaluate how the model would perform in real-world applications. The analysis of the test images shows that the model can successfully detect sugar beet plants. The number and locations of sugar beet plants detected by the model were verified by comparing them with ground truth values. These test images demonstrate the practical application potential of the model in the field.

As a result, it has been observed that the YOLOv8 model provides 96.3% accuracy and efficiency in sugar beet detection. The model has yielded successful results in both the training and testing phases. The findings of this study may contribute to productivity and plant health monitoring efforts in sugar beet fields. In the future, it is planned to test the model on larger and more diverse datasets and adapt it to different agricultural products.

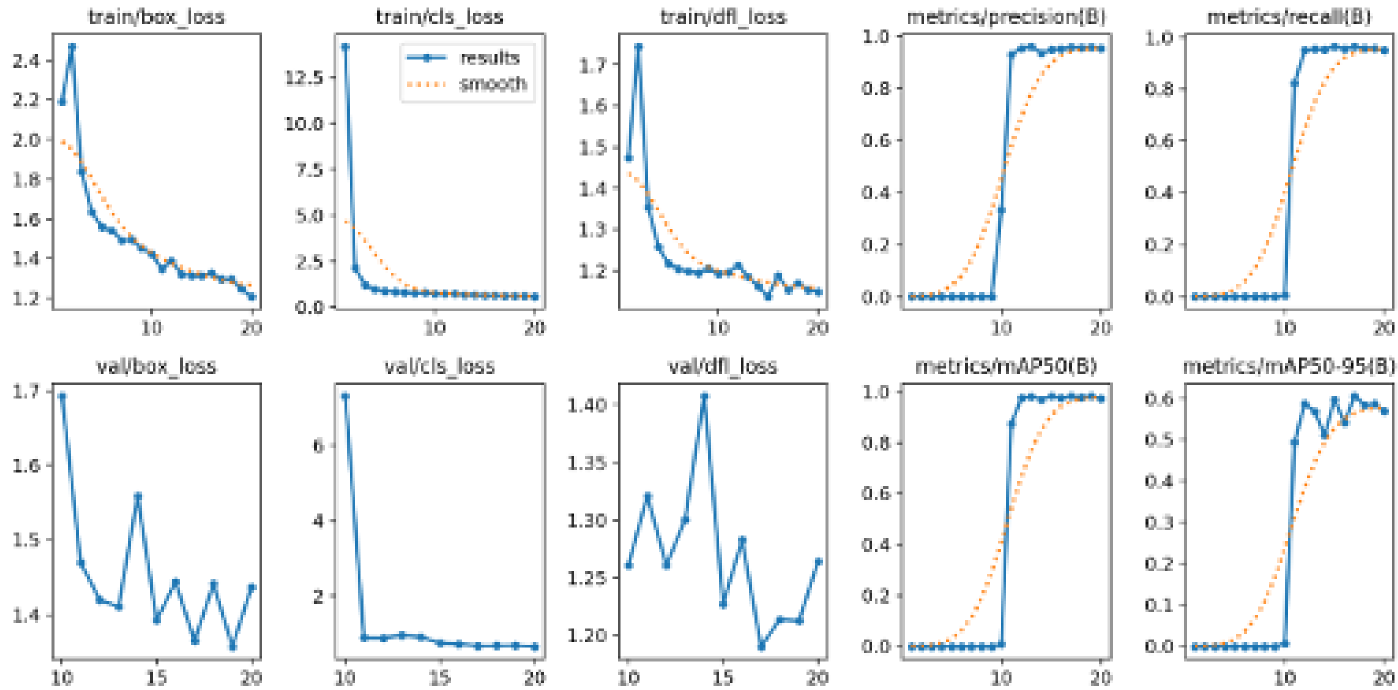

Figure 6 Training and Validation Result Graphs

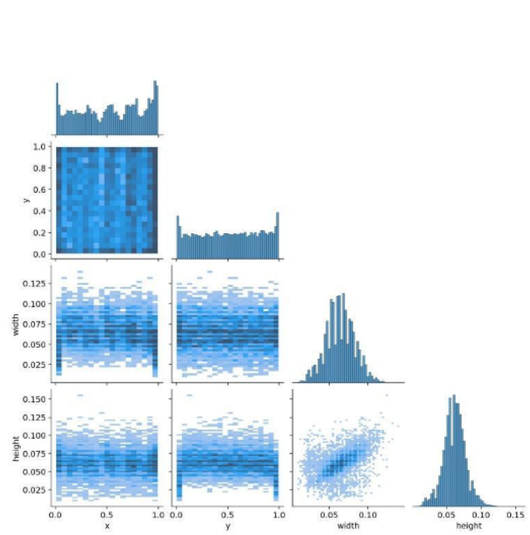

Figure 7 Result of Labels Correlogram

Figure 8 Test Image

DISCUSSION

This study aimed to evaluate the effectiveness of the YOLOv8 model in detecting sugar beets using drone imagery. The results obtained demonstrate that the model can accurately and precisely detect sugar beets. The data augmentation techniques employed during the model's training process have increased the diversity of the dataset and enhanced the model's generalization capability. This has enabled the model to perform successfully not only in specific environments but also in different environmental conditions.

PERFORMANCE METRICS AND EVALUATION OF RESULTS

The evaluation metrics of the model include various criteria such as accuracy, precision, recall, F1 score, and mAP. The result of the performance metrics can be seen in Table 1. Precision measures the ratio of correct detections made by the model, while recall evaluates how well the model can detect all true sugar beet plants [30]. The obtained high precision and recall values indicate that the model minimizes both false positives and false negatives. The F1 score summarizes the overall performance of the model by providing a balanced combination of these two metrics.

Table 1 Performance Metrics

Accuracy	F1	Recall	mAP
96.3%	96%	94.9%	97.4%

The obtained F1 score graph illustrates how the accuracy and error rates of the model improved over time during the training process. It's observed that the model's accuracy increased and errors decreased as the training progressed. This indicates the model's learning capacity and its ability to adapt to the dataset. Additionally, the labels correlogram image allows us to analyze the labeling accuracy and correlation between labels. This analysis confirms that the model produces consistent and accurate labeling.

REAL-WORLD APPLICATIONS OF THE MODEL

The images used during the testing phase were selected to simulate real-world conditions. The analysis of these test images demonstrates that the model can successfully detect sugar beets. This finding indicates that the model can be practically used in agricultural applications. Particularly, such a model is believed to have significant potential for monitoring field productivity and assessing plant health.

LIMITATIONS AND FUTURE WORK

This study has several limitations. Firstly, the dataset used consists of images obtained from a single field. Evaluating the model's performance with datasets obtained from different geographical regions and varying climate conditions is essential for generalizability. Additionally, exploring the applicability of the model to other agricultural products could be an important research topic for future studies.

In the future, the model is planned to be tested on larger and more diverse datasets. Additionally, the aim is to further enhance the model's performance by exploring different deep learning models and data augmentation techniques. Such studies could provide more effective and efficient solutions for monitoring and managing agricultural production.

CONCLUSION

This study has demonstrated that the YOLOv8 model provides high accuracy and efficiency in sugar beet detection. The model has shown successful results in both the training and testing phases. The findings obtained can contribute significantly to productivity and plant health monitoring in agricultural production. Such deep learning models offer significant potential for digital transformation and smart farming applications in the agricultural sector.

Availability of data and material

Not applicable.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

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