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Advanced YOLOv8-Based Efficient Detection Method for Sugarcane Stem Nodes

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Abstract: *The precise identification of sugarcane stem nodes is crucial for intelligent seed cutting, planting placement, sugarcane garden production management process optimization, yield improvement, and economic benefits. However, efficiency, model complexity, and real-time performance are still issues with the sugarcane stem node detection methods are currently in use. This study decided to visually detect distinguish between sugarcane stem nodes in a structured scene using the advanced YOLOv8 model in order to address this issue. For the purpose of to create an image training set and a test set, a field sugarcane image collection experiment was first designed. The collected sugarcane images were manually labeled. The YOLOv8 network was then utilized as the sugarcane stem node detection model to find the ideal hyperparameter combination and train the model. Finally, field-based recognition experiments are carried out to verify the method's effectiveness and efficiency. Experimental results show that the precision, recall, mAP, single-frame inference time and model size of our method on the test set are 0.973, 0.958, 0.974,19.80 ms and 6.30 MB respectively. Compared with the Edgeyolo_S_Coco network and Edgeyolo_Tiny network, the mAP value of the YOLOv8_n network has increased by 1.70% and 1.30% respectively, the single-frame inference time has been reduced by 4.71 ms and 1.50 ms respectively, and the model size has been reduced by 33.70 MB and 17.50 MB respectively. This method has advantages in detection performance and generalization ability, and can effectively meet the requirements for algorithm accuracy and model complexity in outdoor environments, providing solid technical support for sugarcane harvesting and planting in intelligent agricultural production.*

Keywords: YOLOv8; object detection; stem node detection; sugarcane

INTRODUCTION

As an important component of agricultural economic development, promoting high-quality development of sugarcane industry is of great significance for ensuring sugar supply, accelerating agricultural transformation and upgrading, and promoting high-quality economic development [1]. Currently, the development model of China's sugarcane industry is undergoing profound changes, and there is an urgent need to make agricultural technological innovation a key driving force for promoting the modernization of the sugarcane industry [2]. At present, the field operation of sugarcane still relies heavily on manual labor, such as sugarcane seed preparation and sugarcane planting, which not only has low work efficiency, but also cannot guarantee planting uniformity and accuracy [3]. With the continuous development of smart agriculture, computer technology has gradually begun to be applied to research in sugarcane planting and harvesting, effectively alleviating the problem of labor shortage in society and improving operational efficiency [4]. However, the accuracy and efficiency of current sugarcane stem node detection methods need to be improved and cannot be widely applied. Therefore, designing an efficient and accurate sugarcane stem node detection system is a bottleneck problem facing the intelligent management of sugarcane orchards.

Currently, some domestic and foreign scholars have conducted relevant research on sugarcane node detection. Moshashai et al. from Iran [5] conducted preliminary research on sugarcane stem node recognition using grayscale image threshold segmentation method, while Dhingra Gittaly et al. [6] studied a method based on local mean and H component in HVS color space for image segmentation processing, using the maximum grayscale value to determine the stem node position. The recognition rate was 90.77%, and the average time was 0.481 539 seconds. Chen Wen et al. [7] explored a machine vision based method for feature extraction and recognition of sugarcane stem nodes. The S and H component images of sugarcane segments were processed differently in the HSV color space, and the support vector machine method was used to process sugarcane stem nodes and internodes. After clustering analysis, the average recognition rates of stem node number and position were 94.118% and 91.522%, respectively. Wang Weiwei et al. [8] conducted research on sugarcane stem node recognition and localization methods based on hyperspectral imaging technology. They collected data using a spectrometer above the image acquisition device, extracted stem node feature bands, and established a model to recognize stem nodes. The positioning errors of the left and right ends of the stem nodes were less than 0.9 mm and 2.4 mm, respectively. The above research achieved sugarcane recognition by combining artificial features and utilizing traditional machine learning methods. However, traditional machine learning methods suffer from poor robustness and weak generalization ability in complex environments of sugarcane fields due to the need to pre specify manual features. Therefore, the recognition performance needs to be further improved.

In recent years, deep learning technology has been widely applied in the field of agriculture, and many researchers have also conducted research on stem node recognition based on deep learning [[9],[10],[11],[12],[13],[14]]. Xu Hongzhen et al. [15] improved the YOLOv3 network by reducing the number of residual structures composed of intermediate convolutional layers, achieving an accuracy of 90.38% and an average time of 28.7 ms. Sangaiah Arun Kumar et al. [16] based on the improved YOLOv4 sugarcane stem node recognition model, directly passed the effective feature layer into the enhanced feature extraction network for path aggregation construction. The single frame image recognition time was about 6 ms, and the recognition accuracy was 98.68%. Bereket Getachew et al. [17] achieved sugarcane bud recognition and localization by improving the LeNet-5 network model. The model takes 1.2 seconds to detect a single image and has a recognition accuracy of 92%. Xie Zhongjian et al. [18] implemented sugarcane stem node recognition based on improved YOLOv5, providing a model lightweight method at the cost of small accuracy loss. Lu Zhiheng et al. [19] proposed a stem node recognition method based on an improved YOLOv5obb model, which achieved an accuracy of 97.1% on the sugarcane dataset. Qu Zhong et al. [20] improved the YOLOv5 network by using multi-scale prediction structure and K-means algorithm to optimize the bounding box. The improved object detection model has an mAP of 93.8%. Dai Jiuxiang et al. [4] optimized the YOLOv5 network by adding the CBAM attention mechanism module and introducing VarifocalNet. The accuracy of sugarcane stem node recognition reached 89.89%. The above research focuses on improving model accuracy and has achieved significant results, but the vast majority of studies rely on high-performance computers for experimentation, which requires high hardware requirements. This makes it difficult to apply it to current rural planting environments and cannot meet the goal of low-cost and high-quality operations.

Through the above research, it can be seen that deep learning technology performs well in image feature extraction and object detection, especially in complex environments, demonstrating its unique advantages. Compared to traditional machine learning methods, deep learning methods not only exhibit higher robustness, but also have excellent generalization ability. However, in the field of sugarcane stem node detection, current research mainly focuses on improving the accuracy of algorithms, while neglecting the importance of real-time operation and lightweight models. High complexity models require high memory and computing resources, which contradicts the trend towards miniaturization of devices and also increases the cost burden of mechanization in sugarcane cultivation. Therefore, how to reduce the computational cost and volume of the model while maintaining system performance has become the core challenge for sugarcane production equipment to achieve mechanization and intelligent operations.

To meet the practical needs of sugarcane farmers and sugarcane production equipment, this study proposes an efficient detection method for sugarcane stem nodes based on YOLOv8. The main tasks of this method include: (1) designing and conducting sugarcane image acquisition experiments in natural environments, manually annotating, and randomly dividing to construct a sugarcane image dataset; (2) Using YOLOv8 network as the sugarcane stem node detection model, optimizing the hyperparameter combination to achieve optimal model performance; (3) Design and conduct comparative experiments on different detection models to comprehensively evaluate their performance and complexity. The research results can provide technical support for intelligent harvesting and planting of sugarcane, thereby meeting the practical needs of sugarcane production equipment in reducing costs and improving efficiency.

MATERIALS AND METHODS

Materials

Image acquisition: An image acquisition experiment was conducted in November 2023 in the sugarcane field of the Agricultural Machinery Research Institute of the Chinese Academy of Tropical Agricultural Sciences in Zhanjiang, Guangdong Province (21 ° 10'N, 110 ° 16'E). We have constructed image datasets for two sugarcane varieties, New Tai Sugar 22 and Gui Sugar 49. As shown in Figure 1, the stem bark of New Tai Sugar No. 22 exhibits a light-yellow green color, while Gui Sugar No. 49 shows a purple red color. During the experiment, iPhone 11 and HUAWEI Mate 60 Pro were used as the shooting cameras, and the image size was set to 4032×3024 pixels and save in color image JPG format. A total of 450 images were captured, each containing 3-5 stem nodes, totaling approximately 1800 sugarcane stem nodes. These images provide important visual information for subsequent data analysis and research.

Dataset processing and production: The quality of the dataset has a crucial impact on the accuracy of training recognition models and their performance in practical applications. To ensure the clarity and representativeness of the data, 440 sugarcane images were selected. To ensure the effectiveness of model training and validation, these images were divided into training and validation sets in a 7:3 ratio, with 310 images used as the training set and the remaining 130 images as the testing set.

New Tai Sugar No. 22 Gui Sugar No. 49

Fig. 1 Image acquisition experiment of different varieties of sugarcane

Annotate the sugarcane dataset and generate a label file that includes the category identification of each sugarcane stem node and its normalized bounding box coordinates in the image.

Table 1 Details of the dataset

Data set	Training data set images/page	Validating data set images/page	Test data set images/page
New Tai Sugar No. 22	100	40	60
Gui Sugar No. 49	135	35	70

Method

YOLOv8 Model: Accurate detection of sugarcane nodes in outdoor scenes is a key step in achieving subsequent intelligent planting and harvesting tasks. At present, detection methods are mainly divided into two-stage strategies represented by the R-CNN series [[21],[22],[23],[24]] and single-stage strategy object detection frameworks represented by the YOLO series [[25],[26],[27]]. Compared to existing object detection methods, YOLOv8 has attracted more attention for its high-speed iterative updates while maintaining high accuracy. This model adopts a more lightweight network structure and utilizes more efficient inference techniques (such as TensorRT engine acceleration), with better detection performance and ease of deployment and application in real-world scenarios. Therefore, YOLOv8 with high detection accuracy and speed was selected as the sugarcane stem node detection network. As shown in Figure 2, the overall structure of YOLOv8 includes three parts: backbone network, neck network, and detection head.

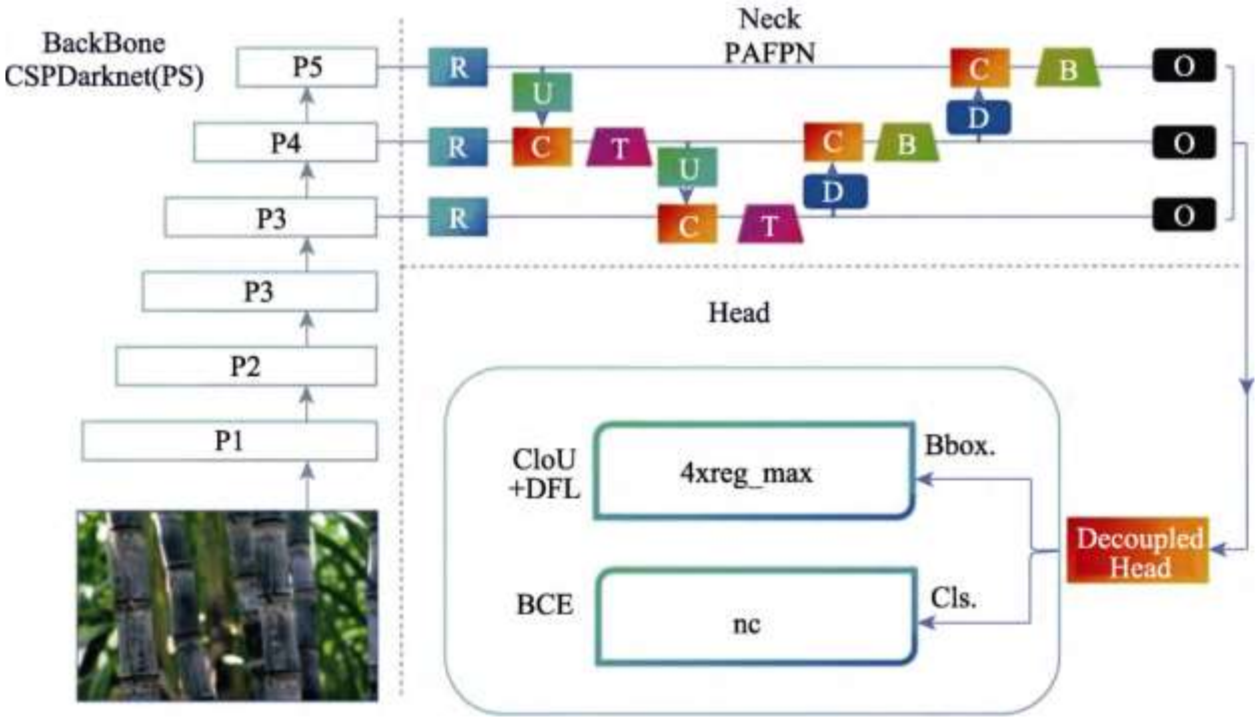

Fig. 2 The overall structure of YOLOv8

Backbone network and neck network: In order to achieve better training results for the network under limited GPU resources, YOLOv8 adopted Darknet53 network and PAFPN network in BackBone and Neck, respectively. By replacing the C3 module in YOLOv5 with C2F model, the network's efficient feature extraction ability was effectively improved. As shown in Figure 3, the main process of the C2F module structure is as follows: first, one Conv convolution is performed, and then the chunk function is used to evenly split the out into two vectors and save them to a list; Then, input the latter half into the Bottleneck Block, where there are n Bottlenecks in the Bottleneck Block; Finally, append the output of each Bottleneck to the list.

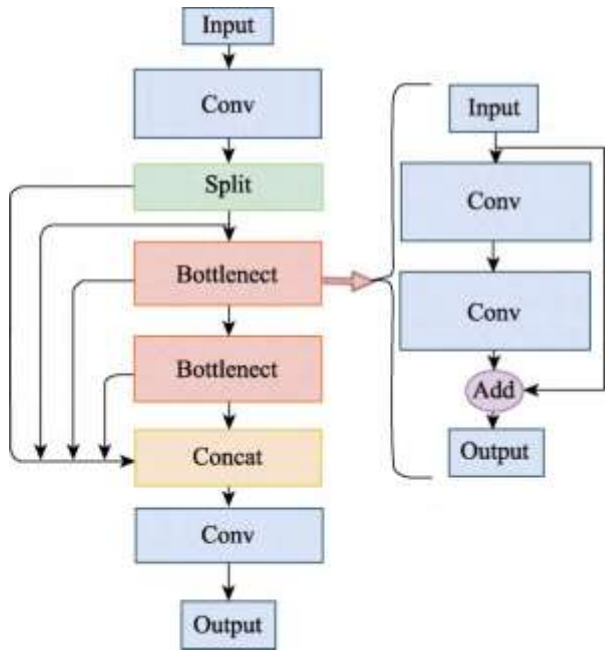

Fig. 3 C2f module structure

Predictive Network: Object detection algorithms can be divided into two categories based on the existence of prior anchor box criteria: anchor based and anchor free. The decoupling head was first proposed by TIAN et al. [28] and has been widely used in Anchor Free based object detectors, such as YOLOX, due to its advantages of fast convergence and improved regression performance.

As shown in Figure 4, YOLOv8's prediction network uses Decoupled Head, and due to the use of DFL thinking, the number of channels in the prediction head also becomes 4×reg_max. Compared to YOLOv5, in order to improve regression performance, YOLOv8 replaces the C3 module in the Head with C2f, removes the 1×1 convolution before upsampling, and directly feeds the features output from different stages of Backbone into the upsampling operation, achieving feature fusion of feature maps of different sizes and reducing inference costs. Finally, an efficient decoupling head with faster inference speed is proposed.

RESULTS AND ANALYSIS

Experimental configuration and training results

To fairly evaluate the performance of each algorithm, it is ensured in the experiment that the training platform and hyperparameter configuration used by each algorithm are basically consistent. The details of this research experimental platform are as follows: The central processing unit (CPU) is an Intel Xeon Gold 6 256 processor, with a clock speed of 3.60 GHz, 48 physical cores and 24 threads, and a memory capacity of 1024GB. The graphics card is NVIDIA RTX A6000 (GPU) with 48 GB of video memory. The operating system adopts Ubuntu 18.04 and is installed with CUDA 11.8.130, CUDNN 8.6.0, NVIDIA driver 535.104, Opencv 4.8.0, and training framework Pytorch 2.0.1.

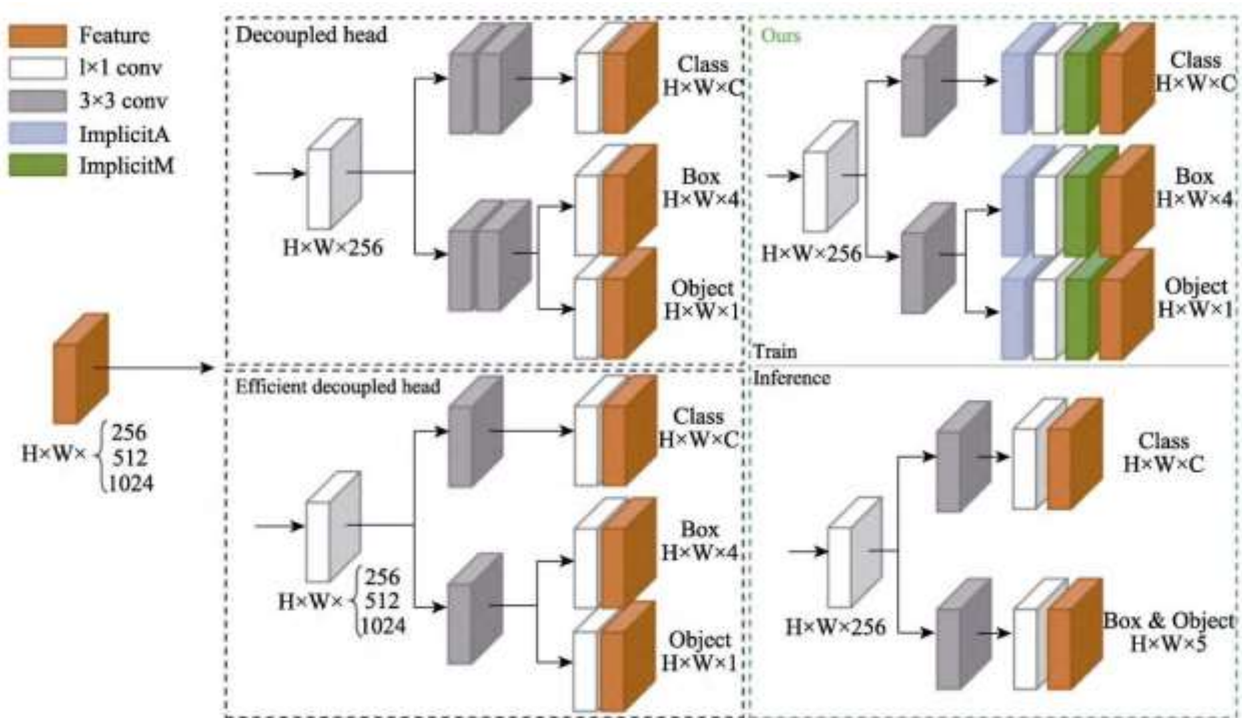

Fig. 4 Decoupling prediction head structure diagram

(1) Parameter settings: Use the official pre trained models Edgeyolo_Tiny and YOLOv8_n as the initial models, set the input image pixel size to 1024×1024, and set Max_epoch to 300. Meanwhile, set the Batch size to 16, the initial learning rate to 0.01, the momentum factor to 0.90, and the weight decay coefficient to 0.0005.

(2)Training strategy: During the training process, the K-means clustering algorithm is used to accurately determine the optimal anchor frame aspect ratio through adaptive computation. To further enhance the generalization ability and robustness of the model, various image enhancement methods are adopted. Firstly, using Mosaic data augmentation technology, the diversity of training samples and background complexity of the model are increased; Secondly, the Mixup method is used to generate new training samples by linearly interpolating between the original image and the labels, thereby improving the model's generalization ability; In addition, EMA (incremental moving average) technology is introduced to smooth the model parameters and further improve the stability of the model; In terms of color space, HSV color space enhancement is used to enhance the model's adaptability to different lighting conditions and color changes by randomly adjusting the hue, saturation, and brightness of the image; Finally, the image is horizontally flipped using the Flip method to enhance the model's ability to recognize symmetry.

Figure 5 shows the model loss and average accuracy (AP) of the sugarcane stem node recognition network during the training process as a function of iteration times. The loss changes and performance indicators of the model during training and validation: changes in bounding box loss (box-loss), classification loss (cls_loss), and distribution focus loss (dfl_loss), as well as precision, recall, and mean accuracy (mAP). Observing the image, it can be observed that the loss curve gradually decreases and remains stable, which means that the network error gradually decreases and the generalization performance is good. As the training epochs increase, the mAP curve gradually rises and stabilizes, although there may be some fluctuations in the initial stage, the fluctuations gradually decrease during the training process. In depth analysis shows that the loss curve trends on the training set and validation set are consistent, as is the mAP performance, with no significant deviation, indicating that the network has not experienced overfitting or underfitting. From the perspective of parameter convergence, based on the convergence trends of the loss curve and mAP curve, as well as consistent performance on the training and validation sets, it can be confirmed that the sugarcane stem node network has reached convergence.

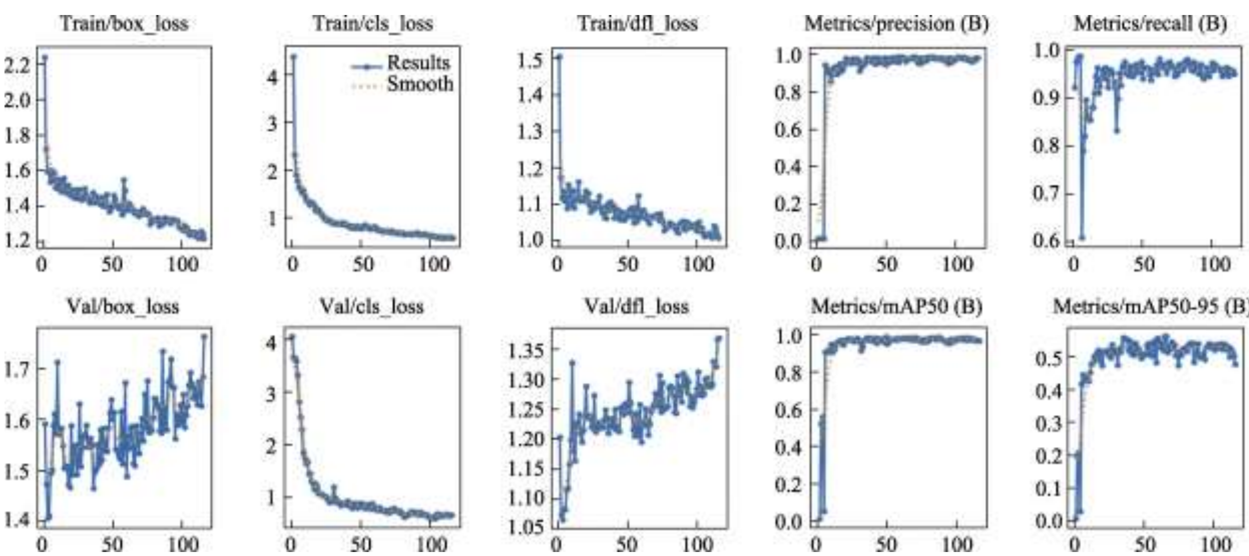

Fig. 5 Fitting curve of sugarcane stem node detection network

Sugarcane Stem Node Identification Test and Result Analysis

In this study, a set of sugarcane stem node recognition experiments was designed, and Edgeyolo_SeCo network, Edgeyolo_Tiny network, and YOLOv8_n network were used to recognize the test images of the New Tai Sugar 22 sugarcane and Gui Sugar 49 sugarcane,

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respectively. The model detection effect is shown in Figure 6. The experiment uses precision, recall, mAP value, inference time, and model size as evaluation criteria, and the calculation formula is as follows:

$$P = \frac{T_{\mathrm{p}}}{T_{\mathrm{p}} + F_{\mathrm{p}}} \tag{1}$$

$$R = \frac{T_{\mathrm{p}}}{T_{\mathrm{p}} + F_{\mathrm{N}}} \tag{2}$$

$$\mathrm{AP} = \sum_{k=1}^{N} P(k)\Delta r(k) \tag{3}$$

Among them, T_{p} represents the number of correctly identified sugarcane stem nodes (true cases), represents the number of incorrectly identified sugarcane stem nodes (false positive cases), and F_{N}represents the number of unrecognized sugarcane stem nodes (false negative cases). P and R represent accuracy and recall, respectively, and are important indicators for evaluating the performance of detection models. AP is the area under the precision recall curve, reflecting the overall performance of the model. The inference time is the time required for detecting a single sugarcane image, used to measure the efficiency of the model. Model size represents the model size, and the number of network parameters plays a crucial role in actual deployment, which has a significant impact on the running speed and performance of the model.

From Figure 6, it can be seen that for the two varieties of sugarcane, New Tai Sugar 22 and Gui Sugar 49, the Edgeyolo_Tiny network, Edgeyolo_Tiny network, and YOLOv8_n network can all recognize the sugarcane stem nodes in the images well. Compared with the Edgeyolo_SeCo network and the Edgeyolo_Tiny network, the YOLOv8_n network effectively overcomes the drawbacks of missed detection and duplicate detection. In addition, in practical operations, the vibration generated by the seed cutting machine or the daily operations of sugarcane farmers may cause varying degrees of image quality blur, which further increases the difficulty of sugarcane stem node recognition. Figure 7 shows the detection performance of YOLOv8_n network under image blur conditions. From the figure, it can be observed that even in the case of poor image quality, the network can still accurately identify and frame sugarcane stem nodes, fully demonstrating the excellent performance of YOLOv8_n network in robustness and overall performance.

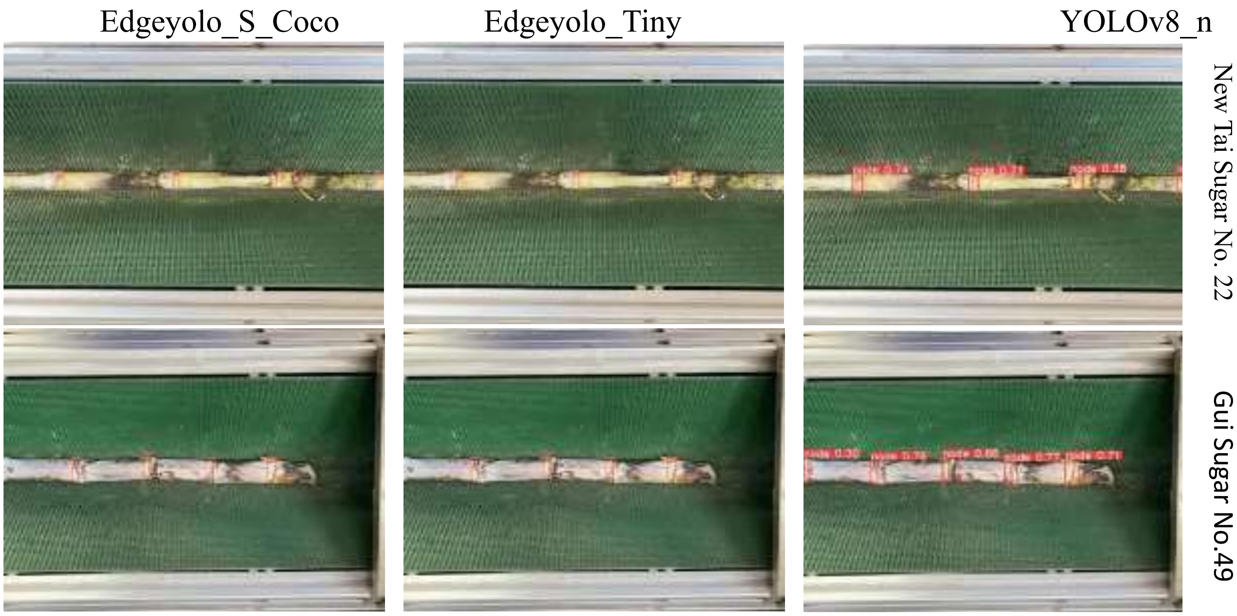
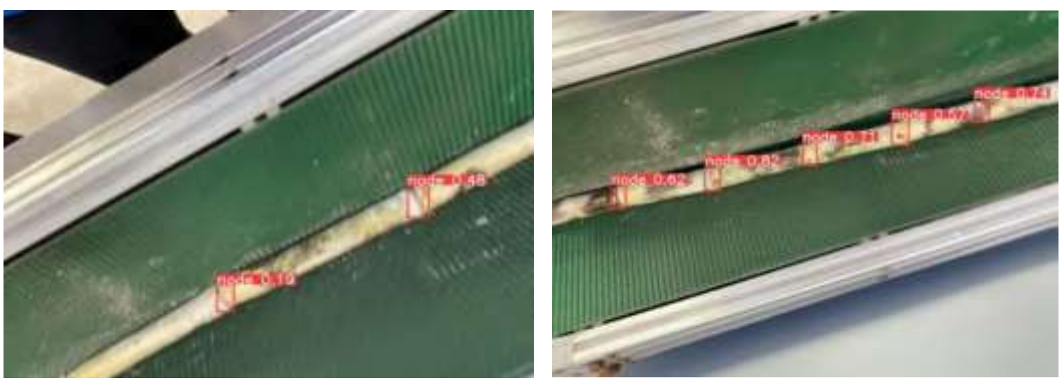


Fig. 6 Detection results of different networks for different sugarcane varieties



Number of sugarcane stem nodes is <3 Number of sugarcane stem nodes is ≥3

Fig. 7 Detection of sugarcane stem nodes under poor image quality conditions

From Table 2, it can be seen that the accuracy, recall, mAP, single frame inference time, and model size of YOLOv8_n network on the test set are 0.973, 0.958, 0.974, 19.80 ms, and 6.30 MB, respectively. Compared with the Edgeyolo_SeCo network and the Edgeyolo_Tiny network, the mAP of the YOLOv8_n network increased by 1.70% and 1.3% year-on-year, the single frame inference time decreased by 4.71 ms and 1.5 ms year-on-year, and the model size decreased by 33.70 MB and 17.50 MB year-on-year, respectively. The experimental results show that the sugarcane stem node detection network proposed in this study has more advantages in detection performance and generalization ability, and can effectively meet the requirements for algorithm accuracy and model complexity in outdoor environments.

Tab. 2 Performance comparison of different sugarcane stem node detection networks

Network model	Precision	Recal	mAP	Single-frame inference time/ms	Model size/MB
Edgeyolo_S_Coco	0.959	0.982	0.957	24.51	40.00
Edgeyolo_Tiny	0.966	0.988	0.961	21.30	23.80
YOLOv8_n	0.973	0.958	0.974	19.80	6.30

DISCUSSION

This study proposes a lightweight sugarcane stem node detection method based on YOLOv8. The study first conducted field sugarcane image acquisition, constructed sugarcane image datasets for two varieties, New Tai Sugar 22 and Gui Sugar 49, and divided the datasets into training, validation, and testing sets through manual annotation. Subsequently, a lightweight EdgeYOLO network was proposed to determine the optimal hyperparameter combination and achieve accurate detection of sugarcane stem nodes. In structured scenarios, the accuracy, recall, mAP, single frame inference time, and model size of this method on the test set are 0.973, 0.958, 0.974, 19.80 ms, and 6.30 MB, respectively. Compared with the Edgeyolo_SeCo network and the Edgeyolo_Tiny network, the mAP value of the YOLOv8_n network has increased by 1.70% and 1.3% respectively, the single frame inference time has been reduced by 4.71 ms and 1.5 ms respectively, and the model size has been reduced by 33.70 MB and 17.50 MB respectively. The research results indicate that the proposed sugarcane stem node detection network has significant advantages in detection performance and generalization ability, and can effectively meet the requirements for algorithm accuracy and model complexity in outdoor environments, providing technical support for sugarcane harvesting and planting in agricultural intelligent production.

Overall, the lightweight sugarcane stem node detection method proposed in this study performs excellently in terms of detection performance and generalization ability, fully meeting the accuracy and cost-effectiveness required for sugarcane stem node detection algorithms in outdoor environments. Future research can effectively apply this algorithm to practical edge devices to meet the operational requirements in real-time and resource constrained environments. In addition, integrating this algorithm into agricultural machinery such as sugarcane cutting machines or planting machines to achieve close integration with agricultural equipment will provide more intelligent services for agricultural production, improving the accuracy and efficiency of mechanical operations.

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