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Light weight YOLOv8 for real-time sugarcane stem node detection, counting, and monitoring in complex natural environments

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Abstract

Automated sugarcane stem node extraction can be extremely useful to promote single-stem node plantlets and tissue culture techniques. It can be utilized to reduce labor, plantations, and logistics costs while providing a high yield in sugarcane cultivation. Real-time stem node counting and monitoring can be utilized for controlling the production of billets and their quality. This study not only presents an approach for real-time sugarcane stem node detection and localization but also counting and tracking for production monitoring. Smaller and lighter scaled down light weight YOLOv8 model is applied to optimize the deep learning model. A dataset of 2870 images is collected in natural sugarcane field complex environments, with each image annotated in two classes in the YOLOv8 format. The model achieved a high mean average precision of 0.974 and a low detection time 7.17 milli seconds. The model achieved 94.08% overall accuracy. Additionally, automated sugarcane stem node counting and monitoring offers a scalable solution for real-time sugarcane stem node extraction. The trained model demonstrates exceptional performance in real-time scenarios, facilitating precise stem node detection, localization, counting, and monitoring.

Subject Classification: *Primary 93A00, Secondary 94A00.*

Keywords: *Sugarcane bud detection, Sugarcane stem node detection, YOLOv8, Deep learning, Precision agriculture.*

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1. Introduction

Sugarcane holds a prominent position as a major cash crop, and beyond its ecological impact, sugarcane farming plays a vital role in maintaining soil fertility and conserving water resources. Single-stem node cultivation in sugarcane agriculture, also known as single-stem node sets or single-eye planting, is considered advantageous for several reasons, such as uniform growth, disease control, optimized resource utilization, higher yield potential, ease of harvesting, economic considerations, and adaptability to modern agricultural practices. There is an enormous scope for machine vision and deep learning in sugar cane agriculture.

1.1 *Related Work*

In various agricultural operations of sugarcane production [1] such as soil preparation, planting, fertilization, spraying, and harvesting various sensors and intelligent control systems are introduced. The technological evolution has enabled us to use state-of-the-art sensors [2] in monitoring, decision making, and management processes for sugarcane cultivation. Machine vision and deep learning can also be used for detecting sugarcane diseases [3] using techniques like CNN and support vector machines. Similarly, sugarcane yield estimation can be performed using automated detection [4] of sugarcane crop lines from UAV images using deep learning. The process of plantation can be automated with the sugarcane planters enabled with machine vision and deep learning. Sugarcane harvesting quality [5] is necessary for high yield and productivity. Information related to sugarcane billets and sowing situations through system recognition feedback can be recorded and analyzed for detection and recognition by the pre-seed cutting [6] sugarcane planter. Single stem node plantlets and tissue Culture Techniques for Seed Multiplication [7] in Sugarcane are considered to be the best techniques in sugar cane cultivation. Most farmers are adopting single-stem node cultivation these days due to high yield and low wastage. The first step in this process is to extract the stem nodes from sugarcane stems as shown in Figure 1. Mostly, this task is done manually by chipping tools. This task is very labor intensive and costly. However, this task can be automated with the help of deep learning and computer vision. First step in the task of automatic stem node extraction is to identify the sugarcane stem node(eye) and localization [8] for cutting/chipping. To attain this task with the help of deep learning there is a need for an efficient data-set and a model fast object detection capabilities.

Table 1

Related research on detection methods for sugarcane stem nodes

Authors	AP[1]	DT[2]	Dataset Collection
Zhou, Fan, et al., [9]	0.93	539 ms	Lab environment.
Chen et al., [10]	0.9512	145 ms	Natural complex environment.
Zhou, Zhao, et al., [11]	0.9968	415 ms	Lab environment.
Wen et al., [12]	0.984	130 ms	Natural complex environment.
Wang et al., [8]	0.99	33.33 ms	Lab environment.
Xu et al., [13]	0.9	1580 ms	Lab environment.
Yu et al., [14]	0.92	**4.4 ms**	Natural complex environment.

[1]Average Precision [2]Detection Time

Most of the related sugarcane bud detection methods as indicated in Table 1 have limitations. For stem node detection in real-time, fast detection and the complex natural environment are main challenges. These stems are completely covered in leaves. These leaves also make the background of the sugarcane pictorial data very complex. So, data prepared in a natural sugarcane environment is more desirable.

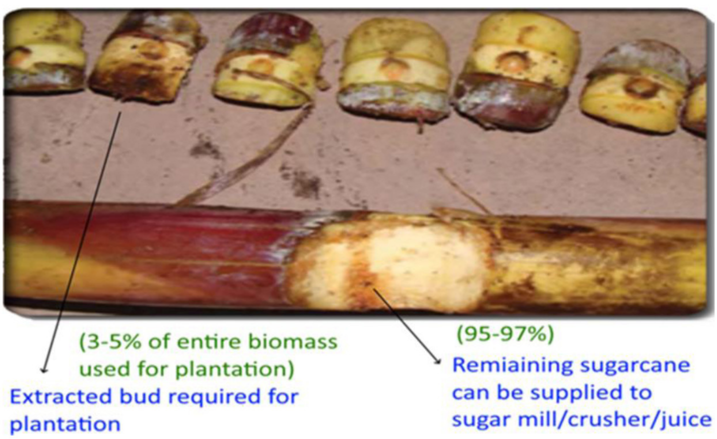

Figure 1

Sugarcane stem nodes

1.2 *Our Contribution*

This paper aims to develop an object detection method for an intelligent sugarcane stem node detection system, with primary contributions including:

- A lightweight object detection model for the real-time sugarcane stem-node detection in complex natural environments.
- With a diverse dataset collected in natural environments (in sugarcane farms) and conditions, the model is added with the feature of counting the detected class objects in real-time for production monitoring.

2. Method and Methodology

First, a dataset in natural agricultural environments is collected. 2870 images are taken in different sugarcane fields in eighteen different places in daylight, with natural lighting using mobile phone camera. During the data gathering process, no artificial lighting sets are used to guarantee diversity and representativeness. No special setup or artificial setup is created during the data collection process. No particular variety of sugarcane is included to keep generalization of data.

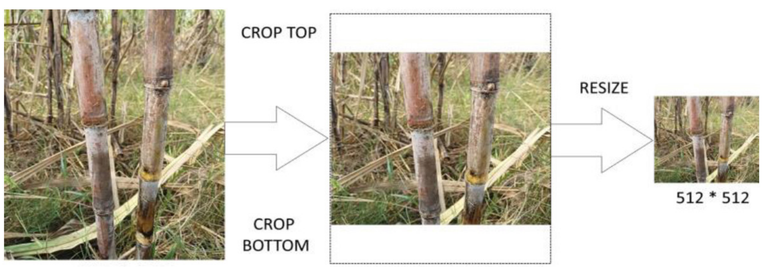

Figure 2

Dynamic Image Resizing

2.1 *Data Pre-processing and Annotation*

Every original image in the collection had 4080 pixels in height and 3072 pixels in width. In order to ensure consistency and expedite processing, all pictures were first cropped to a resolution of 3072 by 3072 pixels and subsequently downsized to 512 by 512 pixels dimensions while maintaining the aspect ratio. Dynamic image resizing is applied to keep aspect ratio intact. Figure 2. represents the pre-processing method. The

2870 images (12054 images after augmentation) in the dataset have been tagged using the labeImg annotation tool. There are two classes 'ring_with_eye' and 'ring'. With 3000 annotations for the 'ring_with_eye' class and 3667 annotations for the 'ring' class, each image is annotated. An annotation with class 'ring' represents a sugarcane stem ring not containing a node in current view. An annotation with class 'ring_with_eye' represents a sugarcane stem ring containing a node in current view. However, each ring contains a node, but it is not necessary that a node is present in the view. A ring not containing the stem node is represented by class 'ring'. Figure 3. displays different label graphs representing annotation distribution among all images in dataset.

Figure 3

Distribution of labels

2.3 *Data Augmentation*

To enhance the model's robustness different augmentation [15] is applied to current image data set. The brightness of the obtained images is varied by a factor of +10% to-10% to simulate intense sunlight and low light. Further, 90 Rotate Clockwise, 90 Rotate Anti-Clockwise and Horizontal-Flip data augmentation steps are applied. Ultimately, 12054 images were retrieved after this process.

2.4 *Training Process*

Training is conducted using the Light weight detection model based on YOLOv8 [16] . YOLOv8 provides anchor free [17] object detection. It has nano, small, medium, large and extra-large versions available. Nano model is smallest of all. This model is further scaled down to make it light weight for sugarcane stem node detection. This light weight model is selected to keep the model light weight and faster. Table 2. Indicates the size difference between original YOLOv8n model and our light weight model. The model is trained using an automatic optimizer setup. Input image size is 640x640 pixels for compatibility with the model's architecture. The momentum value is set to 0.937, learning rate of 0.01 and weight decay of 0.0005 are used to control model parameters and avoid overfitting.

Table 2

Light weight model comparison with normal YOLOv8n model

	Layers	Parameters	Size
YOLOv8n(nano)	225	3157200	8.9 GFLOPs
Our light weight model	168	1718034	6.8 GFLOPs

2.5 *Evaluation Metrics*

Class loss, box loss, DFL loss (Directional Feature Loss), mAP (mean Average Precision) at different IoU (Intersection over Union) [18] are commonly used evaluation metrics for object detection models.

2.5.1 Class Loss

Class loss measures the accuracy of class predictions made by the model.

$$L_{class} = -\left(\frac{1}{N}\right)\sum_{i=1}^{N}\sum_{i=1}^{C} y_{i,c}\log(\hat{y}_{i,c}) \tag{1}$$

Where, N is the total number of bounding boxes, C is the total number of classes, $y_{i,c}$ is the true class probability of the ith bounding box for class c and $\hat{y}_{i,c}$ is the predicted class probability of the ith bounding box for class c.

2.5.2 Box Loss

Box loss measures the accuracy of bounding box predicted by the model.

$$L_{box} = \frac{1}{N}\sum_{i=1}^{N}(Smooth_{L1}(b_{i,x} - \hat{b}_{i,x}) + Smooth_{L1}(b_{i,y} - \hat{b}_{i,y}) + Smooth_{L1}(\sqrt{b_{i,w}} - \sqrt{\hat{b}_{i,w}}) + Smooth_{L1}(\sqrt{b_{i,h}} - \sqrt{\hat{b}_{i,h}})) \tag{2}$$

Where, N is the total number of bounding boxes, $b_{i,x}, b_{i,y}, b_{i,w}, b_{i,h}$ are the true coordinates and dimensions of the ith bounding box, $\hat{b}_{i,x}$, $\hat{b}_{i,y}$, $\hat{b}_{i,w}$, $\hat{b}_{i,h}$ are the predicted coordinates and dimensions of the ith bounding box.

2.5.3 DFL Loss (Directional Feature Loss)

DFL loss measures the feature similarity between predicted and ground truth directional vectors for oriented objects.

$$L_{DFL} = \frac{1}{N}\sum_{i=1}^{N}\left(1 - \frac{v_i \cdot \hat{v}_i}{\|v_i\| \cdot \|\hat{v}_i\|}\right) \tag{3}$$

Where, N is the total number of oriented objects, v_i is the true directional vector [19] of the ith object, $\hat{v}_i$ is the predicted directional vector of the ith object.

2.5.4 mAP (mean Average Precision)

mAP measures the average precision across all classes and is calculated at different IoU thresholds such as 50% and 50-95%.

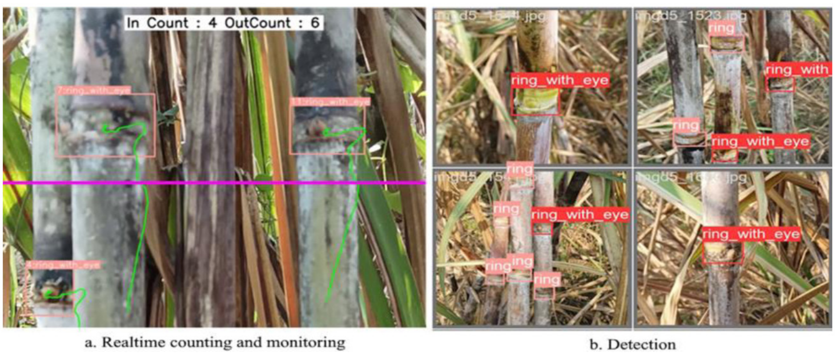

Figure 4

Prediction in real time

3. Results and Analysis

The model successfully predicted both classes in the dataset, with the results shown in Figure 4(b). The detection and localization of the rings and rings containing eyes are represented by the bounding boxes. The trained model attained the following results, as shown in Table 3. The system also attained 139.74 FPS of throughput and 7.17 milli seconds detection time. A high mAP value represents the capability of an object detection model. The model exhibited 94.08% accuracy. Counting sugarcane stem nodes in real-time can be very useful for resource optimization and informed decision- making. For example, in this study, counting detected and localized sugarcane stem nodes can be useful in real-time tracking, monitoring and predicting throughput of the machine. In Figure 4(a) real-time counting and monitoring is shown. Figure 5 represents other results obtained for training and validation results of evaluation parameters class loss, box loss and dfl loss. Figure 6 shows results for precision, recall and mean average precision.

Table 3

Results

Class	P	R	mAP50	mAP50-95	FPS	Detection time
all	0.909	0.888	0.953	0.638		
ring_with_eye	0.937	0.932	**0.974**	0.69	139.74	**7.17 ms**
ring	0.881	0.844	0.931	0.587		

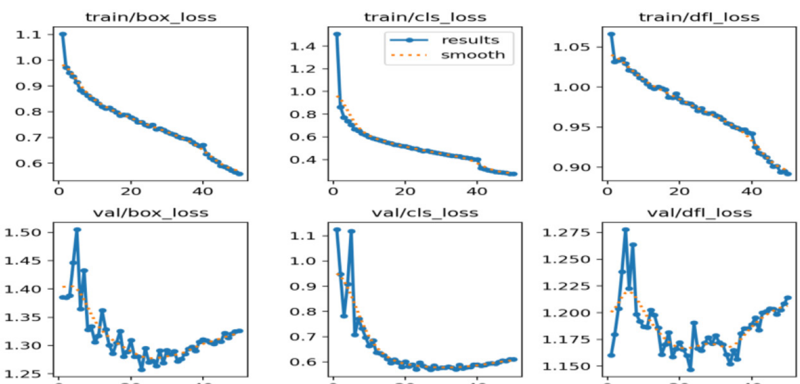

Figure 5

Box loss, class loss, dfl loss results

4. Conclusion

4.1 *Summary of Findings*

The study is using a large dataset of natural sugarcane field images for sugarcane stem node detection. The dataset was manually annotated into 'ring' and 'ring_with_eye' classes. Extensive pre-processing and augmentation techniques were applied to improve the dataset's quality. A lightweight version of the YOLOv8n object detection algorithm is used with a reduced number of layers, parameters, and size to make it smaller and faster. The resulting model attained a mean average precision of 0.974 and a high accuracy of 94.08%. The model resulted in a 7.17 milli seconds detection time and a throughput of 139.74 FPS.

4.2 *Future Scope*

Refining the model architecture, exploring advanced data augmentation techniques and integrating the detection model with existing agricultural systems and machinery are the key areas of improvement for advancing sugarcane stem node detection and localization. The hardware optimization can reduce detection time and make the models more suitable for the deployment on edge devices or embedded systems.

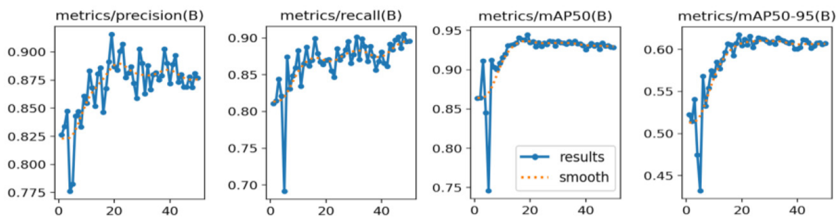

Figure 6

Precision, recall and mean Average precision

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