DESIGN AND EXPERIMENTATION OF A POTATO PLANTER MISSED AND REPEATED PLANTING DETECTION SYSTEM BASED ON YOLOv7-TINY MODEL /

基于 YOLOv7-tiny 模型的马铃薯播种机漏重播检测系统的设计与试验

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ABSTRACT

In response to the issues of missed and repeated planting during the operation of the chain-spoon type potato planter in China, as well as the low recognition rate for missed planting and the difficulty in identifying repeated planting using existing detection methods, an innovative Potato Planter Missed and Repeated Planting Detection System has been designed. This system is built with a PLC as the lower-level controller and an industrial computer as the core, incorporating the YOLO object detection algorithm for detecting missed and repeated plantings during the operation of the potato planter. Using the YOLOv7-tiny object detection network model as the core, and combining model training with hardware integration, the system performs real-time detection of the potato seed situation within the seed spoon during the operation of the potato planter. It can quickly distinguish between normal planting, missed planting, and repeated planting scenarios. By incorporating the working principles of the planter, the system designs a positioning logic to identify the actual coordinates of missed and repeated planting locations when a lack or excess of planting is detected. This is achieved through the positioning module, enhancing the system's capability to accurately obtain coordinate information for actual missed and repeated planting positions. The system was deployed and tested on a 2CM-2C potato planter. The results indicate that the detection accuracy for missed and repeated plantings reached 96.07% and 93.98%, respectively. Compared to traditional sensor detection methods, the system improved the accuracy of missed planting detection by 5.29%. Additionally, it successfully implemented the functionality of detecting repeated plantings, achieving accurate monitoring of quality-related information during the operation of the potato planter.

摘要

针对我国链勺式马铃薯播种机作业过程中存在漏播、重播以及现有的检测方法对漏播的识别率较低且难以识别重播的问题，创新设计了一种以 PLC 为下位机，以工控机为核心搭载 YOLO 目标检测算法的马铃薯播种机漏重播检测系统。以 YOLOv7-tiny 目标检测网络模型为主体，经过模型训练与硬件相结合，在马铃薯播种机工作过程中对种勺内种薯情况进行实时检测，能够快速区分正常种、缺种及重种等情况。结合播种机的工作原理设计定位逻辑，实现在检测到缺种、重种情况时通过定位模块完成对实际漏播、重播位置坐标信息的获取。将该系统部署在 2CM-2C 马铃薯播种机上进行相关试验测试，结果表明：该系统对于漏播、重播的检测准确度分别达到 96.07%与 93.98%，与传统传感器检测方法相比，漏播检测精度提高 5.29%，并且实现了重播检测的功能，实现对马铃薯播种机作业质量相关信息的准确检测。

INTRODUCTION

The potato is a root food crop second only to maize, wheat and rice. China is the largest potato-growing country *(Li et al., 2020)*. The potato planter is a crucial implement for the development of the potato industry, and its operational quality directly affects the growth and development of potatoes, thus indirectly impacting potato yields *(Li et al., 2024)*. In recent years, the mechanization level of potato planting in China has continuously improved, but the level of intelligence remains relatively low *(Ma et al., 2023)*. In the process of potato planting, it is essential to accurately control various key indicators. The phenomena of missed and repeated plantings caused by changes in the quantity of seed potatoes in the seed spoon significantly affect the quality of planting *(Li et al., 2023)*.

In response to the issue of missed planting, domestic experts and scholars have gradually delved into research. Zhang Xiaodong and others designed an automatic compensation system for a potato planter using infrared photoelectric sensors, a microcontroller, and a stepper motor *(Zhang et al., 2013)*. Liu Quanwei and others designed a missed planting compensation system for a potato planter based on the ATmega16 microcontroller, and wrote the monitoring and compensation system program in the C language *(Liu et al., 2013)*. Wang Guanping proposed a new compensation solution for missed planting detection using the PIC16F877 microcontroller, which consists of a circuit for generating signals from missed planting detection, an infrared missed planting detection circuit, and a nest-eye wheel-type planting system *(Wang et al., 2016)*. Currently, the mainstream method for detecting missed planting in potatoes mostly involves sensors to detect whether there are seed potatoes in the seed spoon. However, this method is prone to interference from external factors, resulting in detection errors and difficulty in identifying whether there is a phenomenon of repeated planting during the planting process.

With the development of computer vision technology, deep learning methods utilizing deep neural networks can autonomously learn various features in images and perform feature fusion, achieving intelligent detection of targets. These methods are gradually being widely applied in various recognitions within agricultural environments *(Li et al., 2023)*. Given the current issues in potato planter planting quality detection, this paper proposes an image processing-based missed and repeated planting detection technology. This technology can not only detect replanting but also further improve the accuracy of missed planting detection. Combined with a positioning module, it obtains information on the locations of missed and repeated plantings, thereby providing a statistical analysis of the planting quality in the target field.

MATERIALS AND METHODS

Overall design of the system

The Potato Planter Missed and Repeated Planting Detection System is based on the 2CM-2C potato planter as its working platform. It consists of a DF30 industrial camera, an industrial control computer, SIEMENS S7-200SMART PLC, and a positioning module, all integrated with a display screen. The primary working principle involves the industrial control computer carrying a pre-trained target detection neural network model. The industrial camera captures real-time images of each seed bucket during the potato planting process. This facilitates real-time detection and differentiation of the potato seed situation within each spoon. Upon detecting instances of missed or repeated planting, signals are sent to the PLC. The PLC, in turn, sends commands to the positioning module to acquire corresponding coordinates of the planting positions. This process enables accurate monitoring of missed and repeated planting information during the planting operation in the target field.

Detection scheme design

In the mechanized planting process of potatoes, the quantity of potato pieces taken from the seed box by the seed spoon, driven by the planting chain, is a crucial factor influencing planting quality *(Lei et al., 2022)*. Therefore, considering the potato pieces within the seed spoon as the detection target, the detection method involves assessing the quantity of potatoes in each seed spoon to determine whether there is a phenomenon of missed or repeated planting at the corresponding planting point. To ensure the integrity of the target image and the accuracy of the detection results, the imaging device is installed directly above the ascending end of the planting chain, focusing on the topmost seed spoon as it enters the planting tube. As the planting chain rotates, the top seed spoon moves into the planting tube, and the seed spoons below sequentially reach the detection position for assessment, repeating this process to complete the detection of each seed spoon. The schematic diagram of the missed and repeated planting detection is illustrated in Figure 1.

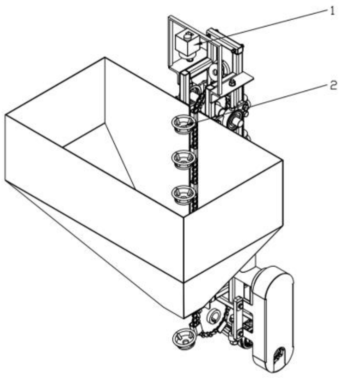
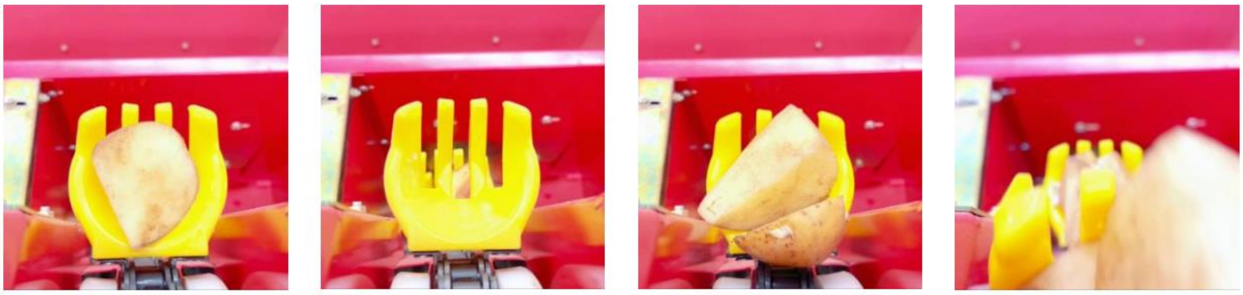


Fig. 1 - The schematic diagram for missed and repeated planting detection
1. The Camera Installation Position; 2. The Detection Target

Situation analysis of detection targets

Based on the image capture position, the condition of potato pieces within the seed spoon can be primarily classified into the following four scenarios: when there is only one potato piece inside the seed spoon, it is considered a normal situation, as shown in Figure 2a; if there are no potato pieces inside the seed spoon, it indicates a situation of missing planting, as illustrated in Figure 2b, which can lead to the phenomenon of missed planting during seeding; if there are two or more potato pieces inside the seed spoon, it indicates a situation of repeated planting, as depicted in Figure 2c, which can lead to the phenomenon of repeated planting during seeding; when the planting chain is in motion, there may be partial overlap in the images during the alternating process of the target seed spoon, making it challenging for the image capture device to collect complete seed spoon information. To prevent erroneous judgments in such cases, this condition is defined as incomplete recognition, as shown in Figure 2d.



a b c d

Fig. 2 - Situation analysis of detection targets

a. Normal situation; b. Situation of missing planting; c. Situation of repeated planting; d. Incomplete recognition.

Image acquisition

The image capture location is in Jiaozhou City, Shandong Province, China. The potato variety used in this study is Dutch 15. Potato seed pieces were cut, with each piece's weight controlled between 45-50g, ensuring 1-2 sprouts per piece. Using the 2CM-2C potato planter from Qingdao Hongzhu Agricultural Machinery Co., Ltd. as the platform, industrial cameras were employed for image acquisition. The cut potato pieces were placed in the target seed spoon to simulate normal planting, missed planting, and repeated planting scenarios. Static shots were taken of the target, capturing 300 images. To ensure the continuity and authenticity of the detection, potato pieces were poured into the seed box, and the movement of the seed spoon was recorded in videos during the planter's operation. From the video, 900 images were extracted. All images had a resolution of 640×640 pixels and were uniformly saved in .JPG format. Part of the image data from static shots and video extraction is shown in Figure 3.

Fig. 3 - Partial image data

Dataset construction

After filtering the collected images, the annotation process was performed using the visual image annotation tool Labelimg to label the potato pieces within each seed spoon. The annotated labels are utilized for classification and object detection tasks. In alignment with the previously discussed detection target scenarios, four labels were set: 'Normal,' 'Repeat,' 'Missing,' and 'Incomplete.' These labels correspond to the normal planting, repeated planting, missed planting, and incomplete recognition scenarios during the detection process.

Due to the complex and dynamic field operating environment of the potato planter, to ensure accurate model training and enhance the model's ability to recognize potato pieces in different scenarios and environments, data augmentation techniques were applied to the collected image data. Operations such as adding noise, adjusting brightness, cropping, panning, rotation and cut-out were performed for data augmentation (*Su et al., 2023; Nithya R et al., 2022*). The enhancement effect is illustrated in Figure 4, and the total number of augmented images reached 5400. The dataset was then divided into training, testing, and validation sets with a ratio of 7:1:2, comprising 3780 images for training, 540 for testing, and 1080 for validation.

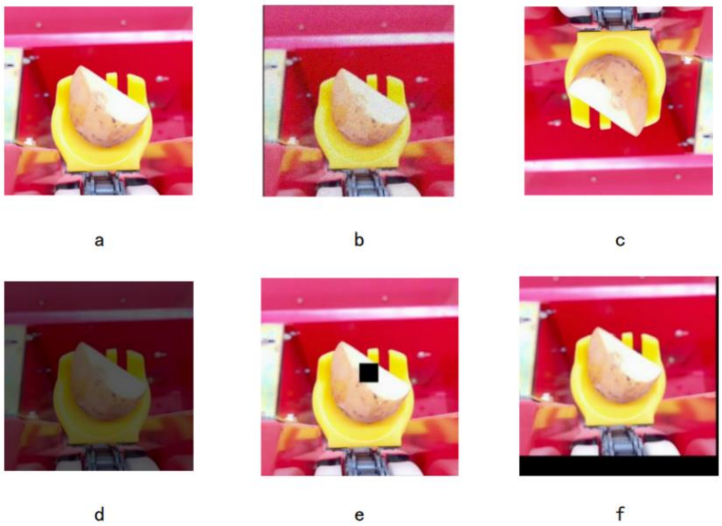


Fig. 4 - Example of data augmentation
a. Original figure; b. Adding noise; c. Rotation; d. Adjusting brightness; e. Cut-out; f. Panning.

Model training

The model selected is YOLOv7-tiny, a streamlined version based on YOLOv7. It is more lightweight and adopts a cascaded model scaling strategy. While ensuring detection accuracy, it achieves fewer parameters and faster detection speed *(Wang et al., 2023)*. This model is suitable for real-time detection requirements in the context of missed and repeated planting during the potato planting process.

The hardware used for training the model is a laptop running Windows 11 (64-bit), equipped with an AMD Ryzen 7 5800H processor, NVIDIA GeForce RTX 3050 Ti GPU. The training environment is set up with Python 3.9.17, PyTorch 1.12.1, and CUDA and cuDNN versions 11.6 and 8.4, respectively.

The training utilized the weight file YOLOv7-tiny.pt. The dataset was iterated for 300 epochs during training, with a batch size of 16 samples per iteration and one weight update performed afterward. To enhance speed while maintaining recognition accuracy, the input image size was set to 480×480. The entire training process took 7 hours and 36 minutes.

Analysis of training results

In order to better evaluate the detection performance of the model in recognizing missed and repeated planting in potatoes, this study employs metrics such as Precision (P), Recall (R), F1 Score, Average Precision (AP), and Mean Average Precision (mAP) as evaluation indicators *(Zhang et al., 2023; Yi et al., 2020; Tian et al., 2023)*. Precision is the proportion of correctly predicted positive samples among the total positive samples in the model's predictions. Recall reflects the model's ability to find positive samples. F1 Score, Mean Average Precision, and Average Precision are all related to Precision and Recall *(Li et al., 2023; Chang et al., 2023)*. The calculations for these evaluation metrics are as follows:

$$P = \frac{TP}{TP + FP} \tag{1}$$

$$R = \frac{FP}{FP + TN} \tag{2}$$

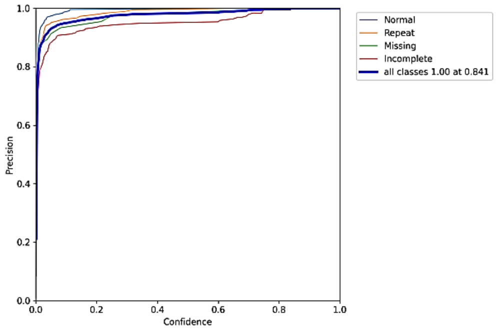
$$F1 = 2 \cdot \frac{P \cdot R}{P + R} \tag{3}$$

$$AP = \int_0^1 P \cdot (R) dR \tag{4}$$

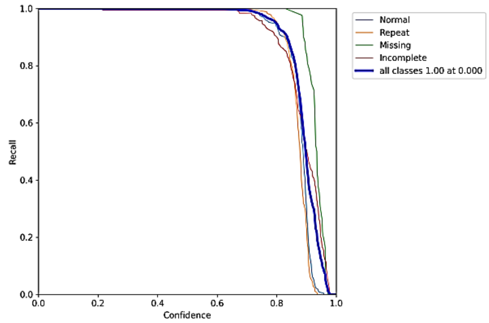
$$\mathrm{m}AP = \frac{1}{N} \sum_{i=1}^{N} AP_i \tag{5}$$

TP (True Positives): the number of samples correctly classified as positive. FP (False Positives): the number of samples incorrectly classified as positive.TN (True Negatives): the number of samples correctly classified as negative. FN (False Negatives): the number of samples incorrectly classified as negative.

The accuracy curve (P_curve) and recall curve (R_curve) obtained during training are shown in Figures 5(a) and 5(b), respectively. The F1 Score is the harmonic mean of precision and recall *(Zheng et al., 2023)*, and the F1 curve is depicted in Figure 5(c). By calculating the precision and recall, the precision-recall curve (PR curve) can be plotted. This curve has recall as the horizontal axis and precision as the vertical axis *(Wu et al., 2023)*. The area under the PR curve is the Average Precision (AP), and the average of AP for all classes is the Mean Average Precision (mAP). The mAP value reflects the overall recognition and classification accuracy performance of the network for object detection *(Zheng et al., 2023).* The accuracy-recall curve obtained during training is shown in Figure 5(d), where the average precision (AP) for each label exceeds 99%, and the mean average precision (mAP) reaches 99.6%. The loss function results and confusion matrix for the trained model are illustrated in Figures 5(e) and 5(f), respectively.



a)



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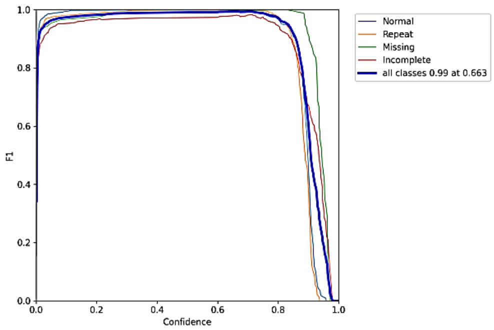
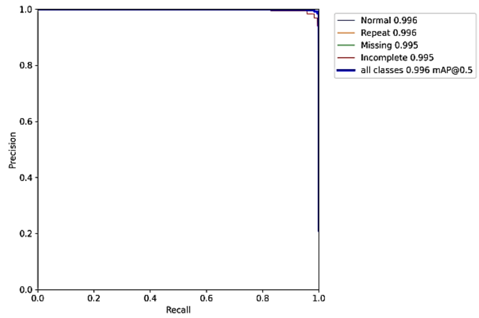
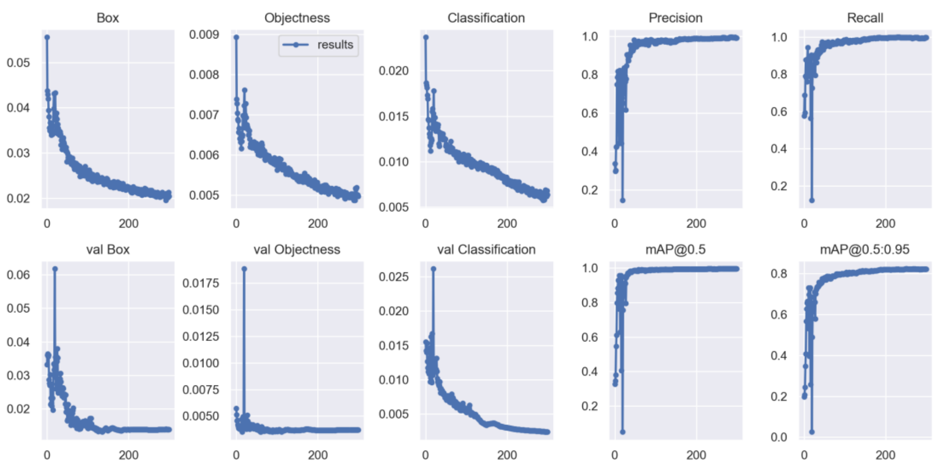


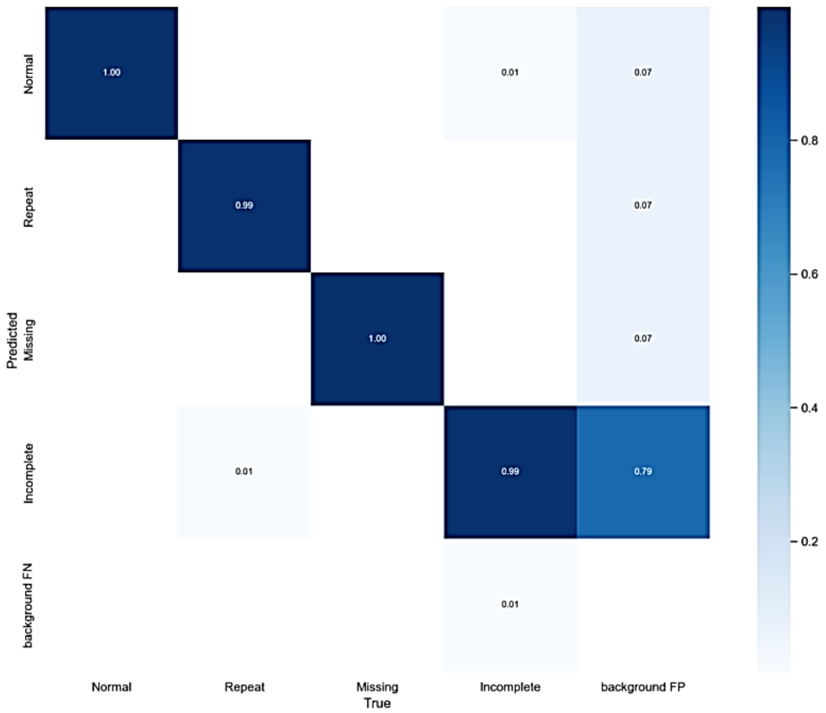
c)



d)



e)



f)

Fig. 5 - Model training results
a. P_curve; b. R_curve; c. F1_curve; d. PR_curve; e. Results; f. Confusion_matrix.

Since the batch size is set to 16, 16 images are read at a time. The actual labels and accuracy of the first round of the validation set are shown in Figure 6(a). In addition, the model was validated using video images with a resolution of 480P/30fps and a duration of 30 seconds, containing 29 seed spoons, including 15 normal plantings, 6 missed plantings, and 8 repeated plantings. During the validation process, 927 frames were extracted for detection, taking 19.927 seconds, and achieving a detection accuracy of 100%. Some screenshots of the video detection results are shown in Figures 6(b) and 6(c).

a b c

Fig. 6 - The results of the validation set and video detection
a. The first round of the validation; b. Screenshot1; c. Screenshot

Transfer model

To ensure compatibility with the hardware of the system and the planter, and to better achieve real-time detection, the trained model was transferred to the industrial control computer. The industrial control computer has a relatively small size, is easy to install, and runs on the Windows 10 operating system. In terms of environment configuration, Python version 3.9.17 and PyTorch version 1.12.1 were used, with the model running on the CPU.

The design of the positioning scheme

Since the detection device is located above the planting chain, and the detection target is the upper end of the planting chain as it ascends, the actual planting coordinates of the potato should be the position coordinates after the potato falls into the soil during the planting process. Therefore, the movement of the potato from detection to soil entry needs to be analysed, and the time duration *t* for this movement is calculated. After the image recognition module identifies a missed or repeated planting, it sends a signal to the PLC. The PLC, after a time interval *t*, sends a command to the positioning module for reading and parsing the positioning data. This process allows obtaining relatively accurate coordinates for the missed and repeated plantings.

Analysis of potato movement

The movement of the potato inside the seed spoon, from detection to entering the soil, can be roughly divided into three parts. The first part is when the potato reaches position 1, it rotates 180° with the seed spoon, enters the planting tube, and reaches position 2. The second part is when the potato moves with the planting chain in the planting tube from position 2 to position 3. The third part is when the potato leaves the planting tube (position 3) and falls to the soil (position 4). The motion diagram is shown in Figure 7.

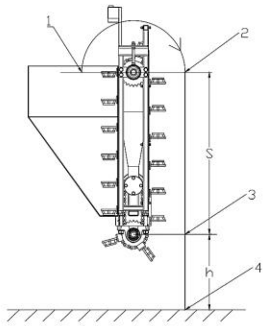


Fig. 7 - Schematic diagram of seed potato movement
1. Position 1; 2. Position 2; 3. Position 3; 4. Position 4.

Calculation of seed potato campaign time

Based on the previous analysis of the movement of the seed potato from detection to entering the soil, the calculation for the movement time *t* is as follows:

The forward speed of the planter is v_0, and the radius of the ground wheel is *r*. Therefore, the rotational speed of the ground wheel is given by:

$$n_1 = \frac{v_0}{2\pi r} \tag{6}$$

The planting chain is driven by the ground wheel, and the tooth number of the ground wheel sprocket is z_1, while the tooth number of the planting chain sprocket is z_2. Therefore, the transmission ratio between the ground wheel and the planting device is given by i:

$$i = \frac{n_1}{n_2} = \frac{z_2}{z_1} \tag{7}$$

Based on the transmission ratio i, the rotational speed of the planting chain sprocket, n_2, can be obtained as:

$$n_2 = \frac{n_1 z_1}{z_2} \tag{8}$$

The tooth spacing of the seed discharge chain is *p*. The linear velocity v_1 of the seed discharge chain can be calculated as:

$$v_1 = \frac{n_2 z_2 p}{60 \times 1000} = \frac{n_1 z_1 p}{60 \times 1000} \cdot \tag{9}$$

In this case, for the convenience of calculation, the first part of the motion is considered as uniform circular motion. The trajectory of the first part of the motion is a concentric circle with the sprocket of the planting chain. The radius of the planting chain sprocket is r_1, and the angular velocity is equal as well as the movement time.

Therefore, the first part of the movement time t_1 is calculated as:

$$t_1 = \frac{\pi r_1}{v_1} = \frac{60 \times 1000 \cdot \pi r_1}{n_1 z_1 p} \tag{10}$$

The distance from the end of the first part of the motion to the position where the seed leaves the planting tube is denoted as s. In the second part, the seed follows the spoon for uniform motion. Therefore, the second part of the motion time t_2 is calculated as:

$$t_2 = \frac{s}{v_1} = \frac{60 \times 1000 s}{n_1 z_1 p} \tag{11}$$

In the third part of the motion, the vertical direction is free fall motion and the horizontal direction is uniform motion (the forward speed of the planter). Given that this segment of motion time is only related to the height, let h be the height from the position where the seed leaves the planting tube to the ground. Therefore, the third part of the motion time t_3 is the free fall time of the seed:

$$h = \frac{1}{2} g t_3^{\ 2} \tag{12}$$

$$t_3 = \sqrt{\frac{2h}{g}} \tag{13}$$

The total time of motion is the sum of the three parts of motion time. Combining the above formulas, the total time required for the entire motion process is denoted as t:

$$t = t_1 + t_2 + t_3 = \frac{120000(\pi r_1 + s)\pi r}{v_0 z_1 p} + \sqrt{\frac{2h}{g}} \tag{14}$$

RESULTS

Experimental preparation

To ensure that the developed image recognition-based potato planter skip-seeding detection system meets the practical requirements of agricultural production, experiments were conducted on the relevant functions of the system in the potato test fields in Jiaozhou. The potato variety used for the experiment is Dutch 15, and diced seed potatoes were employed, with each piece controlled to a mass of 45-50 g and a diameter of 30-50 mm, as illustrated in Figure 8. The experimental equipment used was the 2CM-2C one-ridge, two-row potato planter. The potato planter skip-seeding detection system was assembled and fixed according to the design scheme, integrating it with the structure of the planter. Basic functionality of each component was checked to ensure its proper operation. The assembly of the system is shown in Figure 9.

Fig. 8 - Seed potato cubes

Fig. 9 - System assembly

Comparison experiment on missed and repeated planting detection accuracy

In this study, field experiments were conducted to compare the proposed target detection scheme based on the YOLO model with the traditional optoelectronic sensor-based detection scheme. Both detection schemes were simultaneously applied using the same planter to assess missed and repeated planting situations, as well as the detection performance of the two schemes. The field experiment is illustrated in Fig.10.

Fig. 10 - Field experiment

2CM-2C planter with a single row of 19 seed spoons was tested for missed and repeated seeding under the same chain speed (0.35 m/s). The rotating cycles were set at 10, 15, 20, 25, and 30, respectively. The number of detected and actual instances of missed and repeated seeding were recorded during the planting process, aiming to calculate the detection accuracy. The comparative experimental results of missed and repeated planting detection are shown in Tables 1 and 2.

Table 1

The comparative experimental results of missed planting detection

Test	Number of rotating cycles	Seeding number	Scheme	Number of missed plantings detected	Actual number of missed plantings	Accuracy	Missed planting rate
1	10	190	1	16	17	94.12%	8.94%
			2	16		94.12%	
2	15	285	1	21	23	91.30%	8.07%
			2	22		95.65%	
3	20	380	1	30	34	88.23%	8.95%
			2	33		97.05%	
4	25	475	1	38	42	90.48%	8.84%
			2	41		97.62%	
5	30	570	1	44	49	89.79%	8.59%
			2	47		95.92%	

Table 1 presents the experimental data for missed planting detection, while Table 2 provides the experimental data for repeated planting detection. Where Scheme 1 is based on the photodetector detection system, and Scheme 2 is based on the YOLOv7-tiny model detection system.

Table 2

The comparative experimental results of repeated planting detection

Test	Number of rotating cycles	Seeding number	Scheme	Number of repeated plantings detected	Actual number of repeated plantings	Accuracy	Repeated planting rate
1	10	190	1	-	18	-	9.47%
			2	17		94.44%	
2	15	285	1	-	28	-	9.82%
			2	26		92.86%	
3	20	380	1	-	37	-	9.73%
			2	35		94.59%	
4	25	475	1	-	46	-	9.68%
			2	43		93.47%	
5	30	570	1	-	55	-	9.65%
			2	52		94.54%	

Based on the above results, it can be seen that during the experiment, the average missed planting rate of the planter was 8.68%, and the average repeated planting rate was 9.67%. Scheme 1 achieved an average accuracy of 90.78% in missed planting detection, with no repeated planting identification function. Compared to Scheme 1, Scheme 2 achieved an average accuracy of 96.07% in missed planting detection, an improvement of 5.29%. It also implemented replanting detection with an accuracy of 93.98%.

Missed and repeated planting positioning information acquisition

In the above experiments, the positioning module obtained the coordinate information of the actual seeding positions for missed and repeated instances based on the detection results. Partial coordinates information for missed and repeated seeding positions is provided in Table 3.

Table 3

Partial coordinates information for missed and repeated seeding positions

Location point	Longitude coordinates	Latitude coordinates
Row 1, North to South repeated planting 4	120°03′12.00784″E	36°27′29.67500″N
Row 3, North to South missed planting 1	120°03′12.03886″E	36°27′30.11943″N
Row 5, North to South missed planting 6	120°03′12.28203″E	36°27′28.92467″N
Row 6, North to South repeated planting 11	120°03′12.60862″E	36°27′27.18578″N
Row 8, North to South repeated planting 9	120°03′12.35399″E	36°27′29.09525″N
Row 9, North to South repeated planting 4	120°03′12.31591″E	36°27′29.88054″N
Row 10, North to South missed planting 7	120°03′12.86716″E	36°27′26.58084″N

CONCLUSIONS

This paper addresses the issues of low accuracy in detecting missed seeding and the difficulty in detecting repeated seeding during the potato planting process using existing detection methods. It proposes a missed and repeated seeding detection method based on the YOLOv7-tiny model and combines it with hardware to form a comprehensive detection system. Experimental tests conducted at a seeding chain line speed of 0.35 m/s show that the detection accuracy for missed seeding can reach 96.07%. Compared to traditional methods using photoelectric sensors, the accuracy for missed seeding detection has improved by 5.29%. The system also successfully detects repeated seeding with an accuracy of 93.98%. Furthermore, it acquires the coordinates of the missed and repeated seeding positions during detection in real-time.

The design and functionality implementation of this system address the deficiencies of traditional detection methods, enhancing the detection capability for missed and repeated plantings. It achieves precise monitoring of the operational quality of potato planters and the planting conditions in specific areas, thereby advancing the information level of mechanized potato planting.

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