Automated Malabar Chestnut Planting Machine with Deep Learning Visual Recognition and Innovative Mechanisms

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Abstract— Cultivated for its ornamental appeal, the Malabar chestnut demands precise planting for optimal growth, emphasizing the necessity of downward-facing seed germination points. Amidst a scarcity of agricultural labor, there is a growing demand for automated planting solutions. This paper presents an automatic planting machine for Malabar chestnut, utilizing deep learning image recognition to ensure proper seed orientation during planting. The machine incorporates a novel mechanism, leveraging high-speed pneumatic action and mechanical principles to guarantee accurate seed orientation. We provide insights into the architecture and training of the convolutional neural network-based recognizer, the design and analysis of the planting machine, and the system's performance in field tests. Results from field tests affirm an 85% success rate in proper seed planting, achieving an average planting speed of one seed every 3 seconds.

I. INTRODUCTION

Malabar chestnuts (Pachira aquatica) are widely cherished as ornamental potted plants (see Fig. 1). Yet the traditional manual planting process has presented challenges such as high labor intensity, increased costs, and inconsistent quality. A crucial aspect of Malabar chestnut cultivation lies in carefully considering the germination point's orientation during planting to ensure proper growth.

In response to these challenges, this study focuses on developing an innovative automated seeding system tailored for Malabar chestnuts. The proposed system integrates advanced technologies, including convolutional neural network (ConvNet)-based [1] image recognition and pneumatic principles. This combination allows for seamless seed recognition and precise planting automation, addressing labor-related concerns and enhancing overall planting efficiency.

The design incorporates a holistic vision approach, utilizing ConvNet to distinguish between various seed poses. Specifically, the model ensures that seeds are planted with their germination points facing downward. The planting mechanism, employing pneumatic actuation, is designed



Fig. 1. Malabar chestnut, an ornamental potted plant, benefits from optimal growth when seeds are planted with a downward germination point. This study introduces an automated planting machine designed to ensure accurate seed orientation during the planting process.

based on the contact dynamics of the punch head and the seed. The results achieved a simple and cost-effective solution for pragmatic agricultural applications. The contributions of this work include the following:

- *1)* A ConvNet-based seed orientation classifier for Malabar chestnut based on holistic visual recognition.
- An automated planting machine for Malabar chestnut, comprising seed orientation detection and a novel planting mechanism.
- 3) Field tests that verify the efficacy of the proposed system

II. RELATED WORK

A. Agricultural Machinery and Automatic Planting

The literature study reveals the extensive application of agricultural machinery across diverse fields, guided by engineering principles such as agricultural mechanization,

^{*}This work was supported by the Ministry of Science and Technology of the Republic of China, Taiwan, under Contract No.: MOST 111-2221-E-027-106-MY2.

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Fig. 2. Left: Schematic illustration depicting the mechanism design for the automatic planting machine of Malabar chestnuts; right: the prototype.

power and transmission, mechatronics, and control [2]. Sowing and planting, integral agricultural tasks, have been addressed through various furrow opener designs, focusing on their impact on plant emergence rates and final stand outcomes [3]. Automatic garlic planters, developed to alleviate the demand for substantial labor [4, 5], feature essential components like a seed-taking device, a multi-stage conical hopper ensuring precise seed orientation, and a pneumatic control system. The optimal design of spoon dimensions and spacing enhances the single-seed-taking rate in the seed-taking device, while computer vision aids in adjusting garlic clove orientation [6].

Drawing insights from garlic planter design principles for the automatic sowing machine of Malabar chestnut, given the similarity in seed sizes, reveals a critical distinction. The halfmoon of garlic cloves allows conical hoppers to orient the cloves in point-up positions, which does not apply to the highly irregular shape of Malabar chestnut seeds. Therefore, a distinct approach must be devised for the automatic planting machine of Malabar chestnut.

B. Seed Recognition and Visual Classification

Seed recognition and sorting play a crucial role in several agricultural sectors, ensuring the consistency of crop yields, e.g., wheat [7], rice [8], and corn [9]. Traditionally, manual visual inspection has been the primary method, but its high error rate and labor intensity make it less than ideal [10]. The advent of machine vision and computer vision has paved the way for automated seed recognition and sorting. The visual classification relies on various features such as morphology [8, 11], color [8, 11, 12], and texture [8, 12] of the seeds, traditionally extracted through image processing techniques, necessitating the careful design of image preprocessing.

Machine learning and deep learning have facilitated human-level accuracy in diverse applications such as plant disease detection and classification, weed/crop discrimination, fruit counting, land cover classification, and crop/plant recognition [1]. The rise of deep learning, exemplified by ConvNets of substantial depth, has demonstrated the ability to extract abstract features beyond the capabilities of previous methods [1, 13, 14]. An illustrative example is the end-to-end classification of rain conditions on an automobile windshield, where a ConvNet model, trained with extensive data, identifies rain conditions amidst diverse backgrounds without the need for feature preprocessing [15]. Eliminating this preprocessing reduces labor requirements and enhances robustness by extending the variable dimension.

Numerous methods have been employed for seed classification, including Euclidean distance [7], artificial neural network [9, 10], genetic algorithm [9, 12], support-vector machine [8, 9, 12], k-nearest-neighbor [8, 9], and maximum likelihood [11]. In a study on corn seed variety classification, Javanmardi et al. [9] compared various frameworks and found artificial neural networks outperforming support vector machines, k-nearest-neighbors, boosted trees, bagged trees, and linear discriminant analysis, particularly when coupled with feature extraction by ConvNet. The high feature extraction efficacy and classification accuracy of ConvNet motivates the design of our method.

III. Method

A. Automatic Planting Mechanism

The Malabar chestnut planting machine proposed in this study comprises components such as the seed container, seed transmission, seed recognition system, furrow opener, planting system, furrow closer, battery, and PC-based control system, as illustrated in Fig. 2. The seed transmission employs a chain with spoons to extract seeds from the seed container, guiding them through the seed chute into the recognition box Customization of spoon size and spacing based on seed dimensions ensures single seed-taking, and each seed is accurately conveyed into the chute with guidance to land within the locating ring.

The furrow opener adopts a dual-disc structure with a 20° opening, effectively turning over the soil as the machine advances to maintain looseness during seeding. After successful seed planting, optimal seed growth necessitates covering the seeds with a specific soil thickness. To achieve this, we employ a scraper-type furrow closer. By selecting the scraper's appropriate height, angle, and rigidity, effective



Fig. 3. Schematic diagram of the detailed design of the recognition box.

control over soil thickness and uniformity is ensured, facilitating proper coverage for the seeds.

The seed recognition box is a compound device encompassing multiple components for image acquisition, seed holding, and pneumatic seed planting and flipping. The recognition box integrates metal and plastic structures to securely house an endoscope, a pneumatic cylinder, a nozzle, a seed locating ring, and a rubber pad with a star-sign-shaped opening. The locating ring ensures precise seed placement at the center of the rubber pad, facilitating clear imaging of seeds by the endoscope. The star-sign-shaped opening in the nubber pad passively accommodates the seeds during the planting process. This straightforward design provides a pragmatic, cost-effective solution to fulfill the required functionality.

The pneumatic cylinder facilitates swift and precise seed planting into the soil. The 3D-printed housing of the cylinder head combines strength with lightweight characteristics, while the silicone punch head ensures an even distribution of contact pressure on the seeds. This prevents seed damage and enhances friction, allowing seeds to be planted rapidly without altering their orientation. Within the recognition box, a strategically positioned nozzle directs air towards the seed. When the seed orientation is deemed undesirable, an air stream is released from the nozzle to flip the seed until its orientation aligns with the desirable condition, confirmed by the visual recognition system. Fig. 3 provides a detailed depiction of the recognition boxdesign.

The free-body diagram of the pneumatic cylinder and the seed is shown in Fig. 4. The pneumatic pressure acting on the cylinder applies a contact force N on the seed and pushes it downward. The forces and the acceleration of the components follow Newton's laws in the vertical direction,

$$Mg + F - f - N = Ma,$$
 (1)

$$N + mg = ma, \tag{2}$$

where F denotes the pneumatic force, and f is the friction force. By combining (1) and (2), one obtains N as

$$N = \frac{m(F-f)}{M+m}.$$
 (3)



Fig. 4. The Free-Body Diagram of the pneumatic planting mechanism.

The normal force on the seed provides a locking effect through the contact friction between the surfaces of the punch and the seed. Denoting the maximum static friction coefficient as μ_s , the maximum static friction \tilde{f}_s is

$$\tilde{f}_s = N\mu_s. \tag{4}$$

Such static friction can provide a stabilization effect to prevent the seed from rotating during the planting stroke. Assuming the seed as a perfect sphere with a radius of b. The moment around the sphere center can be regarded as generating a resistance to a perturbation defined as an angular acceleration $\tilde{\alpha}$. By seeking the force equilibrium,

$$\tilde{\alpha} = \frac{f_s b}{\frac{2}{5}mb^2}.$$
(5)

Table I lists the parameters used in our prototype. The average radius of the Malabar chestnut is around 7.5 mm. Assuming a static friction coefficient of 0.4 for the silicone punch head, the maximum static friction was derived as 0.95 N. Based on (5), the maximum $\tilde{\alpha}$ was obtained at 1.8e5 rad/s². The planting distance is approximately 3 cm; thus, it only takes around 0.0067 s for the seed to be planted on the earth. The field test results detailed below confirmed the stabilization effect of the design.

B. ConvNet-Based Visual Detection

We employed a holistic vision approach for seed orientation classification, utilizing ConvNet to develop a model capable of distinguishing different conditions of Malabar chestnut seeds based on the entire image without any preprocessing. This image recognition model ensures that seeds are planted in the soil with their germination point facing downwards. In cases where the germination point is not facing downward, the machine autonomously takes corrective actions

TABLE I. PUNCH ACTION DESIGN PARAMETERS FOR SEED PLANTING

М	т	b	F-f	N	а	μ_s	\tilde{f}_s	ã
(g)	(g)	(mm)	(N)	(N)	(m/s^2)		(N)	(rad/s^2)
40	1.8	7.5	55	2.4	1300	0.4	0.95	1.8e5



Fig. 5. Illustration of training image set composition.

until the ConvNet detection confirms a downward germination point.

The model categorizes the input image into three classes: germination point up, down, and no seed present. We downsize the input RGB images to 64×64 pixels for efficient online recognition speed. Seeds were placed in the recognition box for training data collection, using an endoscope camera to capture images. The endoscope's builtin light source ensured consistent lighting conditions among training and working images. The recognition box prevents external illumination interference and maintains consistent lighting. The training set comprises 18,000 images, with 6000 images per category. A breakdown of the training image composition is provided in Fig. 5. To evaluate the model's performance, a separate test set of 300 images was collected, with 100 images for each category.

The ConvNet model is composed of four convolutional layers, four pooling layers, a flattening layer, and additional drop-out layers before the output layer. Convolutional layers extract local features from input data through convolution operations while pooling layers reduce dimensionality and sample the input image, enhancing computational efficiency and robustness. Drop-out layers reduce the risk of overfitting. The architecture includes 16 3×3 convolutional kernels in the first layer, 32 in the second layer, 64 in the third layer, and 128 in the fourth layer. Pooling layers progressively reduce the image size: the first layer from 64×64 to 32×32 , the second from 32×32 to 16×16 , the third from 16×16 to 8×8 , and the fourth from 8×8 to 4×4 . All activation functions for these layers are ReLU. The model uses categorical_crossentropy as the loss function and employs the

Layer (type)	Output Shape	Panam #	
conv2d (Conv2D)	(None, 64, 64, 16)	448	
max_pooling2d (MaxPooling2D)	(None, 32, 32, 16)	0	Convolution Layer 1 And Pooling Lay
conv2d_1 (Conv2D)	(None, 32, 32, 32)	4640	
max_pooling2d_1 (MaxPooling2	(None, 16, 16, 32)	0	Convolution Layer 2 And Pooling Lay
dropout (Dropout)	(None, 16, 16, 32)	0	
conv2d_2 (Conv2D)	(None, 16, 16, 64)	18496	
<pre>max_pooling2d_2 (MaxPooling2</pre>	(None, 8, 8, 64)	0	Convolution Layer 3 And Pooling Lay
dropout_1 (Dropout)	(None, 8, 8, 64)	0	•
conv2d_3 (Conv2D)	(None, 8, 8, 128)	73856	
<pre>max_pooling2d_3 (MaxPooling2</pre>	(None, 4, 4, 128)	0	Convolution Layer 4 And Pooling Lay
dropout_2 (Dropout)	(None, 4, 4, 128)	0	
flatten (Flatten)	(None, 2048)	•	
dense (Dense)	(None, 128)	262272	
dropout_3 (Dropout)	(None, 128)	0	Flattened and Output Layers
dense_1 (Dense)	(None, 3)	387	

Trainable params: 360,099 Non-trainable params: 0

Fig. 6. Architecture of the ConvNet-based seed orientation classifier.



Fig. 7. Schematic diagram of the electronic control system.

Adam optimizer with a fixed learning rate of 0.001. The flattening layer comprises 2048 neurons, connected to the final output layer with three neurons. This architecture has 360,099 trainable parameters; Fig. 6 shows a schematic diagram of the ConvNet architecture. During training, epochs are set to 10, with 1133 batches, each containing 16 sample sets. The performance of the trained model is detailed in Section IVA.

C. Control

Recognition of the seed orientation involves an onboard computation by a Raspberry Pi; the results are transmitted to the relay and electromagnetic valves, controlling the pneumatic cylinder and nozzle for seed planting and flipping. Fig. 7 provides an overview of the entire machine's electronic control system, comprising a computing unit (Raspberry Pi) with intelligent recognition software, sensors (endoscope), and actuation components (transmission motor, pneumatic cylinder, and nozzle). The logic control program is detailed in Fig. 8.

Initially, the seed transmission motor driver receives an activation signal, instructing the stepper motor to set the chain of seed transmission in motion. The spoons affixed to the chain guide the seeds into the chute, covering a specific distance before descending into the recognition box. Subsequently, the program triggers the endoscope camera for recognition, categorizing outcomes into three cases: Case A, signifying seeds with downward-facing germination points; Case B,



Fig. 8. Control block diagram of the automatic planting machine.

indicating seeds with upward-facing germination points; and Case C, denoting an empty recognition box with no seed present.

In Case A, the switch status dictates the course of action. Activating the switch initiates the pneumatic cylinder, facilitating seed planting; deactivating the switch reverts the process to image recognition. The switch pauses the planting action when the machine's movement requires attention. For Case B, the nozzle directs air onto the seed, adjusting its orientation, followed by a subsequent round of visual recognition. In Case C, the program resets to the program's beginning, activating the spoon to feed a seed into the recognition box.

The control logic is handled by a Python program running on the Raspberry Pi, enabling the autonomous operation of each mechanism. This design allows for the independent functioning of multiple assembled mechanisms, ensuring control programs can execute without interference. However, a status check is conducted for each mechanism to verify the completion of seed planting before advancing the planting machine to the next position for subsequent seed planting.

IV. EXPERIMENTS

A. Visual Detection Accuracy

In this experimental assessment of the visual detection model, we obtained 300 images online for testing, and the confusion matrix results are presented in Fig. 9. Notably, among the 300 test images, the model exhibited flawless performance, achieving 100% correctness across all three classes. These findings emphasize the model's robust and accurate classification capabilities.

B. System Tests

The automatic planting process was subjected to rigorous testing on the proposed machine to assess its performance. Out of over 100 planting attempts, the machine successfully deposited the seeds onto the soil and none of the seeds incured damage from the punching force. Evaluation metrics encompassed the overall success rate, planting error rate, speed of visual classification, and the average planting duration per seed. The overall success rate is calculated as the ratio of correctly planted seeds to the total planting attempts. The planting error rate identifies instances where Case A was detected, but the outcome was an upward germination point.



Fig. 9. Confusion matrix for online seed orientation detection.

TABLE II.	RESULT	SUMMARY	OF THE	SYSTEM	TESTS
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Total	Overall	Planting	Detection	Ave. planting
attempts	Success	Error	speed	duration
	rate	rate	(fps)	(s)
100	85%	15%	5.8	4.0

The speed of visual classification quantifies the frame rate per second for executing a single ConvNet classification. Finally, the average planting duration represents the mean time required to plant a single seed.

Table II presents the test results, revealing an 85% overall success rate in 100 planting attempts and a corresponding 15% planting error rate. This outcome highlights the nearly flawless performance of visual detection, while errors are attributed to the pneumatic planting process. Upon a comprehensive analysis of the planting video, two primary failure mechanisms were identified. The first arises from the punch head's detachment at the process's conclusion. Although the silicone punch head's adhesive properties aid seed stabilization during planting, excessive adhesion can cause seed lifting during the cylinder retraction, leading to disorientation upon falling back onto the soil. The second issue stems from seeds tilting against the side wall of the locating ring. This, coupled with the irregular seed shape, may induce an imbalance of forces, resulting in rotation during the punching process.

The planting time for each seed is crucial in determining the efficiency and practicality of this machine. The test results indicate that the average planting duration for a seed is approximately 3 seconds. A detailed analysis of the planting time reveals that ConvNet detection is not the bottleneck, as it operates at an average framerate of 5.8 fps, and the inspection time is a mere 0.17 seconds. The rapid punching action also contributes minimally to the overall time. The predominant duration is allocated to flipping a disoriented seed (approximately 1 second), transporting the seed to the recognition box (1 second), and waiting for the seed to settle after planting (0.5 seconds).

Malabar chestnut seeds are typically egg-shaped, asymmetric with one end slightly protruding and the other flat, usually housing the germination point. About 70% of seeds naturally align within the recognition box with their germination points facing downwards, while the remaining 30% require flipping, some needing multiple attempts. The machine demonstrates that a single mechanism can efficiently plant one seed every 3 seconds. By incorporating three or more mechanisms into the setup, the machine can achieve a planting rate equal to or higher than one seed per second, surpassing the efficiency of manual planting.

V. CONCLUSION

In conclusion, developing and evaluating the automated planting machine for Malabar chestnuts marks a significant advancement in addressing the complexities of seed orientation during planting. The integration of ConvNet image recognition and a novel planting mechanism has proven to be a promising solution, as evidenced by the machine's remarkable efficiency in achieving a planting speed of one



Fig. 10. Field Test Photographs: *upper left*: Malabar chestnuts in the seed container and seed transmission; *upper center*: receiving end of the seed chute; *upper right*: top view of the recognition box; *lower left*: online image of the seed inside the locating ring; *lower center*: seed being punched onto the earth; *lower right*: planting result showing the germination point facing downwards. The white star-shaped traces in the image result from the built-in light source shining through a star-shaped opening in the rubber pad.

seed every 3 seconds. Despite a 15% planting error rate identified during testing, critical insights into potential failure mechanisms, such as punch head detachment and seed tilting, provide valuable feedback for future refinement.

The independent operation of each mechanism, managed by a Python program on the Raspberry Pi, ensures flexible and interference-free execution, laving the groundwork for the scalable implementation of multiple mechanisms. While challenges persist, the overall success of the machine and its efficiency in comparison to manual planting showcase its potential to revolutionize Malabar chestnut planting. Our subsequent research objective entails endowing the autonomous capability of self-navigation to the machine within agricultural environments. A video demonstrating the planting machine's operation is available at: https://www.youtube.com/watch?v=PS5_63MCsnQ.

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