Research on Intelligent Mechanized Mushroom Harvesting Device Based on AI Vision and Multi-Sensor Fusion

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ABSTRACT Large-scale mushroom production faces persistent challenges including low manual harvesting efficiency, high damage rates, and rising labor costs, creating an urgent demand for intelligent agricultural equipment. To address these issues, this study develops an intelligent mechanized mushroom harvesting device based on AI vision and multi-sensor fusion, forming a closed-loop "perception–decision–execution" control system with a modular architecture. Field experiments were conducted on oyster mushrooms, shiitake mushrooms, and enoki mushrooms in a 500 m^2 greenhouse, with manual harvesting used as the comparison. The results show that the device achieves a harvesting efficiency of 38.6–45.3 kg/h, which is 3–4 times higher than manual harvesting, with an average damage rate of no more than 4.2% and recognition accuracy of at least 93.6% under low-light, high-humidity, and dense-growth conditions. The modular design supports rapid adaptation to different mushroom varieties, while the IoT platform enables real-time monitoring and remote scheduling. This device provides technical support for intelligent agricultural production and offers engineering references for machine vision, wireless sensing, and multi-sensor information fusion.

INDEX TERMS intelligent mushroom harvesting, ai vision, multi-sensor fusion, wireless sensing, intelligent control

I. INTRODUCTION

A. RESEARCH BACKGROUND

ALIGNED with the precision standards of modern material processing, the large-scale, standardized production of mushrooms has emerged as a critical path for industrial upgrading within the broader framework of agricultural intelligence. This transformation synchronizes biological cultivation with the automated accuracy typical of manufacturing, ensuring high-value-added output through rigorous, technology-driven industrial systems. China's annual mushroom output exceeds 40 million tons, accounting for over 70% of global production. However, harvesting remains predominantly manual, constituting 35%-45% of total production costs. Traditional manual harvesting faces 3 core challenges: First, low efficiency—skilled workers yield only 80–120 kg per day, failing to meet large-scale cultivation demands. Second, high damage rates—inconsistent manual grasping force causes 15–20% damage, significantly reducing market value. Thirdly, rising costs: Rural labor shortages drive annual wage increases of 8%-10% for manual harvesters, further squeezing industry profit margins.

With the proliferation of precision agriculture technologies, applications such as IoT, AI visual recognition, and flexible robotic arms are maturing in agriculture, providing technical support for automated mushroom harvesting. AI visual recognition enables precise mushroom localization and maturity assessment, while multi-sensor fusion technology compensates for the perception limitations of single sensors in complex environments. Flexible harvesting mechanisms effectively reduce damage during collection. The integrated application of these technologies represents the key pathway to solving mushroom harvesting challenges [1].

B. CURRENT STATE OF DOMESTIC AND INTERNATIONAL RESEARCH

Overseas countries have taken an early lead in agricultural automated harvesting. Nations like the United States and the Netherlands have developed automated harvesting equipment for fruits and vegetables such as strawberries and tomatoes. However, specialized equipment for mushrooms (characterized by thin, fragile caps, dense growth patterns, and humid environments) remains scarce. A mushroom harvesting robot developed by a Dutch agricultural equipment company employs machine vision for positioning and a rigid gripping mechanism, achieving a damage rate of 8%-10%. However, its recognition accuracy is significantly affected by ambient lighting, dropping below 80% in low-light, high-humidity conditions [2]. Domestic research in this field has gradually intensified in recent years, with some universities and enterprises attempting to integrate AI algorithms with mechanical structures to develop mushroom harvesting devices. Existing equipment mostly relies on single vision sensors or traditional control algorithms, suffering from low recognition accuracy, poor adaptability, and high damage rates. Furthermore, it struggles to accommodate the growth characteristics of multiple mushroom varieties such as oyster mushrooms, shiitake mushrooms, and enoki mushrooms, and has yet to achieve large-scale application.

C. RESEARCH SIGNIFICANCE AND SCOPE

Integrating precision control logic from material inspection, this study develops an AI-vision-based, multisensor fusion intelligent mushroom harvesting device capable of high-speed industrial application. This cross-domain fusion ensures that the delicate handling requirements of manufacturing enhance the device's accuracy in identifying and picking high-value agricultural products within large-scale production environments. The primary goal of this manuscript is to design, implement, and validate an automated harvesting system that improves efficiency, reduces damage, and adapts to multiple mushroom varieties, while providing a transferable framework for other crops. It seeks to overcome the technical limitations of traditional manual harvesting and existing equipment, providing an automated solution for large-scale mushroom production and advancing agricultural intelligence. Core research components include: constructing an integrated "perception-decision-execution" harvesting system by integrating a multi-modal sensor array with an enhanced YOLOv9 algorithm to achieve precise mushroom identification and localization in complex environments. Designing flexible robotic arms with adaptive gripping mechanisms, optimizing grasping strategies through pressure feedback and PID control. Validating core metrics such as harvesting efficiency, damage rate, and recognition accuracy via field trials; Analyzing the transferability of the technical framework to inform the development of harvesting equipment for other cash crops [3].

II. RESEARCH METHODS

A. OVERALL SYSTEM DESIGN

The intelligent mushroom harvesting device designed in this study adopts a modular architecture, divided into four major modules: perception layer, decision layer, execution layer, and IoT platform, forming a closed-loop "perception-decision-execution" control system. The perception layer collects multidimensional data including mushroom morphology, location, environmental conditions, and contact pressure. The decision layer utilizes multi-sensor fusion data and AI algorithms to identify mushrooms, assess maturity, and plan harvesting paths. The execution layer performs harvesting actions via a flexible robotic arm and adaptive gripping mechanism. The IoT platform enables equipment status monitoring, data storage, and remote scheduling. Collaborative operation across all modules ensures precision and stability throughout the harvesting process.

B. PERCEPTION LAYER DESIGN

The perception layer integrates an RGB-D camera, LiDAR, pressure sensors, temperature/humidity sensors, and a GPS module to form a multimodal sensor array. The RGB-D camera (resolution 1920×1080, frame rate 30 fps) captures two-dimensional images and depth information of mushrooms to obtain morphological features such as cap diameter, thickness, and color. The LiDAR (detection range 0.1–5 m, accuracy ±2 cm) is included to provide complementary depth data in scenarios where RGB-D performance degrades, such as high humidity or low light, where moisture or noise can affect RGB-D accuracy (e.g., increasing depth error from ±0.1 cm to ±0.2 cm). This redundancy ensures overall positioning reliability in the 500 m^2 indoor greenhouse, where a single high-quality 3D sensor might suffice in ideal conditions but fails under variability, as validated by comparative tests showing 10–15% accuracy improvement with fusion. The LiDAR (detection range 0.1–5 m, accuracy ±2 cm) compensates for visual sensor limitations in low-light or obstructed scenarios, precisely locating mushroom spatial coordinates; Pressure sensors (measurement range 0–5 N, accuracy ±0.01 N) mounted at the gripper mechanism tip collect real-time grasping pressure data; Temperature/humidity sensors and GPS modules record harvesting environment parameters and equipment location information, supporting precision agriculture data accumulation.

C. DECISION LAYER ALGORITHM DESIGN

The decision layer centers on an enhanced YOLOv9 algorithm and a multi-sensor fusion decision model. To address the insufficient recognition accuracy of traditional YOLOv9 in scenarios with dense mushroom growth, an attention mechanism (CBAM) and feature fusion modules (FPN+PAN) are introduced [4]. The network architecture is optimized to enhance recognition capabilities for small and occluded targets. A lightweight design reduces algorithm inference latency, ensuring real-time performance. The core loss function employs a weighted sum of confidence loss, classification loss, and coordinate loss, as follows:

$$L_{total} = \lambda_{conf} \times L_{conf} + \lambda_{cls} \times L_{cls} + \lambda_{loc} \times L_{loc} \quad (1)$$

In the formula, $\lambda_{conf} = 1.0$, $\lambda_{cls} = 1.2$, and $\lambda_{loc} = 5.0$ represent loss weight coefficients adjusted according to the characteristics of the mushroom recognition task, prioritizing coordinate positioning accuracy; λ_{conf} represents the confidence loss, employing a cross-entropy loss function to measure the reliability of a predicted bounding box containing the mushroom target; λ_{cls} denotes the classification loss, also using cross-entropy loss to distinguish mushroom varieties and maturity levels; λ_{loc} signifies the coordinate loss, utilizing the CIoU loss function to precisely calculate the positional deviation between predicted and ground-truth boxes, defined as follows:

$$L_{CIoU} = 1 - IoU + \rho^2(b, b_{gt})/c^2 + \alpha v \tag{2}$$

Where: L_{CIoU} represents the intersection-over-union ratio between the predicted and ground truth bounding boxes; $\rho^2(b, b_{gt})$ denotes the squared Euclidean distance between the centers of the two boxes; c is the diagonal length of the minimum bounding rectangle encompassing both boxes; α is the balance coefficient; v measures the consistency of the width-to-height ratio between the two boxes, calculated as:

$$\begin{aligned} v &= \frac{4}{\pi^2}\left(\arctan\left(\frac{w_{gt}}{h_{gt}}\right) - \arctan\left(\frac{w}{h}\right)\right)^2, \\ \alpha &= \frac{v}{(1 - IoU) + v} \end{aligned} \tag{3}$$

Through optimization with this loss function, the algorithm reduces localization error by 12.3% compared to traditional YOLOv9, providing a foundation for precise mushroom harvesting. The multi-sensor fusion decision model employs a weighted fusion algorithm to integrate data from RGB-D cameras, LiDAR, and pressure sensors. It determines maturity based on mushroom morphological features (cap diameter $\geq$5cm, uniform color), plans robotic arm harvesting paths using spatial coordinate data, and dynamically adjusts gripping force via pressure feedback, forming a "recognition-localization-force adjustment" decision logic.

D. STRUCTURAL DESIGN OF THE EXECUTION LAYER

The execution layer comprises a four-degree-of-freedom flexible robotic arm with an adaptive gripping mechanism. The robotic arm features a maximum working radius of 80 cm and repeatability of $\pm$0.5 mm, driven by servo motors for rapid response and smooth motion. The adaptive gripping mechanism employs flexible silicone claws with an opening range of 3–15 cm, accommodating mushrooms of varying sizes. To minimize damage in dense clusters (cap spacing <2 cm), the gripper is designed with a slim profile (footprint of 2.5 cm when closed), and path planning algorithms prioritize non-intrusive approaches, such as angled insertion from above, reducing adjacent mushroom contact by 85% in tests. To minimize harvesting damage, a PID control algorithm optimizes gripping force. Inputting pressure sensor feedback data, it sets an optimal gripping pressure threshold (0.8–1.2 N). Through dynamic adjustment of the proportional coefficient (K_p = 5.0), integral coefficient (K_i = 0.1), and derivative coefficient (K_d=0.5) to dynamically adjust gripper force. This prevents mushroom damage from excessive force while ensuring adequate grip to avoid dropping. The core PID control formula is:

$$u(t) = K_p\left[e(t) + T_d \times \frac{de(t)}{dt}\right] \tag{4}$$

Where: $u(t)$ represents the output control variable (corresponding to the driving force of the gripper motor), $e(t)$ denotes the pressure deviation (set between 0.8–1.2 N based on mushroom variety: 0.8 N for oyster mushrooms, 1.2 N for shiitake mushrooms, 1.0 N for enoki mushrooms), $de(t)$ is the integral time constant, and $de(t)/dt$ is the derivative time constant. This algorithm achieves a gripping force adjustment response time $\leq$0.3 s and force fluctuation amplitude $\leq \pm$0.05 N, providing control assurance for low-damage harvesting.

E. IOT PLATFORM DEVELOPMENT AND EXPERIMENTAL DESIGN

The IoT platform is built on the MQTT communication protocol using a B/S architecture, integrating data acquisition, equipment monitoring, data analysis, and remote control functions. It receives sensor data from the perception layer, algorithm results from the decision layer, and equipment status information from the execution layer in real time, storing them in a MySQL database. Through a visual interface, it displays core metrics such as harvesting efficiency, damage rate, and identification accuracy, supporting remote adjustment of equipment parameters and harvesting strategies to achieve intelligent management of the harvesting process. The experiment selected three common mushroom species—oyster mushrooms, shiitake mushrooms, and enoki mushrooms—as research subjects. Field trials were conducted in a large-scale mushroom cultivation greenhouse (500 m^2), comparing manual harvesting and automated harvesting groups. Each group underwent three replicates, with each trial lasting 8 hours. Experimental metrics included: harvesting efficiency (kg/h), damage rate (%), recognition accuracy (%), and stability (uninterrupted operational duration). Device performance under varying environmental conditions (low light, high humidity, dense growth) was concurrently recorded. To enhance research design rigor, we used randomized block design for trial plots, controlled for variables like mushroom density and environmental factors, and applied statistical tests (ANOVA) to validate differences between groups.

III. RESULTS AND DISCUSSION

A. COMPARISON OF CORE PERFORMANCE METRICS FOR THE DEVICE

The comparison of core performance metrics between the automated harvesting group and the manual harvesting group is shown in Table 1 below. Data represent the mean $\pm$ standard deviation from three replicates. In terms of core performance metrics, the intelligent mushroom harvesting device demonstrated significantly higher harvesting efficiency than manual harvesting. The average harvesting efficiency for the three mushroom types reached 42.1 kg/h, with a daily average yield of 337.1 kg/8h—a 3.65-fold increase over manual harvesting (92.3 kg/8h). Enoki mushroom harvesting efficiency was highest (45.3 $\pm$ 2.1 kg/h), surpassing manual harvesting (12.3 $\pm$ 1.2 kg/h) by 3.68

times. Primarily due to enoki mushrooms' dense growth and regular morphology (cap diameters concentrated between 5–8 cm, meeting the algorithm's maturity threshold). The AI algorithm achieved a recognition speed of 30 frames per second, with single-frame recognition time $\leq$0.03 s. Recognition time for enoki mushrooms was slightly shorter (average 0.025 s) than for oyster mushrooms (average 0.030 s), though this difference is small and within hardware variability; it contributes marginally to path planning efficiency over multiple cycles. Oyster mushroom harvesting efficiency reached 42.5$\pm$2.3 kg/h, 3.60 times higher than manual harvesting (11.8$\pm$1.1 kg/h). Despite slightly irregular cap shapes, moderate growth density resulted in $\leq$15% occlusion rate. The modified YOLOv9 algorithm achieved 95.2$\pm$1.2% recognition accuracy, supporting efficient harvesting [5].

Regarding damage rates, the average damage rate for the three mushroom varieties harvested by the device was 3.7%, significantly lower than the 17.3% for manual harvesting. Among them, oyster mushrooms had the lowest damage rate (3.1$\pm$0.5%), reducing by 13.4 percentage points compared to manual harvesting (16.5$\pm$2.1%). This advantage stems from the oyster mushroom's robust cap resilience and the precisely calibrated 0.8 N clamping pressure threshold paired with PID control, maintaining force fluctuations $\leq$ $\pm$0.05 N to effectively prevent cap compression damage. Shiitake mushrooms exhibited the highest damage rate (4.2$\pm$0.7%), yet still reduced by 14.0 percentage points compared to manual harvesting (18.2$\pm$2.3%). Analysis reveals two primary causes: First, shiitake stems measure only 1.5–2.0 cm in diameter with fragile texture, resulting in a small contact area during gripping and prone to localized pressure exceeding limits; Secondly, the connection strength between the cap and stem during shiitake growth is relatively weak. Minor vibrations (amplitude $\leq$0.5 mm) during robotic harvesting can still cause minor detachment damage. Future optimization by adjusting the hardness of the gripper's silicone material (from the current Shore 30 to 25) could further reduce the damage rate below 3.5%. Data comparison demonstrates that the PID control algorithm significantly optimizes damage rates, reducing them by 62.1% compared to rigid gripping without pressure feedback [6].

B. EQUIPMENT PERFORMANCE UNDER DIFFERENT ENVIRONMENTAL CONDITIONS

To validate the device's adaptability in complex scenarios, its core performance was tested under varying environmental conditions. Results are shown in Table 2 below. Regarding complex environment adaptability, the device maintained stable performance across different scenarios, with core metrics meeting practical production requirements. Under normal illumination (2000–5000 lx) and humidity (60%–70%), recognition accuracy reached 95.6$\pm$1.0%, damage rate was 3.5$\pm$0.4%, harvesting efficiency fluctuation was <5%, and continuous operation lasted 8 hours without failure. At this point, the RGB-D camera achieved optimal image acquisition quality, with positioning error after fusion with LiDAR being only $\pm$0.2 cm. The single-frame recognition accuracy of the algorithm reaches 96.8%, representing the optimal performance across all scenarios and meeting the harvesting requirements of most standardized mushroom greenhouses. Under low-light conditions (<500 lx), RGB-D camera image noise increased, reducing recognition accuracy to 92.3$\pm$1.4%—a 3.3 percentage point decrease from normal illumination scenarios. However, with supplementary LiDAR positioning, overall positioning accuracy remained at $\pm$0.3 cm. The damage rate increased by only 0.2 percentage points (3.7$\pm$0.5%), with harvesting efficiency fluctuations <8%. This significantly outperforms existing comparable equipment (typically <80% recognition accuracy and >8% damage rate under low light), demonstrating that multi-sensor fusion technology effectively compensates for the low-light limitations of single visual sensors [7,8].

In high-humidity environments (>85%), moisture easily condenses on sensor surfaces, increasing depth data collection errors in RGB-D cameras (from $\pm$0.1 cm in normal conditions to $\pm$0.2 cm) and reducing LiDAR detection range stability. Under these conditions, device recognition accuracy reaches 94.1$\pm$1.2% with a damage rate of 3.9$\pm$0.6%. Harvesting efficiency fluctuations remain below 6%, with continuous fault-free operation exceeding 8 hours. This performance is primarily attributed to the device's waterproof and dustproof design (IP65 rating) and its algorithm's noise-resistant processing module, which effectively filters image blurring and radar data anomalies caused by moisture. Compared to devices without anti-interference design, recognition accuracy improves by 15.7%. In dense growth scenarios (cap spacing < 2 cm) where mushroom occlusion rates reach 20%-25%, the CBAM attention mechanism of the improved YOLOv9 algorithm precisely extracts mushroom features within occluded areas. This achieves an identification accuracy of 93.2$\pm$1.3% and a damage rate of 4.0$\pm$0.7%. This represents an 8.4 percentage point improvement over the traditional YOLOv9 algorithm, effectively resolving misidentification and missed detection issues in dense environments. Overall, the device exhibits less than 5% performance degradation in complex conditions, demonstrating significantly superior stability compared to existing equipment. It is adaptable for mushroom harvesting in greenhouses under various climatic conditions.

C. EQUIPMENT MODULAR ADAPTABILITY

By replacing gripping mechanisms and adjusting algorithm parameters, the device's adaptability to three mushroom varieties was tested. Results show: Replacing specialized gripping mechanisms for oyster mushrooms, shiitake mushrooms, and enoki mushrooms took <10 minutes each. Algorithm parameter adjustments can be completed remotely via the IoT platform. After adaptation, harvesting metrics for all mushroom varieties met design requirements, demonstrating excellent versatility of the modular design. Compared to ex-

TABLE 1. Comparison of Core Performance Metrics

Harvesting Method	Mushroom Variety	Harvesting Efficiency (kg/h)	Damage Rate (%)	Maturity Selection Accuracy (%)	Daily Harvest Volume (kg/8h)
Intelligent Device Harvesting	Oyster Mushroom	42.5±2.3	3.1±0.5	95.2±1.2	340.0±18.4
	Shiitake Mushroom	38.6±1.8	4.2±0.7	93.6±1.5	308.8±14.4
	Enoki Mushrooms	45.3±2.1	3.8±0.6	94.8±1.1	362.4±16.8
Manual Harvesting	Oyster mushroom	11.8±1.1	16.5±2.1	98.3±0.8	94.4±8.8
	Shiitake Mushroom	10.5±0.9	18.2±2.3	97.9±0.9	84.0±7.2
	Enoki Mushrooms	12.3±1.2	17.1±2.0	98.1±0.7	98.4±9.6

TABLE 2. Performance Comparison of the Device in Different Scenarios

Environmental Conditions	Recognition Accuracy (%)	Damage Rate (%)	Continuous Trouble-Free Operation Time (h)	Harvesting Efficiency Fluctuation Range (%)
Normal illumination (2000–5000 lx), humidity 60%–70%	95.6±1.0	3.5±0.4	>8	<5
Low light (<500 lx), humidity 60%–70%	92.3±1.4	3.7±0.5	>8	<8
Normal light, high humidity (>85%)	94.1±1.2	3.9±0.6	>8	<6
Dense growth (cap spacing < 2 cm)	93.2±1.3	4.0±0.7	>8	<7

isting similar equipment, this device exhibits significant core performance advantages. Recognition accuracy surpasses that of a Dutch company's mushroom harvesting robot (below 80% under low-light, high-humidity conditions) by 12.3–15.6 percentage points. Damage rates are reduced by 3.8–6.5 percentage points compared to the Dutch robot (8%–10%). Harvesting efficiency exceeds that of a device developed by a domestic university (25–30 kg/h) by 28.7%–45.3%. Quantitative data comparisons fully validate the feasibility and superiority of the "AI vision + multi-sensor fusion + flexible execution" technical solution. Synergistic module integration elevates the device's overall performance to industry-leading standards. The integration of modules improves the device's overall performance.

Modular design enables multi-species adaptability, allowing harvesting of oyster mushrooms, shiitake mushrooms, and enoki mushrooms through simple component replacement and parameter adjustments, addressing the limited versatility of existing equipment. The IoT platform facilitates real-time monitoring and remote scheduling of harvesting data, providing detailed field data support for precision agriculture and aligning with the trend toward intelligent agriculture.

D. RESULTS AND DISCUSSION

This study still has certain limitations, and the experimental data clearly indicate directions for future optimization: First, the recognition accuracy of the device in scenarios with severe mushroom occlusion (occlusion area > 30%) drops to 88.0±2.1%, a decrease of 5.2 percentage points compared to densely growing scenarios (occlusion rate 20%-25%). The missed recognition rate reaches 3.5%, and the misrecognition rate reaches 8.5%. This primarily stems from severe loss of mushroom feature information when coverage exceeds a certain threshold, rendering the CBAM attention mechanism ineffective at extracting useful features. Introducing a Transformer module to enhance feature fusion is proposed, which is expected to elevate recognition accuracy in heavily obstructed scenarios to over 92%. Secondly, the unit manufacturing cost of the equipment is approximately 180,000 yuan, with imported RGB-D cameras and LiDAR accounting for 45% (about 81,000 yuan) of the total cost. This exceeds the cost of manual harvesting equipment (approximately 50,000 yuan per set). Based on a daily harvest of 337 kg, the equipment payback period is approximately 2.5 years when considering CAPEX only; however, including OPEX (estimated at ¥15,000/year for electricity, maintenance, and remote operator salary), the payback period extends to 3.2 years. A full economic assessment confirms long-term benefits exceed costs after this period. While long-term economic benefits are significant, this hinders large-scale adoption in the short term. Domestic component substitution (projected to reduce sensor costs by 30%-40%) is needed to control manufacturing costs below ¥120,000 and shorten the payback period to 1.8 years.

Furthermore, detailed data analysis indicates room for optimization in adaptability across different mushroom varieties: Enoki mushroom harvesting efficiency exhibits greater variability (±2.1 kg/h) compared to oyster mushrooms (±2.3 kg/h) and shiitake mushrooms (±1.8 kg/h). This stems primarily from enoki's slender stems, which are prone to shaking during robotic transport after grasping, resulting in stem breakage (accounting for 40% of total enoki damage). Although the servo motors provide smooth motion with ±0.5 mm repeatability, residual vibrations can occur if gripping force is marginally insufficient for slender stems; future optimizations include adding damping mechanisms to further minimize this. The time required to harvest a single shiitake mushroom (0.8±0.1 s) is longer than for oyster mushrooms (0.6±0.1 s) and enoki mushrooms (0.7±0.1 s). This is because shiitake mushrooms grow in more dispersed locations, increasing the path planning distance for the robotic arm. Future efforts can optimize the robotic arm's transport trajectory and gripping angle based on the growth characteristics of different mushroom varieties to further enhance harvesting stability and efficiency. Furthermore, the accumulated dataset of 12,000 mushroom morphology records and 8,000 environmental sensor readings enabled training more versatile recognition and control models. This provides data support for extending the technical framework to soft fruits and vegetables like strawberries and blueberries. Preliminary strawberry recognition tests have been completed, achieving 91.5% accuracy with damage rates controlled at 5.2%, validating the feasibility of technology transfer.

IV. CONCLUSION

By incorporating the high-precision detection logic used in material analysis, this study developed an AI-vision-based, multi-sensor-fused intelligent mushroom harvesting device featuring an integrated "perception-decision-execution" control system. This cross-industrial synergy ensures that the delicate handling and rigorous sorting standards of the industry are applied to optimize the automated harvesting process for large-scale agricultural production. Field experiments validated the device's feasibility and superiority, with key conclusions as follows:

1. The device integrates RGB-D cameras, LiDAR, and other multimodal sensors with an enhanced YOLOv9 algorithm, enabling precise mushroom identification and localization in complex environments. Recognition accuracy reaches 93.6% in challenging scenarios, with stable operation maintained under low light, high humidity, and dense growth conditions, demonstrating outstanding perception capabilities. 2. The flexible robotic arm, paired with an adaptive gripping mechanism featuring pressure feedback and PID control, significantly reduces harvesting damage rates. The average damage rate for three mushroom varieties is $\leq$4.2%, markedly outperforming traditional manual harvesting (15%-20%). Harvesting efficiency reaches 38.6-45.3 kg/h, increasing daily yield by 3-4 times compared to manual methods, substantially boosting harvesting efficiency and economic benefits. 3. Modular design ensures excellent versatility, enabling rapid adaptation for harvesting multiple mushroom varieties including oyster mushrooms, shiitake mushrooms, and enoki mushrooms. The IoT platform enables intelligent management and data accumulation throughout the harvesting process, providing technical support and data assurance for precision agriculture. 4. This device overcomes the technical bottlenecks of low efficiency, high damage rates, and high costs in traditional mushroom harvesting. Its comprehensive performance surpasses existing comparable equipment. Integrating the high-precision detection logic of machinery, the "AI vision + multi-sensor fusion + flexible execution" framework is transferable to harvesting various cash crops and raw driving arge-scale agricultural intelligence upgrades. This technical synergy ensures that the delicate materials handling and rigorous sorting standards inherent in manufacturing are applied to diverse agricultural environments to optimize industrial production efficiency.

AUTHOR CONTRIBUTIONS

Conceptualization –Yubo Wang, Han Yu, You Chen, Sen Li, Hao Zhang and Yubo Wang; methodology – Yubo Wang, Han Yu, Sen Li, Hao Zhang and Yubo Wang; investigation – Yubo Wang, Han Yu, You Chen, Sen Li, Hao Zhang and Yubo Wang; writing-original draft preparation – Yubo Wang, Han Yu, You Chen, Sen Li, Hao Zhang and Yubo Wang. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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