SPADE: A DEEP LEARNING FRAMEWORK FOR AUTOMATED SEED POTATO CUTTING
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SPADE：基于深度学习的马铃薯种薯切块机器人决策框架

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ABSTRACT
Traditional manual cutting of seed potatoes is a labor-intensive, time-consuming, and inconsistent process that limits large-scale agricultural productivity. To address these challenges, this study aimed to develop and validate an automated, high-speed robotic system for precise cutting angle estimation. SPADE (Smart Potato Angle Decision Engine), an innovative framework integrating deep learning and machine learning algorithms, is proposed. The SPADE framework is implemented in three stages. First, a custom detection model, termed BUD-YOLO, was developed for the high-precision identification of potato eyes. Second, the K-means algorithm was employed to partition the spatial coordinates of the detected eyes into two distinct clusters. Finally, a Support Vector Machine (SVM) determined the optimal cutting plane by identifying the maximum-margin hyperplane between these two clusters. The proposed SPADE framework was implemented and tested on a custom-built robotic platform with a sample of 100 potatoes. The system achieved an 85% cutting qualification rate with an average processing time of 2.5 seconds per potato, a speed approximately 2-3 times faster than traditional manual labor (5-9 seconds per potato). This study successfully demonstrates an end-to-end solution for the automated cutting of seed potatoes. The developed SPADE framework not only achieves a competitive qualification rate but also significantly enhances production throughput, offering substantial practical value for the advancement of intelligent agricultural equipment.

摘要
传统的手工切割马铃薯种子是一种劳动密集型、耗时且不一致的过程，限制了大规模农业生产力。为解决这些挑战，本研究旨在开发并验证一个能够进行精确切割角度估算的自动化、高速机器人系统。我们提出 SPADE（智能马铃薯角度决策引擎），这是一个创新框架，整合了深度学习和机器学习算法。SPADE 框架分为三个阶段。首先，开发了一个定制的检测模型，称为 BUD-YOLO，用于高精度识别马铃薯芽眼。其次，使用 K-means 算法将检测到的芽眼的空间坐标分为两个独立的聚类。最后，支持向量机（SVM）通过识别这两个聚类之间的最大边际超平面来确定最佳切割平面。提出的 SPADE 框架在定制的机器人平台上使用 100 个马铃薯样本进行了实施和测试。整个系统实现了 85%的切割合格率，平均处理时间为每个马铃薯 2.5 秒。这一处理速度约为传统人工劳动的 2-3 倍（每个马铃薯 5-9 秒）。本研究成功展示了马铃薯种子自动切割的端到端解决方案。所开发的 SPADE 框架不仅实现了具有竞争力的通过率，更重要的是显著提升了生产效率，为智能农业装备的发展提供了重要的实践价值。

INTRODUCTION
The potato (*Solanum tuberosum L.*) is a cornerstone of global food security, essential for meeting worldwide dietary needs and driving agricultural development (*Johnson and Cheein, 2023*). The efficiency of its cultivation is pivotal to the modernization of the industry.

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Within the cultivation workflow, a critical preparatory step involves uniformly cutting seed potatoes, ensuring each piece contains at least one eye to facilitate germination (*Zhang et al., 2025*).

However, this stage has traditionally relied heavily on manual labor, a practice that is not only time-consuming and costly but also results in inconsistent cutting quality, which directly constrains crop yields (*UN Food & Agriculture Organization, 2023*). Consequently, the development of automated, precision-cutting systems has become a pressing need for advancing the potato industry.

In recent years, artificial intelligence (AI), powered by deep learning, has significantly advanced agricultural automation (*Kamilaris and Prenafeta-Boldú, 2018*). Object detection models, particularly the YOLO series (*Bochkovskiy et al., 2020; Jocher et al., 2023; Redmon and Farhadi, 2018*), have been successfully applied in various agricultural scenarios, such as strawberry detection (*He et al., 2025*), disease identification (*Ray et al., 2025*), and yield estimation (*Zhang et al., 2025*). Within the field of potato processing, considerable research has been devoted to the fundamental task of eye identification (*Gu et al., 2024; Huang et al., 2025a*). Nevertheless, a significant research gap persists: existing work is often limited to "detection" and fails to extend to the more complex “decision-making” level. Research on intelligently planning an optimal cutting path based on multiple detected eyes—that is, estimating the best cutting angle—remains notably scarce (*Du et al., 2021*). The true challenge lies in endowing machines with the capacity for autonomous decision-making to maximize the economic value of the seed pieces (*Li et al., 2025; Shen et al., 2023*).

To bridge this gap, an innovative intelligent decision framework named SPADE (Smart Potato Angle Decision Engine) is proposed and constructed. The SPADE framework decomposes the complex task of cutting angle estimation into a three-stage machine learning pipeline. In the detection stage, a customized model based on YOLOv8-OBB, termed BUD-YOLO, was developed to achieve high-precision identification of potato eye locations. In the second stage, the spatial coordinates of the detected eyes are processed using the K-means clustering algorithm, effectively partitioning them into two clusters. In the final decision stage, a Support Vector Machine (SVM) *(Nidamanuri et al., 2022)* determines the cutting angle by computing the optimal separating hyperplane that maximizes the margin between the two clusters. The proposed end-to-end SPADE framework demonstrates a viable pathway from simple object perception to complex intelligent decision-making, providing a technical blueprint for the development of next-generation intelligent agricultural equipment.

MATERIALS AND METHODS

Experimental platform and data acquisition

All experimental data were acquired on a custom-built automated cutting platform (Fig.1), which integrates three core modules: data acquisition, processing, and physical execution. The platform primarily consists of a central control computer, a WH-L2140.K214L camera, a Delta parallel robot, and a conveyor belt driven by a stepper motor. The industrial camera, featuring a resolution of 1920 × 1080 pixels and an acquisition frame rate of 60 FPS, was mounted vertically above the conveyor belt to ensure the capture of orthographic views of the potatoes (*Huang et al., 2025b*).

A total of 400 potato samples of the “Dutch 15” variety were used for the experiment. Data acquisition was conducted under indoor natural lighting conditions. The acquisition procedure was as follows: when a sample was transported to a designated position on the conveyor belt and detected by an infrared sensor, the system triggered the camera for an initial capture. To obtain multi-angle views of the sample, an operator then manually rotated it by approximately 45°, and the camera was triggered again. This process was repeated 8 times for each potato, yielding 8 images of different poses per sample and resulting in a final dataset of 3200 raw images.

Subsequently, the open-source annotation tool Labelme was used to manually annotate all images. Two categories were defined for annotation: “bud” (the potato eye) and “potato” (defined as the minimum oriented bounding box enclosing the main body of the potato). To construct and evaluate the models, this dataset was randomly partitioned into a training set (2560 images) and a test set (640 images) at an 8:2 ratio. To enhance the model’s robustness and generalization capability, data augmentation—including random rotation, flipping, and scaling—was applied exclusively to the training set, expanding its size to 7680 images. The test set was not subjected to any augmentation to ensure an objective and fair evaluation of the final model’s performance.

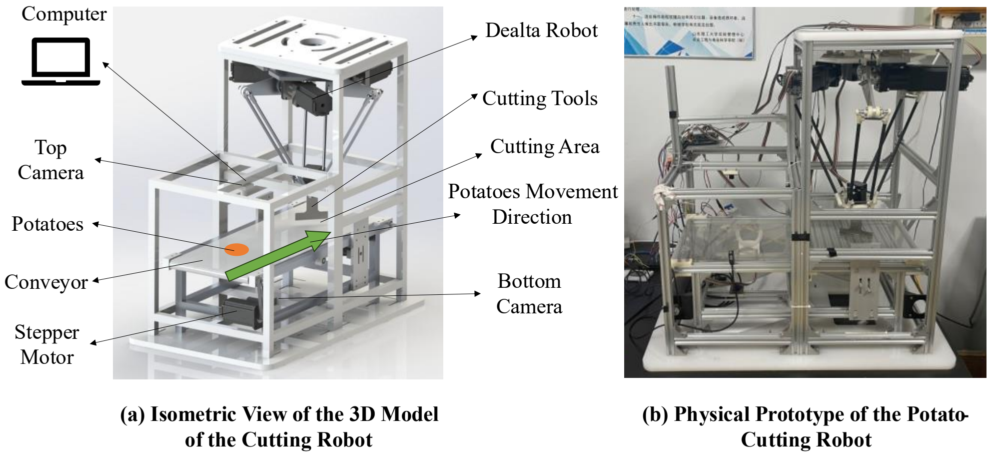

Fig. 1 - The robotic platform for automated potato cutting

The three-stage framework for cutting angle estimation

Stage one: Bud detection based on BUD-YOLO

The first stage of the framework is dedicated to accurately locating the position and orientation of all potato eyes from the input potato image. For this purpose, the YOLOv8-OBB (Oriented Bounding Box) model was modified and designated as BUD-YOLO. YOLOv8-OBB was selected as the baseline model due to its ability to generate rotated bounding boxes, which is well-suited for representing irregular and non-aligned targets such as potato eyes. The core modification focuses on improving the detection of the typically small potato eyes by integrating an additional P2 detection head into the Neck of YOLOv8-OBB. The P2 head originates from shallower layers of the Backbone network and possesses a smaller receptive field, making it more sensitive to small-scale features. This enhancement substantially increases the model's capability to detect minute buds. The detailed network architecture of BUD-YOLO is illustrated in Fig. 2. The final output of this stage consists of precise coordinates and rotation angles corresponding to all detected buds.

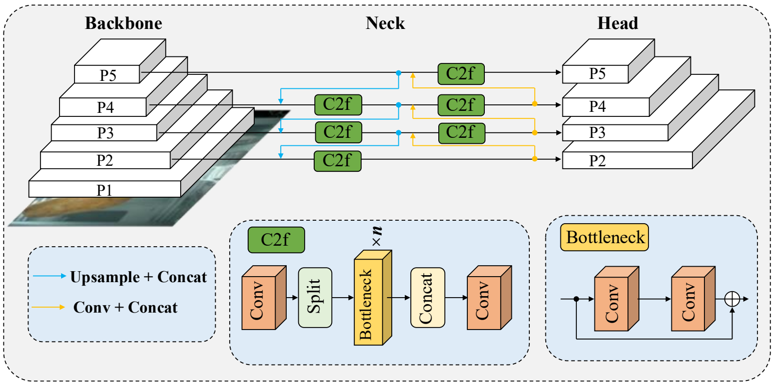

Fig. 2 - Network architecture of BUD-YOLO

Stage two: Spatial clustering of buds based on K-means

The objective of this stage is the spatial organization and partitioning of the discrete potato eyes detected in the previous stage. The center coordinates of all buds output by BUD-YOLO are defined as a sample set $D = \{x_1, x_2, ..., x_m\}$, which is then processed using the K-means clustering algorithm. The K-means algorithm was selected for its computational efficiency and its suitability for partitioning spatial data, as required in this study. The algorithm aims to divide the sample set D into *k* = 2 non-overlapping clusters, $C = \{C_1, C_2\}$, by minimizing the Within-Cluster Sum of Squares (WCSS). This objective function, *E*, is defined as follows:

$$E = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|_2^2 \tag{1}$$

where μ_i is the mean vector, or centroid, of cluster C_i, and $\|\cdot\|^2$ represents the squared Euclidean distance.

The algorithm iteratively performs two steps until convergence: (1) an assignment step, where each sample x is assigned to the cluster of its nearest centroid; and (2) an update step, where the centroid of each cluster is recalculated. The output of this stage is the classification of all bud samples into one of two distinct categories.

Stage three: Optimal cutting angle decision based on SVM

The final stage of the SPADE framework determines the optimal cutting path based on the clustering results. The problem is formulated as a binary classification task and a Support Vector Machine (SVM) is employed as the classifier. The core principle of SVM—identifying an optimal separating hyperplane that maximizes the margin between classes—aligns perfectly with the objective of selecting the "safest" cutting path.

Given the labeled training set $\{(x_i, y_i)\}, i = 1,2, \ldots, m$, from Stage Two, where x_i are the coordinates of the bud and $y_i \in \{+1, -1\}$ is its assigned cluster label, the goal of a linear SVM is to find a hyperplane $w^{\mathrm{T}}x + b = 0$. This problem can be formulated as the following convex quadratic programming problem:

$$\begin{gathered} \text{Minimize } \frac{1}{2}\|w\|^2 \\ \text{subject to } y_i(w^{\mathrm{T}}x_i + b) \geqslant 1,\ i = 1,2, \ldots, m \end{gathered} \tag{2}$$

where $\boldsymbol{w}$ is the normal vector to the hyperplane and *b* is the bias term. Minimizing $\|\boldsymbol{w}\|^2$ is equivalent to maximizing the classification margin $\frac{2}{\|w\|}$.

After solving this problem, the resulting optimal separating hyperplane, $f(x) = w^{\mathrm{T}}x + b$, is defined as the optimal cutting plane for the robot. Its normal vector, w, determines the final cutting angle.

Model training and implementation details

Hardware and software environment

The hardware platform was a Lenovo Legion Y7000P laptop equipped with a 12th Gen Intel® Core™ i5-12500H CPU and an NVIDIA GeForce RTX 3050i Laptop GPU. The software environment was based on the Ubuntu 20.04 LTS operating system. The experiments were conducted using the PyTorch 2.0.0 deep learning framework with CUDA 11.7 for GPU acceleration. All code was written and executed in a Python 3.9 environment.

Model training hyperparameters

The BUD-YOLO model was trained using the following hyperparameter configuration. Input images were uniformly resized to 416 × 416 pixels before training. The batch size was set to 16. Adam was used as the optimizer, with an initial learning rate of 0.001 and a weight decay parameter of 0.0001. The entire training process was conducted for 300 epochs. To refine the model weights more effectively in the later stages of training, a cosine annealing strategy was adopted to dynamically adjust the learning rate. Furthermore, to enhance model performance, Mosaic and Mixup data augmentation strategies were introduced, each applied randomly with a probability of 0.5 during training.

Performance evaluation metrics

Detection model performance evaluation

To assess the performance of the BUD-YOLO model on the potato and bud detection tasks, the following standard metrics were used:

$$P = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{3}$$

$$R = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{4}$$

where TP, FP, and FN represent True Positives, False Positives, and False Negatives, respectively.

$$AP = \sum_{i=1}^{N} P(i)\Delta R(i) \tag{5}$$

Clustering performance evaluation

As bud clustering is an unsupervised process, two internal validation metrics were employed—the Davies-Bouldin Index (DBI) and the Dunn Index (DI)—to evaluate its effectiveness.

A lower DBI value signifies that clusters are more compact and better separated.

$$DBI = \frac{1}{k}\sum_{i=1}^{k}\max_{i \neq j}\left(\frac{\text{avg}\left(C_i\right)+\text{avg}\left(C_j\right)}{d\left(C_i, C_j\right)}\right) \tag{6}$$

A larger DI value indicates better clustering performance.

$$DI = \frac{\max\limits_{i \neq j} d(C_i, C_j)}{\max\limits_{1 \le l \le k} \dim(C_l)} \tag{7}$$

where diam(*C*) represents the diameter of a cluster, the maximum distance between any two points within the cluster.

System-Level cutting performance evaluation

To assess the final output quality of the entire automated system, the cutting qualification rate was defined as the core metric. First, the viability of a cut tuber piece is defined. A piece is considered “viable” if and only if it contains one or more buds. Cutting Qualification Rate (*Q*): Defined as the percentage of viable tuber pieces (MN) relative to the total number of pieces produced after cutting (M).

$$Q = \frac{M_N}{M} \times 100\% \tag{8}$$

Additionally, the Average Processing Time required for the entire system, from detection to the completion of the cut, was recorded and analyzed to evaluate operational efficiency.

RESULTS AND DISCUSSION

Bud detection performance: Validation of BUD-YOLO’s effectiveness

To validate the effectiveness of the proposed BUD-YOLO model for the bud detection task, a comprehensive performance comparison was conducted against the baseline model, YOLOv8m-OBB, on the test set comprising 640 raw images. The evaluation results are presented in Table 1.

Table 1

Performance comparison between the YOLOv8m-OBB and BUD-YOLO models

Model	Map(%)	AP_{bud}	AP_{potato}	P(%)	R(%)	FPS
YOLOv8m-OBB	96.40	93.40	99.40	93.30	93.70	101
BUD-YOLO	97.20	95.10	99.50	95.20	94.20	132

As the quantitative data in Table 1 indicate, our proposed BUD-YOLO model demonstrates superiority across several key metrics. Specifically, BUD-YOLO achieved a mAP of 97.20%, an improvement of 0.8 percentage points over the baseline model. Most notably, for the critical “bud” category detection, its Average Precision (AP_{bud}) significantly increased from 93.40% to 95.10%, a substantial gain of 1.7 percentage points. This result provides strong evidence that our strategy of incorporating a P2 detection head to enhance small-object detection capabilities is effective. Furthermore, BUD-YOLO exhibits a good balance between Precision (P) and Recall (R). In terms of inference speed, BUD-YOLO reached 132 FPS, which not only meets but exceeds real-time processing requirements and is superior to the baseline, indicating that our improvements did not introduce additional computational overhead.

To provide a more intuitive illustration of BUD-YOLO’s performance advantages, Fig. 3 presents a visual comparison of the detection results from both models on the same test images. It can be clearly observed that in challenging scenarios containing small, obscure buds, the baseline YOLOv8m-OBB model is prone to missed detections (as seen in Fig. 3(f), where some buds were not identified). In contrast, BUD-YOLO is able to robustly detect these targets (Fig. 3(b)), a direct result of its enhanced feature extraction capability for small objects. These visual results further corroborate the improvements in accuracy and robustness of the BUD-YOLO model, providing a reliable data foundation for the subsequent clustering and cutting-angle decision stages.

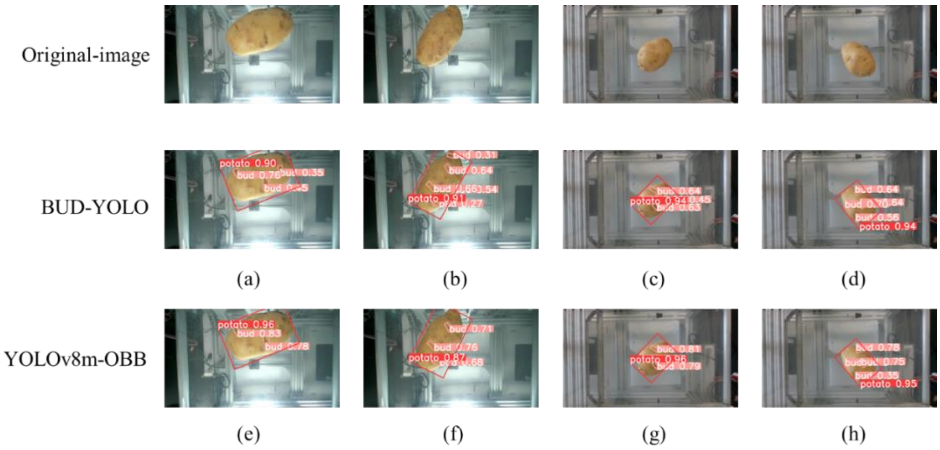

Fig. 3 - Visual comparison of detection results between YOLOv8m-OBB and BUD-YOLO

Performance of bud clustering and classification

Following the precise detection of all potato eyes by BUD-YOLO, the performance of the second and third stages of the SPADE framework, namely, spatial clustering and classification-based decision-making for the buds, was subsequently evaluated.

First, to validate the effectiveness of the *K*-means algorithm in spatially partitioning the potato eyes, 100 images were randomly selected from the test set. The coordinates of their buds and the center points of the potato extremities were extracted to serve as samples. The clustering results were then quantitatively evaluated using the Davies-Bouldin Index (*DBI*) and the Dunn Index (*DI*). As shown in Fig. 4, the clustering algorithm achieved an average DBI of 0.530 and an average DI of 1.005. According to the evaluation criteria, a low DBI value combined with a high *DI* value indicates that the K-means algorithm successfully partitioned the discrete eye points into two internally compact and well-separated clusters.

Fig. 6 provides an intuitive visualization of this effect, where different symbols ("□" and "△") clearly mark the eyes assigned to the two distinct spatial clusters, providing a structured data input for the subsequent SVM classification.

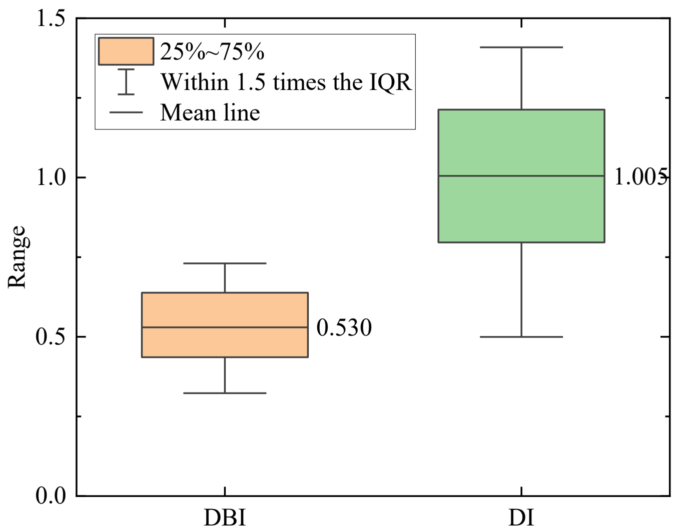

Fig. 4 - Quantitative evaluation of K-means clustering performance

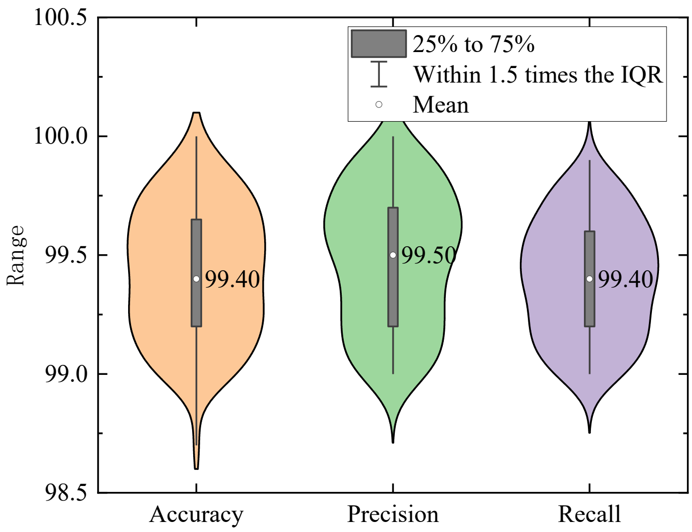

Fig. 5 - Performance evaluation of the SVM classifier

Next, the performance of the Support Vector Machine (*SVM*) classifier, which determines the final cutting angle, was evaluated. Using the same 100 samples, the SVM's classification accuracy, precision, and recall for the two bud clusters were assessed. The corresponding performance results are presented in Fig. 5.

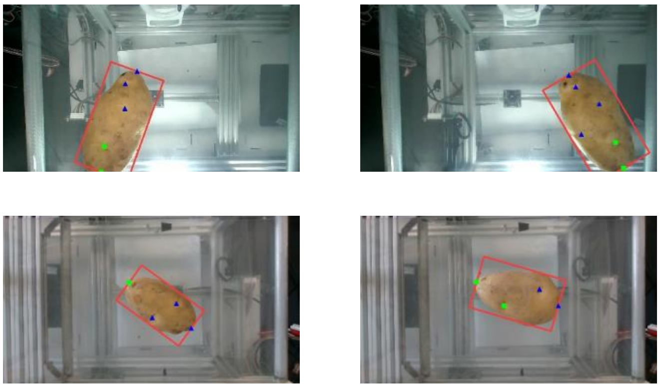

Fig. 6 - Visualization of K-means clustering results

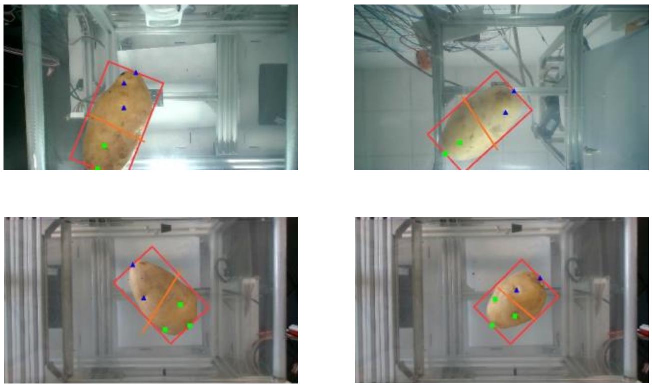

Fig. 7 - SVM-based bud classification and cutting plane decision

The box plots illustrate the distribution of the SVM classifier’s accuracy, precision, and recall across the 100 test samples. The results demonstrate that the model’s performance is not only exceptionally high on average (mean accuracy of 99.43%, precision of 99.51%, and recall of 99.38%) but also features a highly concentrated distribution, indicating a high degree of stability and reliability in its classification decisions.

Fig. 7 further illustrates the operational effectiveness of the SVM classifier on an actual sample. The red separating line in the figure is the optimal separating hyperplane identified by the SVM, which successfully and perfectly separates the two bud clusters. This proves that the SVM can reliably determine a “safe” cutting path, providing a decisive basis for achieving precise cutting.

Automated cutting experiment results

To comprehensively evaluate the overall performance of the proposed automated cutting system in a real-world application scenario and to directly compare it with traditional manual operations, an end-to-end experiment was conducted on our custom-built robotic platform. The experiment tested a total of 100 individual potato samples, with the system automatically completing the entire process from image acquisition and angle estimation to robotic cutting execution.

The experimental results clearly demonstrate the decisive advantage of the automated system in terms of production efficiency. The average processing time for our robotic system to handle a single potato was 2.5 ± 0.4 seconds. In contrast, according to industry benchmarks, the average time for a skilled worker to complete the same task is approximately 5 to 9 seconds. This means the processing efficiency of our automated system is two to three times greater than that of traditional manual labor.

While ensuring high efficiency, the system also maintained a high quality of cutting. Across the 100 trials, the system’s cutting qualification rate reached 85%. Although this figure is slightly lower than the 95% rate achievable by a skilled worker under ideal conditions, it is crucial to consider that the robot can perform continuous 24/7 operations tirelessly and with perfect consistency. The overall output quality and stability offered in long-term, large-scale production far surpass what is achievable with manual labor.

Furthermore, an analysis of the failure cases revealed that the unqualified samples primarily occurred with potatoes that had very few initial buds or an extremely dispersed bud distribution. This indicates that there is room for further optimization of the system’s qualification rate, for instance, by incorporating more sophisticated cutting strategies (e.g., non-linear or multiple cuts) to address these challenging samples.

In conclusion, this automated cutting system not only successfully validates the feasibility of the proposed SPADE framework but also demonstrates a transformative advantage over traditional manual labor in core performance metrics—especially production efficiency—proving its significant potential for industrial application and commercial value.

CONCLUSIONS

The SPADE framework efficiently and accurately estimates the optimal cutting angle through a three-stage machine learning pipeline. The system achieved an 85% cutting qualification rate, and its average processing speed reached 2.5 seconds per potato, an efficiency two to three times greater than that of traditional manual operations.

This indicates that the technical approach proposed in this study is not only technically feasible but also demonstrates immense application potential in enhancing production efficiency. Future work will focus on enhancing the system's adaptability to a broader range of potato varieties and optimizing cutting strategies to promote the further maturation and application of this technology.

ACKNOWLEDGMENTS

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