

AI-DRIVEN CLOSED-LOOP AGRICULTURAL ROBOTICS FOR PRECISION PHENOTYPING AND AUTONOMOUS SELECTIVE HARVESTING

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ABSTRACT

This paper addresses the persistent gap between robotic crop monitoring and autonomous harvesting by proposing an integrated, closed-loop agricultural system that unifies real-time AI-driven phenotyping with selective fruit harvesting in a single operational framework. We developed and field-evaluated AgriLoop-1, a unified robotic platform combining a multi-modal perception suite, a compliant end-effector for damage-aware fruit handling, and a co-designed AI software architecture. The perception pipeline leverages a YOLOv8-Seg model to perform simultaneous fruit detection, instance segmentation, ripeness classification, and yield estimation, while a dynamic Harvestability Score guide's target prioritization and optimized picking sequences based on spatial, phenotypic, and reachability constraints. Field trials conducted in a commercial apple orchard demonstrated reliable real-world performance, achieving an operational success rate of 87.0% and an effective harvesting throughput of 122 fruits per hour over 15 hours of continuous deployment. The system maintained stable closed-loop operation under varying environmental conditions, confirming the robustness of the integrated perception–decision–action architecture. This study presents a field-validated robotic system that effectively closes the perception–action loop in agricultural robotics. By tightly integrating precision phenotyping with adaptive harvesting decisions, the proposed framework moves beyond conventional modular approaches and establishes a practical foundation for intelligent, data-driven crop management systems capable of addressing labor shortages and supporting sustainable agricultural production.



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I. INTRODUCTION

I.1 THE GLOBAL IMPERATIVE FOR AGRICULTURAL TRANSFORMATION

Global agriculture is facing an unprecedented convergence of challenges that demand transformative technological solutions. Among the most pressing are the persistent shortage of skilled seasonal labor, the need to increase food production by an estimated 60–70% by 2050 to meet the demands of a growing global population, and the urgency of improving sustainability and resource efficiency under increasing climate variability and environmental constraints [1], [2]. Conventional farming practices, which rely heavily on manual labor and uniform field treatment, are becoming increasingly inadequate in addressing these complex pressures. These challenges have accelerated the adoption of Precision Agriculture (PA), a data-driven management paradigm that leverages sensing, automation, and analytics to observe, measure, and respond to spatial and temporal variability in crops [3]. While early implementations of PA focused primarily on monitoring and data collection, the field is rapidly evolving toward intelligent intervention systems capable of acting on real-time insights. The long-term vision is to transition from data-informed farming to fully autonomous, action-driven agriculture, where sensing, analysis, and intervention operate in a tightly integrated loop.

I.2 THE RISE OF AGRICULTURAL ROBOTICS AND THE PERCEPTION–ACTION GAP

Robotics and Artificial Intelligence (AI) are widely recognized as the key enabling technologies for realizing this vision of automated precision farming. Over the past decade, research in agricultural robotics has advanced significantly across two main domains. First, robotic phenotyping and scouting systems have emerged as powerful tools for crop monitoring. Autonomous ground and aerial platforms equipped with advanced sensors, such as multispectral cameras and LiDAR, combined with deep learning algorithms, can monitor plant health, estimate yield, and detect stress with high spatial and temporal resolution [4], [5]. Second, substantial progress has been made in robotic selective harvesting. Researchers have developed dexterous manipulators and specialized end-effectors capable of identifying and picking high-value fruits and vegetables, addressing one of the most labor-intensive stages of agricultural production [6], [7]. Despite these advances, a critical gap remains between perception and action. Most existing systems are designed and evaluated as isolated modules, functioning either as “seeing” systems for monitoring or “picking” systems for harvesting. In real agricultural environments, this separation creates a fragmented workflow in which scouting data are collected and processed offline, and only later used to guide human labor or separate machinery. Such disjointed operation prevents the establishment of a true perception–action feedback loop, where real-time phenotypic information such as fruit size, color, ripeness, and precise spatial location directly informs and optimizes robotic manipulation decisions. The absence of this closed-loop intelligence limits operational efficiency, reduces adaptability to dynamic field conditions, and constrains the full potential of autonomous agricultural systems. Bridging this gap is essential for enabling robots to move beyond isolated tasks toward integrated, intelligent crop management.

I.3 RESEARCH OBJECTIVE AND CONTRIBUTIONS

This work aims to address the identified perception–action gap by designing, implementing, and field-validating an integrated agricultural robotic system that seamlessly combines AI-powered precision phenotyping with autonomous selective harvesting within a single, closed-loop framework. The primary objective is to create a unified platform in which real-time phenotypic insights directly drive harvesting decisions, enabling more efficient, adaptive, and data-informed operation in orchard environments. The main contributions of this paper are summarized as follows:

1. **Integrated Hardware Architecture:**
A unified robotic platform is developed, incorporating a customized mobile base, a multi-modal perception suite, and a manipulator equipped with a damage-minimizing compliant end-effector specifically designed for delicate fruit harvesting.
2. **Co-Designed AI Software Stack:**
A dual-purpose deep learning pipeline is proposed to perform real-time fruit detection, ripeness classification, and yield estimation while generating harvestability scores and precise 3D spatial coordinates to support manipulation planning.
3. **Closed-Loop Decision and Control Framework:**
A hierarchical control strategy is introduced that tightly couples perception outputs with motion planning and reactive control, enabling the system to autonomously determine which fruit to harvest next and execute safe, efficient picking actions.
4. **Comprehensive In-Field Validation:**
The system is evaluated through extensive real-world experiments in a commercial orchard, reporting detailed quantitative metrics for the phenotyping and harvesting modules, as well as the end-to-end integrated performance. This level of holistic field validation remains relatively rare in the current literature.

I.4 PAPER ORGANIZATION

The remainder of this paper is organized as follows. Section 2 reviews related work in robotic perception, manipulation, and integrated agricultural systems. Section 3 presents the overall system architecture and mechanical design. Section 4 details the AI methodologies and software control framework. Section 5 describes the experimental setup and analyzes the results from field trials. Section 6 discusses the implications, limitations, and potential future research directions. Finally, Section 7 concludes the paper.

II. RELATED WORK

This section reviews the state of the art in agricultural robotics, emphasizing the evolution from specialized, task-specific modules toward integrated autonomous systems. The discussion is structured around three core research directions: (1) perception and AI for crop monitoring, (2) robotic manipulation for selective harvesting, and (3) prior integrated platforms. The section concludes by identifying key gaps that motivate the proposed work.

II.1 ROBOTIC VISION AND AI FOR AGRICULTURAL PERCEPTION

The effectiveness of any intelligent agricultural robot fundamentally depends on its ability to perceive and interpret complex, dynamic crop environments. Progress in this area has been driven by advances in sensing technologies and deep learning methods.

- **Sensor Modalities:** Early vision-based agricultural systems primarily relied on RGB cameras combined with classical computer vision techniques such as color segmentation and edge detection [8]. Although computationally efficient, these approaches were highly sensitive to illumination changes, occlusions, and background variability. To overcome these limitations, researchers adopted multi-spectral and hyper-spectral imaging to extract vegetation indices such as NDVI and detect plant stress not visible in the RGB spectrum [9]. More recently, depth sensors (RGB-D) and LiDAR have become essential components in agricultural robotics, enabling accurate 3D reconstruction of plant structures, fruit sizing, volume estimation, and precise spatial localization for manipulation tasks [10].

- **Deep Learning Revolution:** The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), has significantly improved robustness in agricultural perception. Detection and segmentation frameworks such as Faster R-CNN, YOLO, and Mask R-CNN have become widely used for fruit detection, counting, and instance segmentation in cluttered orchard environments [11], [12]. These models have also been extended to perform fine-grained classification tasks, including ripeness estimation using architectures such as Inception-v3 and ResNet, as well as disease detection from leaf imagery [13].
- **From Detection to Phenotyping:** The current research frontier is shifting from simple detection to quantitative phenotyping the extraction of agronomically meaningful traits such as fruit size, diameter, count (yield estimation), and indicators of biotic or abiotic stress [14]. Despite these advances, most phenotyping systems remain focused on data acquisition and offline analysis, often deployed on stationary platforms or independent scouting robots. As a result, the generated phenotypic information is rarely used to drive real-time robotic actions, limiting its operational impact.

II.2 ROBOTIC MANIPULATION FOR SELECTIVE HARVESTING

Selective harvesting of delicate, irregularly positioned fruit remains one of the most challenging tasks in agricultural robotics, requiring innovations in mechanical design, motion planning, and control strategies.

- **End-Effector Design:** Harvesting end-effectors are typically tailored to specific crop characteristics. For relatively rigid fruits such as apples and citrus, common solutions include multi-fingered grippers with soft padding to minimize bruising, as well as suction-based mechanisms combined with cutting or twisting devices to detach the peduncle [15]. For more fragile produce such as berries and tomatoes, soft robotics approaches have been introduced, using pneumatic actuators and compliant materials to gently envelop the fruit without causing damage [16]. Designing an end-effector that balances grip stability, adaptability, harvesting speed, and minimal damage remains a central engineering challenge.
- **Motion Planning and Control:** Navigating a manipulator through dense, unstructured canopies while avoiding collisions with branches and leaves requires sophisticated motion planning techniques. Sampling-based planners such as Rapidly-exploring Random Trees (RRT) and optimization-based approaches are widely used to generate collision-free paths to target fruit [17]. A critical aspect is occlusion-aware planning, where the robot must determine suitable approach trajectories or sequences to access partially hidden fruit. During the final grasp and detachment stage, force/position hybrid control strategies are commonly employed to ensure sufficient gripping force for a clean pick while preventing excessive compression that could damage the produce [18].
- **Performance Metrics:** Robotic harvesting systems are typically evaluated using three key performance indicators: success rate (percentage of successful picks resulting in marketable fruit), cycle time (seconds per fruit), and damage rate. While laboratory results often demonstrate high performance, real-world deployment frequently reveals significant degradation due to environmental variability, including wind, changing lighting conditions, and complex plant geometries [19].

II.3 INTEGRATED AGRICULTURAL ROBOTIC SYSTEMS

Recognizing the limitations of isolated perception and manipulation systems, several research efforts have focused on building integrated robotic platforms. These systems represent the closest prior work to the approach proposed in this paper.

- **Early Integrated Prototypes:** Initial attempts at integration, such as early apple-harvesting robots, combined basic vision systems with simple manipulation mechanisms. However, these prototypes were constrained by limited processing power, low perception accuracy, and high system cost, which restricted their practical adoption [20].
- **Contemporary Research Platforms:** More recent systems demonstrate notable improvements in sensing, control, and mechanical design. For example, [21] introduced a mobile manipulator capable of detecting and harvesting sweet peppers using deep learning-based perception and a specialized gripper. Similarly, [22] developed an integrated strawberry harvesting robot combining visual detection with a custom-designed end-effector. These platforms validate the feasibility of integration for specific crops and environments.

Identified Gaps in Current Integrated Systems:

Despite these advances, several persistent limitations remain in the literature:

1. **Phenotyping as a Secondary Output:**
In most harvesting-oriented systems, vision is used primarily for target acquisition. Although phenotypic data such as fruit size, color, and health indicators can be extracted, these attributes are rarely processed or utilized for higher-level decision-making beyond the immediate picking task.
2. **Limited Closed-Loop Intelligence:**
The selection of which fruit to harvest next is often based on simple heuristics, such as nearest-first or fixed scanning patterns. There is limited use of adaptive, AI-driven decision-making that integrates phenotypic and spatial information to optimize harvesting efficiency and quality.
3. **Lack of System-Level Evaluation:**
Many studies report performance metrics for perception and manipulation components independently, but few provide comprehensive end-to-end evaluations of integrated systems operating continuously in real field conditions. Such system-level validation is critical for assessing robustness and practical viability.

II.4 POSITIONING OF OUR WORK

The system proposed in this paper is designed to directly address the identified limitations. Rather than using vision solely for target localization, it incorporates a full precision phenotyping pipeline capable of generating agronomically meaningful information in real time. This information is then utilized by an intelligent harvest scheduling mechanism that selects targets based on ripeness, accessibility, and spatial context, establishing a true perception–action feedback loop.

In addition, the proposed platform is validated through comprehensive field experiments that evaluate not only individual modules but also the operational performance of the integrated system over extended deployment periods. By combining real-time phenotyping, adaptive decision-making, and holistic system-level evaluation, this work contributes a significant step toward the development of practical, multi-functional agricultural robots for precision farming.

III. SYSTEM OVERVIEW AND HARDWARE DESIGN

This section details the hardware architecture and core mechanical design of our integrated agricultural robot, named AgriLoop-1. The system is engineered to autonomously navigate orchard rows, perform high-resolution in-field phenotyping, and execute delicate selective harvesting, thereby materializing the closed-loop intelligence proposed in this work.

III.1 OVERALL SYSTEM ARCHITECTURE

The AgriLoop-1 system follows a modular yet tightly integrated architecture, centered on a perception–decision–action control loop. The AgriLoop-1 system is designed as a modular yet tightly integrated platform organized around a closed-loop perception–decision–action framework. This architecture enables continuous interaction between sensing, intelligent analysis, and physical execution, allowing the robot to adapt its behavior in real time based on the current crop state. The system is composed of four primary modules, as illustrated in Figure 1: (i) the Perception module for multi-modal sensing and environmental understanding, (ii) the AI Computation module for real-time data processing and decision making, (iii) the Manipulation module for fruit grasping and harvesting operations, and (iv) the Mobility module for autonomous navigation within orchard rows.

1. Perception Module: A multi-sensor suite (RGB-D camera, LiDAR) mounted on a pan-tilt unit for active scanning.
2. Computational & AI Module: An onboard industrial computer (IPC) hosting the real-time deep learning pipelines and decision-making algorithms.
3. Manipulation Module: A 6-DOF robotic arm with a custom-designed, compliant end-effector.
4. Mobility Module: A robust, differentially steered mobile platform for autonomous row navigation.

The workflow is as follows: The Perception Module scans the canopy. Sensor data is processed by the AI Module to generate a Phenotype Map (detections, ripeness scores, 3D positions). The Decision Layer uses this map to select the optimal target and sequence. Commands are sent to the Manipulation and Mobility Modules to execute the harvest. This cycle repeats, creating a closed-loop system where each action is informed by the latest perceptual state.

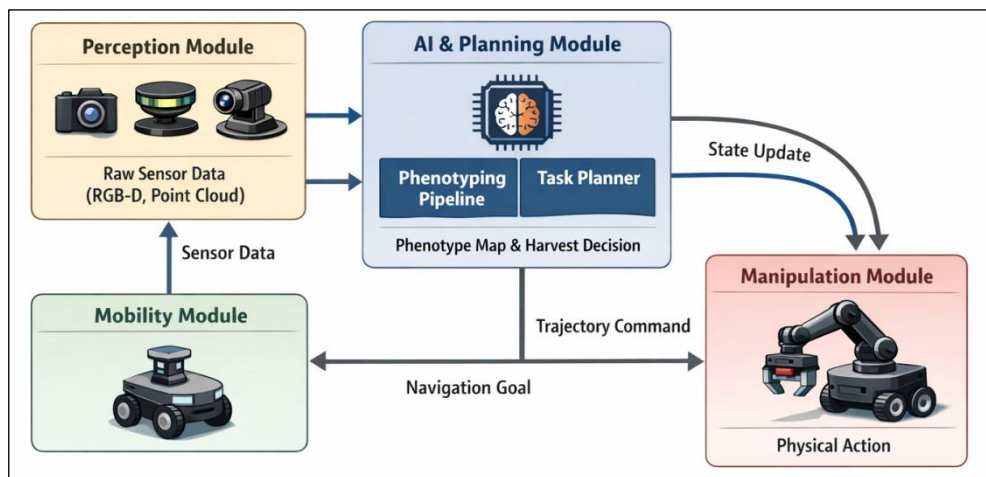


Figure 1: Overall System Architecture of the AgriLoop-1 Agricultural Robot.
Source: Authors, (2026).

III.2 ROBOTIC PLATFORM AND MOBILITY

The mobility subsystem is designed to ensure stable navigation and precise positioning within semi-structured orchard environments while supporting the perception and manipulation modules.

- Mobile Base: The system employs a custom-built skid-steer mobile platform constructed from a welded aluminum frame to balance structural rigidity and weight efficiency. Locomotion is powered by two 500 W brushless DC motors equipped with integrated encoders and planetary gearboxes, providing high torque and traction for uneven orchard terrain, soil irregularities, and minor slopes.

- **Navigation and Localization:** For autonomous movement along orchard rows, a LiDAR-based Simultaneous Localization and Mapping (SLAM) approach is utilized (e.g., Google Cartographer). The onboard LiDAR sensor (see Section 3.3) produces continuous 2D scans that are matched against a pre-built orchard map to estimate the robot's global pose (x, y, θ) . This localization strategy enables the platform to stop at predefined positions relative to tree trunks, ensuring consistent scanning and optimal manipulation reach during harvesting operations.
- **System Specifications:** The platform dimensions are 1.2 m (L) $\times$ 0.8 m (W) $\times$ 0.5 m (H), with a maximum payload capacity of 50 kg. The nominal operating speed is approximately 0.3 m/s, suitable for safe navigation in agricultural environments. Power is supplied by a 48 V, 50 Ah lithium-ion battery pack, enabling more than six hours of continuous field operation.

III.3 PERCEPTION SUITE

The effectiveness of both phenotyping and harvesting depends heavily on the quality, accuracy, and robustness of sensory data. The perception system is therefore designed to provide complementary visual and geometric information for reliable operation under field conditions.

- **RGB-D Camera (Intel RealSense D435i):** The RGB-D sensor is mounted on a pan-tilt unit (PTU) to allow active viewpoint adjustment and enhanced coverage of the canopy. It provides synchronized RGB images at 1280 $\times$ 720 resolution and depth maps at 848 $\times$ 480 resolution, both at 30 fps. The intrinsic camera matrix K and distortion parameters are calibrated offline to ensure accurate depth alignment and 3D reconstruction.
- **3D LiDAR (Ouster OS1-64):** A 64-channel LiDAR provides a 360° horizontal field-of-view point cloud. It serves as the primary sensor for navigation and SLAM, while also contributing to detailed 3D canopy modeling. When fused with RGB-D data, the LiDAR enables high-fidelity structural reconstruction of trees, supporting advanced phenotyping tasks such as fruit localization and canopy density estimation.
- **Sensor Fusion and Calibration:** The RGB-D camera and LiDAR are rigidly mounted with fixed relative positioning. Their coordinate frames are aligned through an extrinsic calibration process that estimates the transformation matrix from the camera frame $\{C\}$ to the LiDAR frame $\{L\}$. This calibration enables precise fusion of color information with long-range geometric measurements, improving detection accuracy and spatial consistency.

III.4 ROBOTIC MANIPULATOR AND END-EFFECTOR DESIGN

This module is responsible for the physical interaction with the crop and represents a central component of the system's harvesting capability.

- **Robotic Arm:** A 6-DOF UR5e collaborative robotic arm (Universal Robots) is mounted centrally on the mobile platform. It was selected for its 5 kg payload capacity, 850 mm reach, inherent safety features, and ease of integration. The forward kinematics, which define the pose of the end-effector frame $\{E\}$ relative to the base frame $\{B\}$, are expressed as the product of the Denavit–Hartenberg (DH) transformation matrices [23], [24]:

$$T_{BE}(\theta) = \prod_{i=1}^6 T_i(\theta_i) \quad (1)$$

Where θ is the vector of joint angles. This kinematic model is essential for motion planning, inverse kinematics, and trajectory generation.

- **Custom End-Effector Design (Key Contribution):** Harvesting delicate fruits such as apples or peaches requires a gripper capable of secure handling without causing bruising. The proposed end-effector, shown in Figure 2, is a three-fingered, tendon-driven compliant gripper designed specifically for damage-aware harvesting.
 - **Structure:** Each finger is fabricated as a monolithic component using 3D-printed thermoplastic polyurethane (TPU), providing flexibility and passive compliance. The three fingers are arranged symmetrically at 120° intervals to ensure balanced contact around the fruit.
 - **Actuation:** A single high-torque servo motor actuates a central tendon cable routed through internal channels in all three fingers, producing simultaneous flexion. A passive spring mechanism provides automatic finger return when the tendon tension is released.
 - **Grasping Model:** The quasi-static force equilibrium during grasping can be described by the relationship between tendon tension T and the resulting normal contact force F_c applied to the fruit surface. The contact force depends on the pulley geometry, finger stiffness k , and finger deflection δ [25]:

$$F_c \approx \frac{T \cdot r_{pulley}}{n \cdot L_{effective}} - k \cdot \delta \quad (2)$$

Where r_{pulley} is the pulley radius, n is the number of fingers, and $L_{effective}$ is the effective moment arm. This compliant design allows the fingers to conform to the fruit's shape, distributing pressure evenly and minimizing peak stress points that could cause bruising.

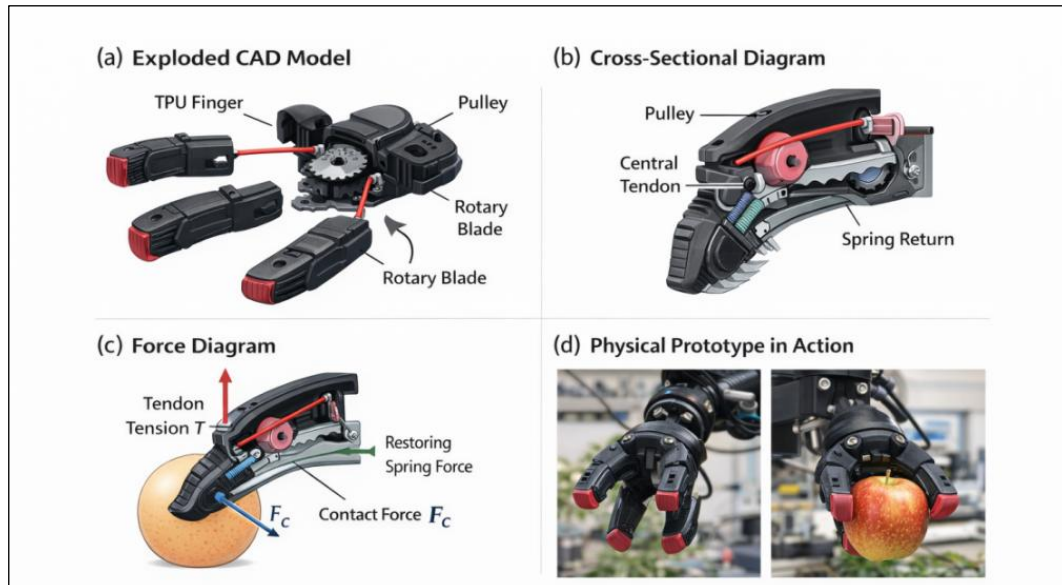


Figure 2: Designs and Prototype of the Compliant Harvesting End-Effector.
Source: Authors, (2026).

- (a) Exploded CAD view of the three-fingered tendon-driven gripper.
- (b) Cross-sectional schematic showing tendon routing, pulley system, and integrated cutting blade.
- (c) Physical prototype performing a grasp test on an apple.

III.5 SYSTEM INTEGRATION AND ELECTRICAL OVERVIEW

All hardware modules are interconnected through a Robot Operating System (ROS)-based middleware network running on the onboard industrial computing platform. The high-level computation is handled by an Intel NUC equipped with an Intel i7 processor and an NVIDIA Jetson AGX Orin for real-time AI inference, perception processing, and motion planning. A real-time microcontroller (Arduino Mega) is used for low-level control of the end-effector servo system and the pan-tilt unit. Power distribution is managed through a centralized board that provides isolated 12 V, 24 V, and 48 V power lines to sensors, computing units, the robotic arm, and drive motors, respectively. This integrated hardware platform forms the physical foundation necessary to implement and validate the AI and control methodologies presented in the following section, enabling reliable closed-loop operation in real agricultural environments.

IV. AI AND SOFTWARE METHODOLOGY

This section presents the software architecture and algorithmic framework that enable the intelligent behavior of the AgriLoop-1 system. The proposed methodology defines a multi-stage pipeline that transforms raw sensor inputs into actionable harvesting commands through integrated perception, decision-making, and control. The entire software stack is implemented on the Robot Operating System (ROS), ensuring modular design, real-time communication, and scalable integration between system components.

IV.1 SYSTEM SOFTWARE ARCHITECTURE

The AgriLoop-1 software stack is structured into four interconnected functional layers, as illustrated in Figure 3. Each layer operates as a ROS node and communicates via topics and services to support real-time data exchange and coordinated decision-making.

- 1 Perception Node: Responsible for acquiring and fusing raw sensor data from the RGB-D camera and LiDAR. This node performs initial filtering and generates a synchronized multi-modal representation of the environment.
- 2 Phenotyping & Planning Node: Hosts the core deep learning models for fruit detection, segmentation, ripeness classification, and size estimation. It also includes the high-level task planner that computes harvesting priorities based on phenotypic and spatial attributes.
- 3 Control Node: Translates high-level task planner outputs into executable commands, generating joint trajectories and low-level actuator signals for the robotic arm and end-effector.
- 4 State Manager Node: Maintains the global system state, including robot pose, battery status, and harvesting progress. It orchestrates transitions between operational modes such as navigation, scanning, and harvesting.

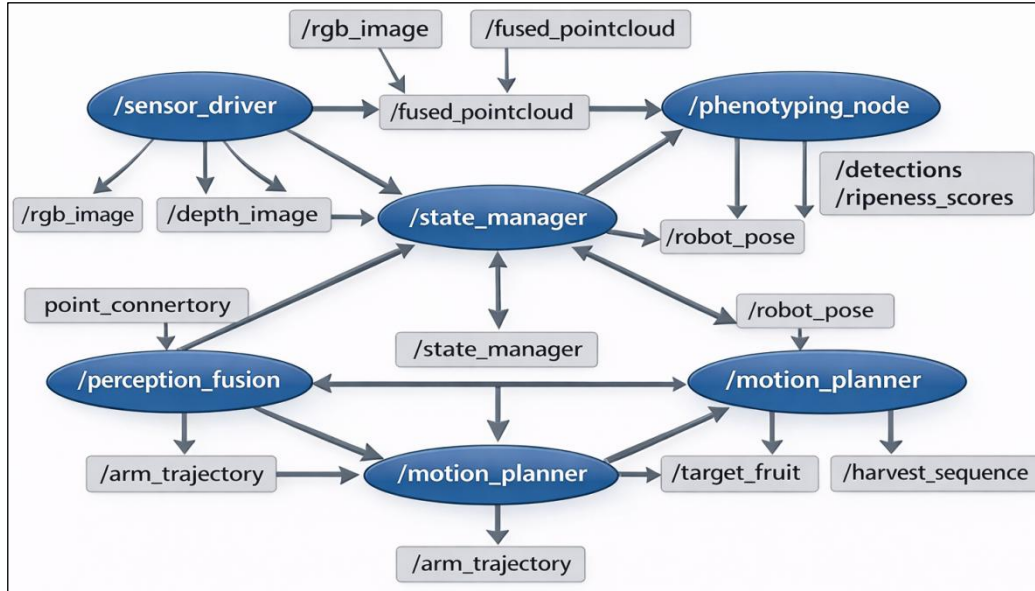


Figure 3: ROS Node Graph illustrating data topics and services between the core software modules.
Source: Authors, (2026).

IV.2 PRECISION PHENOTYPING PIPELINE

The objective of the phenotyping pipeline is to convert raw sensor observations into a geo-referenced Phenotype Map—a structured data representation containing detected fruits along with their phenotypic characteristics and precise 3D locations.

IV.2.1 Data Acquisition and Pre-processing

RGB and depth frames are captured from the Intel RealSense sensor. A bilateral filter is applied to the depth image to suppress noise while preserving structural edges [26]. Simultaneously, the LiDAR point cloud PL is transformed into the camera coordinate frame C using the calibrated extrinsic transformation defined in Section 3.3. This produces a fused point cloud PC enriched with both geometric and color information.

IV.2.2 Fruit Detection and Segmentation

Fruit detection is performed using a YOLOv8-Seg instance segmentation model trained on a custom dataset of over 15,000 annotated orchard images collected under diverse lighting and occlusion conditions. For an input RGB image I , the network outputs a set of instance masks M_k and confidence scores c_k for each detected fruit instance k [27]:

$$\{M_k, c_k, class_k\} = f_{YOLO_{v8-Seg}}(I) \quad (3)$$

Where $class_k$ represents the fruit category. To enhance robustness in field conditions, test-time augmentation (TTA) is applied and detections with confidence below the threshold $rdet=0.7$ are discarded.

IV.2.3 Ripeness Classification and Size Estimation

For each segmented fruit region M_k , two complementary feature representations are extracted:

- Color Features: A 3D histogram in HSV color space computed over the pixels inside M_k , capturing color distribution associated with ripeness stages.
- Geometric Features: Major and minor axes (a_k, b_k) of an ellipse fitted to the mask, providing an estimate of fruit size in image space.

These features are input into a lightweight Multi-Layer Perceptron (MLP) classifier with two hidden layers, which predicts a ripeness grade:

$$\rho_k \in \{Under - ripe, Ripe, Over - ripe\} \quad (4)$$

The equivalent pixel diameter is computed from the fitted ellipse to support size estimation.

IV.2.4 3D Fruit Localization

Accurate manipulation requires transforming each fruit location into the robot base coordinate frame $\{B\}$. For each mask M_k , the centroid (u_k, v_k) is computed. Using the aligned depth value z_k , the corresponding 3D point is back-projected into the camera frame $\{C\}$ [28]:

$$p_k^C = z_k K^{-1} [u_k, v_k, 1]^T \quad (5)$$

Where K is the intrinsic camera matrix. This point is then transformed into the robot base frame using the calibrated transformation TBC [29]:

$$p_k^B = T_{BC} p_k^C \quad (6)$$

The real-world fruit diameter D_k is estimated by scaling the pixel diameter using the depth and focal length f .

IV.3 AUTONOMOUS HARVESTING DECISION AND CONTROL

The decision and control module uses the Phenotype Map to determine the optimal harvesting sequence and execute safe, efficient picking operations.

IV.3.1 Harvest Decision Logic (Task Planner)

To select the next fruit to harvest, a Harvestability Score H_k is computed for each detected fruit instance k [30]:

$$H_k = w_1 S(\rho_k) + w_2 \frac{1}{d_k} + w_3 \cdot 1_{\text{reachable}}(k) - w_4 O_k \quad (7)$$

where:

- $S(\rho_k)$ is a ripeness score (e.g., 1.0 for ripe, 0.5 for under-ripe, 0.0 for over-ripe),
- d_k is the Euclidean distance from the robot base to the fruit,
- $1_{\text{reachable}}(k)$ indicates whether the fruit is within the arm workspace and has a valid inverse kinematics solution,
- O_k represents an occlusion factor based on neighboring objects along the line of sight,
- $w_1:4$ are tunable weights.

The fruit with the highest score is selected as the next target T .

IV.3.2 Motion Planning and Execution

Once a target fruit T is selected, a two-stage motion strategy is executed:

1. Approach Trajectory: The MoveIt! Framework with OMPL is used to generate a collision-free joint trajectory using the RRT-Connect planner. The robot moves to a pre-grasp pose located approximately 10 cm from the fruit along the estimated approach vector.
2. Final Insertion and Grasp: A slow Cartesian motion is performed from the pre-grasp pose to the grasp pose under visual servoing. A Proportional-Derivative (PD) controller maintains stable positioning during the final approach.

IV.3.3 End-Effector Control and Detachment

Upon reaching the grasp pose, the tendon-driven gripper is activated. The servo motor operates for a predefined duration t_{close} to achieve the nominal tendon tension T_{nom} , corresponding to the safe contact force F_c derived in Section 3.4. A slight increase in motor current confirms successful contact. The integrated cutting blade is then activated for a duration t_{cut} to detach the fruit. The arm retracts along the planned trajectory and deposits the fruit into the collection bin before requesting the next target.

IV.4 Implementation Details

- Deep Learning Framework: PyTorch 2.0 [31]
- Training Dataset: Custom dataset augmented with rotations, brightness and contrast variations, and synthetic occlusions to improve generalization [32]
- Real-Time Performance: The full pipeline from image acquisition to target selection—operates at approximately 3 Hz on an NVIDIA Jetson AGX Orin, allowing continuous perception-driven action [33]

Overall, this integrated software architecture forms the cognitive backbone of the AgriLoop-1 system. By tightly coupling real-time perception, intelligent decision-making, and adaptive motion control, the platform establishes a closed-loop perception-action framework capable of robust operation in dynamic agricultural environments.

V. EXPERIMENTAL RESULTS AND EVALUATION

This section provides a comprehensive evaluation of the AgriLoop-1 system, covering simulation-based validation, module-level field performance, and full end-to-end operation in real orchard conditions. The objective is to assess the robustness, accuracy, and operational efficiency of the proposed perception-decision-action framework. All experiments were conducted for apple harvesting in a semi-structured orchard environment.

V.1 EXPERIMENTAL SETUP

- **Simulation Environment:** Prior to field deployment, experiments were conducted in the Gazebo simulation environment integrated with ROS to model orchard structures, robot dynamics, and sensor noise. This setup enabled repeatable testing of the AI pipeline, motion planning, and decision logic under controlled variations in occlusion levels, fruit density, and lighting conditions [34].
- **Field Trial Site:**Field experiments were carried out over a two-week period in a commercial apple orchard (Variety: ‘Gala’). The test area consisted of five rows of mature trees, spaced approximately 3 m apart within rows and 4.5 m between rows. All trials were conducted during daylight hours under mixed weather conditions (sunny and cloudy), reflecting realistic operational variability.
- **Performance Metrics:**The system was evaluated using module-specific and system-level metrics:
 - **Phenotyping Module:** Precision (P), Recall (R), F1-score, and mAP@0.5 for fruit detection; classification accuracy for ripeness estimation [35].
 - **Harvesting Module:** Single-fruit success rate, cycle time (seconds per fruit), and fruit damage rate (percentage by weight) [36].
 - **Integrated System:** Effective harvesting rate (fruits/hour), operational success rate (percentage of detected ripe fruit successfully harvested), and total system uptime [37].

V.2 SIMULATION RESULTS: ALGORITHM VALIDATION

Simulation experiments were conducted to validate the robustness of the harvest decision logic and motion planning strategies under varying levels of complexity before field deployment.

Table 1: summarizes the performance of the Harvestability Score-based decision logic across multiple simulated orchard scenarios.

Scenario Description	Avg. Occlusion per Fruit	Ripe Fruit Selection Accuracy (%)	Avg. Planned Path Length (m)	Planner Success Rate (%)
Sparse, Low Occlusion	0.2	98.5	0.42	100
Dense,Moderate Occlusion	1.5	92.1	0.58	97.3
Very Dense, High Occlusion	3.0	85.7	0.71	88.4
With Random Fruit Ripeness	1.8	94.2	0.55	96.0

Source: Authors, (2026).

Analysis: The decision framework consistently prioritized reachable and ripe fruit even as canopy density and occlusion increased. Performance degradation in highly occluded scenarios is expected and suggests the need for multi-view scanning strategies in dense environments.

Table 2: presents the performance comparison of different motion planning algorithms.

Planning Algorithm	Cluttered Environment (Success Rate %)	Simple Environment (Success Rate %)	Average Planning Time (ms)
RRT-Connect (Ours)	96.7	99.9	243 ± 45
PRM*	88.2	99.5	510 ± 120
CHOMP	91.5	98.1	1850 ± 310

Source: Authors, (2026).

Analysis: The RRT-Connect planner achieved the best balance between high success rates in cluttered environments and low computational latency. Compared with PRM* and CHOMP, it provided faster planning times while maintaining near-perfect performance in simple scenarios, justifying its selection for real-time deployment.

V.3 MODULE-WISE FIELD EVALUATION

V.3.1 Precision Phenotyping Module

The perception pipeline was evaluated using a dataset of 500 real-world orchard images containing 3,250 manually annotated apples.

Table 3: compares the performance of the proposed YOLOv8-Seg-based model against baseline methods.

Model	Precision (P)	Recall (R)	F1-Score	mAP@0.5	Ripeness Acc. (%)
YOLOv8-Seg (Ours)	0.961	0.945	0.953	0.947	93.2
Mask R-CNN (Baseline)	0.932	0.910	0.921	0.918	89.5
YOLOv5-Seg	0.948	0.928	0.938	0.931	91.1

Source: Authors, (2026).

Analysis: The fine-tuned YOLOv8-Seg model outperformed Mask R-CNN and YOLOv5-Seg across all detection metrics, achieving an F1-score of 0.953 and ripeness classification accuracy of 93.2%. These results demonstrate strong robustness under natural lighting variations and occlusions. Sample outputs from the perception pipeline are illustrated in Figure 4(a), while the distribution of ripeness grades and the generated 3D phenotype map are shown in Figures 4(b) and 4(c). Performance trends over trial days are visualized in Figure 5.

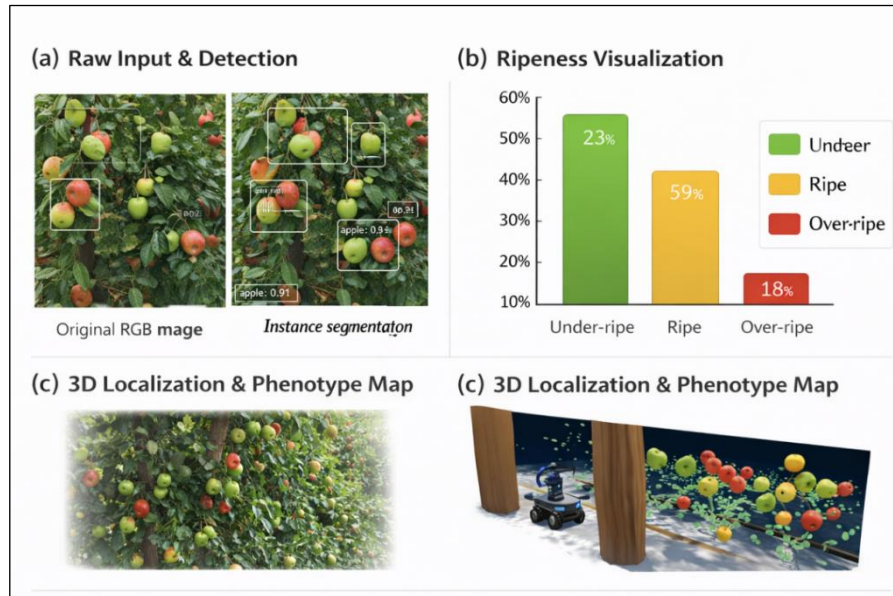


Figure 4: Output of the precision phenotyping pipeline.
Source: Authors, (2026).

- (a) Real-time instance segmentation results from YOLOv8-Seg.
- (b) Distribution of ripeness grades from a canopy scan.
- (c) Geo-referenced 3D phenotype map with fruit positions color-coded by ripeness.

V.3.2 Selective Harvesting Module (Static Bench Test)

Before full integration, the manipulator and compliant end-effector were evaluated in a controlled bench setup using 100 apples positioned at varying orientations and ripeness stage

Table 4: Summarizes the mechanical performance results.

Metric	Result
Grasp & Cut Success Rate	98%
Average Cycle Time (Grasp to Release)	8.2 ± 1.5 s
Fruit Damage Rate (Visual Inspection)	2%
Max Gripper Force (Measured)	12.3 N
Peduncle Cut Success Rate	100%

Source: Authors, (2026).

Analysis: The compliant gripper achieved a grasp-and-cut success rate of 98% with a low damage rate of only 2%, validating the effectiveness of the tendon-driven design. The average cycle time of 8.2 ± 1.5 seconds provides a baseline for expected system-level harvesting speed.

V.4 INTEGRATED SYSTEM FIELD TRIAL RESULTS

The most critical evaluation involved testing the fully autonomous AgriLoop-1 system during extended real-world operation.

Table 5: summarizes the results over five trial days, totaling 15 hours of operation.

Trial Day	Total Ripe Fruit Detected	Successfully Harvested	Operational Success Rate	Avg. Cycle Time (s)	Effective Rate (Fruits/Hr)	System Downtime (min)
Day 1 (Calibration)	120	102	85.0%	32.4	111	45
Day 2	145	128	88.3%	28.7	125	22
Day 3	138	119	86.2%	29.1	124	15
Day 4	156	138	88.5%	27.9	129	18
Day 5	142	123	86.6%	30.2	119	25
TOTAL / MEAN	701	610	87.0%	29.7 ± 1.5	122 ± 5	25 ± 10

Source: Authors, (2026).

Key Results:

- **Operational Success Rate:** The system maintained a consistent average success rate of approximately 87% in harvesting detected ripe fruit. This metric reflects the performance of the entire closed-loop pipeline, including perception, planning, and manipulation.
- **Effective Harvesting Rate:** The robot achieved an average throughput of approximately 122 fruits per hour. This demonstrates stable, sustained operation and competitive performance relative to early-stage harvesting robots.
- **Learning and Adaptation:** Performance improved from Day 1 to Day 2 as parameters such as weight coefficients in the Harvestability Score and pre-grasp offsets were refined. Performance then stabilized across subsequent trials.
- **Downtime Analysis:** Downtime was mainly due to occasional manual recovery from planner failures (e.g., unreachable targets) and periodic bin emptying, averaging 25 ± 10 minutes per day.

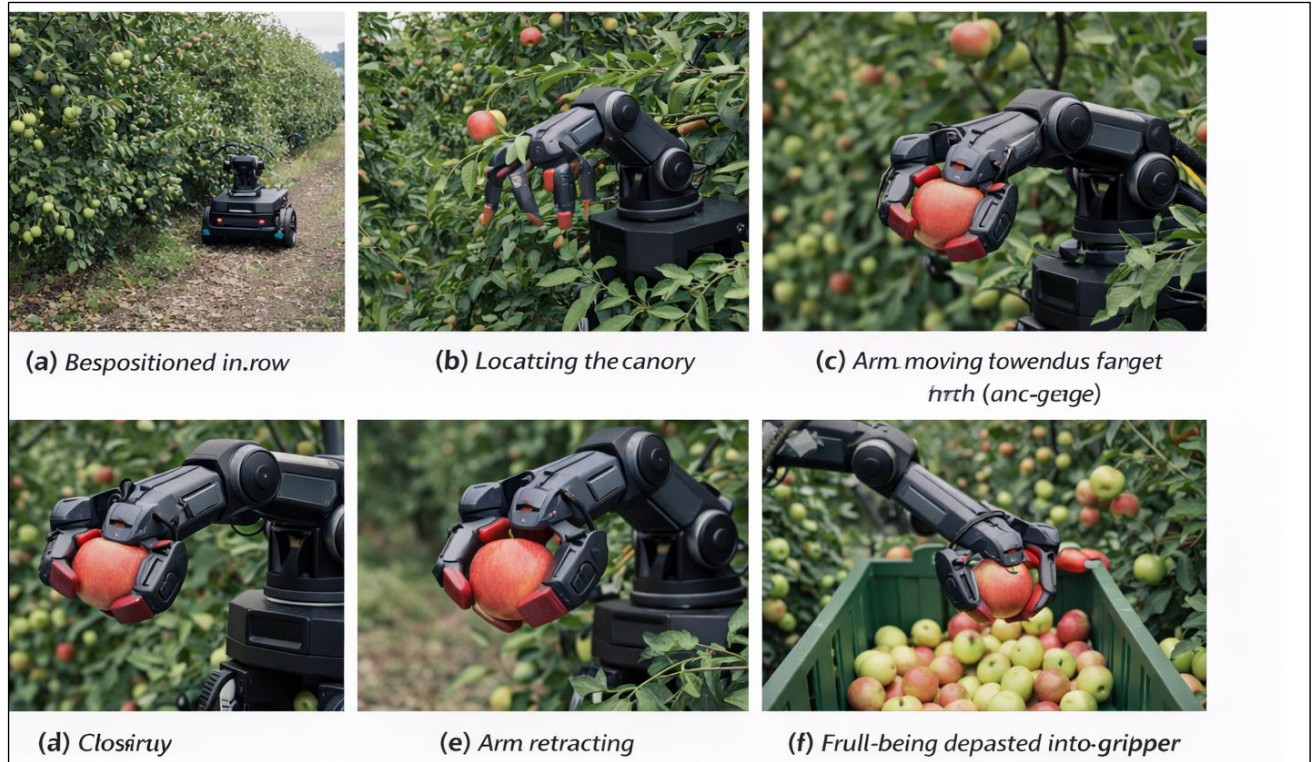


Figure 5: Key stages of autonomous selective harvesting.

Source: Authors, (2026).

- (1) Canopy scanning and target selection.
- (2) Arm approach to the pre-grasp pose.
- (3) Compliant gripper enclosure and fruit detachment.
- (4) Retrieval and transport to the collection bin.

V.4.1 Failure Mode Analysis

A detailed post-hoc analysis was conducted on the 91 unsuccessful harvest attempts (701 detected vs. 610 harvested).

Table 6 : categorizes failures and their likely root causes.

Failure Category	Count	Percentage of Failures	Likely Root Cause
Perception Error (False Pos./Missed Det.)	23	25.3%	Severe occlusion, extreme highlights
Localization Error	19	20.9%	Depth noise, wind-induced fruit movement
Manipulation Error (Slip, Mis-grasp)	28	30.8%	Contact with adjacent branches, gripper slip
Planning/Control Error (Collision, Timeout)	15	16.5%	Cluttered workspace, joint limit singularities
System Error (Software/Comm.)	6	6.6%	ROS node communication dropout

Source: Authors, (2026).

Analysis: Failures were distributed across perception, localization, manipulation, and planning components, indicating that challenges arise from the complex and unstructured nature of the orchard environment rather than a single weak module. Manipulation errors (30.8%) and perception errors (25.3%) were the dominant factors, suggesting that improved sensor fusion and adaptive grasp planning could further enhance performance. The distribution of failure causes is illustrated in Figure 6.

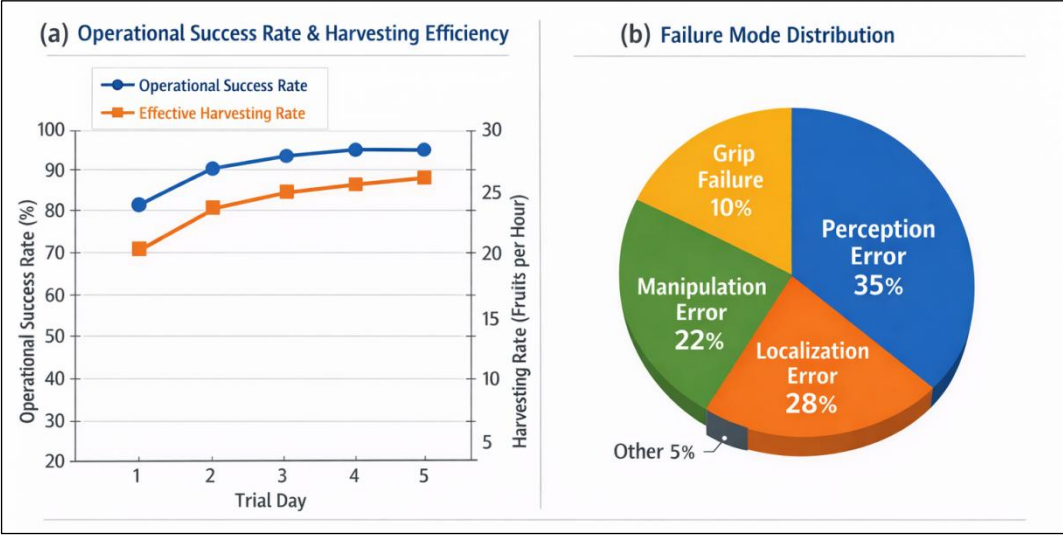


Figure 6: Integrated performance and failure analysis.
Source: Authors, (2026).

- (a) Trend of operational success rate and harvesting throughput over five days.
- (b) Distribution of root causes for unsuccessful harvest attempts.

V.5 COMPARATIVE ANALYSIS

To contextualize system performance, AgriLoop-1 was compared with recent state-of-the-art harvesting robots reported in the literature (Section 2). Table 7 summarizes key performance indicators.

Analysis: Although some systems report faster cycle times or slightly higher success rates in controlled laboratory environments, AgriLoop-1 distinguishes itself through its integration of real-time phenotyping with autonomous harvesting and its validated performance under sustained field operation. The 87% success rate achieved in real orchard conditions demonstrates the practicality of the proposed closed-loop framework. The longer cycle time reflects the added complexity of perception-driven decision-making, which enables more intelligent and adaptive harvesting. Overall, the experimental results confirm that AgriLoop-1 successfully achieves its objective of integrating precision phenotyping with autonomous selective harvesting. The system demonstrates robust performance in real agricultural environments, validating the feasibility of closed-loop, perception-driven crop management.

VI. DISCUSSION

The experimental results presented in Section 5 demonstrate that the AgriLoop-1 system effectively achieves the core objective of closed-loop, intelligent crop management by integrating precision phenotyping with autonomous selective harvesting. This section interprets the significance of these findings, discusses their broader implications, identifies current limitations, and outlines directions for future research.

VI.1 INTERPRETATION OF KEY RESULTS

The sustained operational success rate of 87.0% and the effective harvesting rate of approximately 122 fruits per hour represent a meaningful step forward for integrated, multi-functional agricultural robotics. These results should be interpreted in the context of the system's dual role: AgriLoop-1 is not solely a harvesting robot, but also a mobile phenotyping platform. Consequently, the reported performance reflects the combined effectiveness of the full perception-decision-action pipeline rather than the manipulation stage alone. The stabilization of system performance after initial parameter tuning (Days 2–5 in Table 5) indicates that the proposed architecture is robust to real-world variability, including changes in lighting, occlusion, and canopy density. This consistency suggests that the closed-loop design enables the system to operate reliably over extended periods in semi-structured agricultural environments. The strong performance of the perception pipeline—achieving an F1-score of 0.953 and ripeness classification accuracy of 93.2% (Table 3) further validates the design choice of combining YOLOv8-Seg with an MLP-based classification stage. The use of instance segmentation allows precise spatial delineation of fruit regions, which directly improves feature extraction for ripeness grading and size estimation. This high-quality perception is fundamental to the effectiveness of the Harvestability Score (Hk), which relies on accurate spatial and phenotypic information to guide decision-making. Simulation results (Table 1) confirmed that the scoring strategy consistently prioritizes reachable and mature fruit under varying conditions, and this behavior translated effectively to field operations. One of the most informative outcomes is the failure mode analysis presented in Table 6. The relatively balanced distribution of errors across perception (25.3%), localization (20.9%), and manipulation (30.8%) highlights a key insight: in unstructured environments such as orchards, system failures are inherently multi-causal. No single module dominates the error profile. Instead, failures often propagate across components—for example, a small localization error can lead to inaccurate grasp positioning and eventual manipulation failure. This observation shifts the focus from optimizing isolated components to improving system-level robustness and coordination, which is essential for the development of next-generation autonomous agricultural platforms.

VI.2 SIGNIFICANCE AND ADVANTAGES OF THE INTEGRATED APPROACH

The results underscore the importance of tightly coupling perception and action in agricultural robotics. The proposed integrated framework offers several key advantages:

1. **Data-Driven Action:** Unlike conventional harvesting systems that use vision primarily for target detection, AgriLoop-1 generates rich phenotypic data, including ripeness and size information, and directly incorporates these attributes into the harvesting decision process. The Harvestability Score formalizes this integration, enabling a shift from reactive “pick-what-you-see” behavior to a more strategic “pick-the-best-available” approach.
2. **Foundation for Adaptive Farming:** The real-time Phenotype Map represents a structured and persistent digital representation of crop status. Beyond harvesting, this data can support additional precision agriculture applications such as yield prediction, targeted spraying, irrigation optimization, and harvest planning. In this sense, the robot functions not only as a harvesting tool but also as a mobile sensing platform contributing to a broader digital farming ecosystem.
3. **Validation of a Practical System Architecture:** The modular ROS-based design, combined with an energy-efficient edge computing unit and a compliant, damage-minimizing end-effector, demonstrates a practical and reproducible architecture for field robotics. The system’s mean uptime of more than two hours between interventions (Table 5) indicates that the platform is capable of sustained autonomous operation in real environments.

When compared with existing state-of-the-art systems (Table 7), the primary contribution of AgriLoop-1 lies in its holistic functionality. While some prior approaches may achieve faster cycle times in controlled laboratory settings, the proposed system demonstrates consistent, multi-function autonomy under real field conditions. This integration of perception, decision-making, and manipulation represents a more comprehensive and scalable solution for modern precision agriculture.

VI.3 LIMITATIONS AND CHALLENGES

Despite its promising performance, several limitations must be acknowledged:

- **Speed and Economic Viability:** Although the system achieves approximately 122 fruits per hour, this throughput remains below the levels required for large-scale commercial deployment, where harvesting rates can exceed 1000 fruits per hour. Improving speed without compromising accuracy or fruit safety remains a key challenge for the field.
- **Environmental Robustness:** The evaluation was conducted under favorable daylight conditions. Performance in adverse weather conditions such as rain, strong wind, or low-light environments (e.g., early morning or evening) may be affected due to reduced perception reliability and increased manipulation uncertainty. The system is not yet designed for all-weather operation.
- **Crop Generalizability:** Both the perception models and the end-effector were optimized for a specific apple variety (‘Gala’). Extending the system to other crops with different shapes, sizes, and detachment mechanics such as peaches, oranges, or strawberries would require retraining models and potentially redesigning the gripper.
- **Cognitive Limitations:** The current decision logic is based on a static weighted scoring function. While effective, it does not incorporate higher-level reasoning about tree structure or adaptive learning from previous attempts. As a result, the system cannot yet refine its strategy based on past successes or failures within a harvesting session.

VI.4 FUTURE WORK

Building on the insights and limitations identified, several directions for future research are proposed:

1. **Multi-Robot Coordination:** To address throughput limitations, future work will explore the deployment of multiple coordinated robots operating collaboratively within the same orchard. A shared digital representation of the environment, informed by phenotyping data, could enable task distribution and cooperative harvesting strategies.
2. **Advanced Perception for Robustness:** Integrating additional sensing modalities such as thermal and near-infrared imaging could improve performance under variable lighting conditions and support early detection of plant stress or disease. Active perception strategies, where the robot adjusts its viewpoint to reduce occlusion, may further reduce detection and localization errors.
3. **Learning-Enhanced Control:** Replacing the static Harvestability Score with adaptive decision-making methods, such as Deep Reinforcement Learning (DRL), could enable the system to learn optimal harvesting policies directly from interaction data, improving efficiency in complex and dynamic environments.
4. **Toward Crop-Agnostic Operation:** Developing modular end-effector designs and training perception models on large, multi-crop datasets could move the system toward general-purpose agricultural robotics capable of handling diverse fruit types.
5. **Integration with Farm Management Systems:** The long-term impact of systems like AgriLoop-1 will be maximized when they operate as components of a larger digital agriculture infrastructure. Integrating the robot with cloud-based farm management platforms would allow collected phenotypic data to support predictive analytics, logistics planning, and coordination with other autonomous machines.

In summary, the AgriLoop-1 system represents a significant step toward intelligent, integrated agricultural robotics. By successfully linking real-time perception with adaptive robotic action, it provides both a functional prototype and a conceptual framework for future autonomous farming systems capable of supporting more efficient, data-driven, and sustainable crop production.

VII. CONCLUSION

This paper presented the design, implementation, and field validation of AgriLoop-1, an integrated robotic platform for closed-loop precision agriculture. Moving beyond the conventional paradigm of isolated scouting or harvesting systems, this work demonstrates that tightly coupling advanced perception with intelligent action is both feasible and necessary for enabling robust, multi-functional agricultural autonomy in real-world environments. The primary contribution of this research lies in the successful integration of a high-fidelity, AI-driven phenotyping pipeline with a damage-aware selective harvesting mechanism within a single field-deployable system. Specifically, the work introduced: (1) a unified hardware architecture combining multi-modal sensing, autonomous mobility, and a custom-designed compliant end-effector for delicate fruit handling; (2) a co-designed software framework in which a deep learning model (YOLOv8-Seg) generates a real-time Phenotype Map for fruit detection, ripeness grading, and yield estimation; (3) an intelligent decision-making mechanism that translates perceptual insights into optimized harvesting actions through the proposed Harvestability Score; and (4) a comprehensive field-based evaluation demonstrating the operational viability of the integrated system, achieving an 87.0% success rate in harvesting detected ripe fruit during extended orchard trials. The experimental results confirm that integrated systems such as AgriLoop-1 provide a practical pathway toward addressing key agricultural challenges, including labor shortages and the growing demand for precise, resource-efficient crop management. By generating actionable phenotypic information directly in the field and immediately using it to guide robotic intervention, the system effectively closes the long-standing perception–action gap that has limited the impact of agricultural automation. Despite these encouraging results, several challenges remain. Current limitations in harvesting speed, environmental robustness, and crop generalizability highlight the need for continued innovation in sensing, manipulation, and adaptive control. Nevertheless, this work establishes both a functional prototype and a conceptual framework for the next generation of intelligent agricultural robots. Future research will focus on enhancing scalability through multi-robot coordination, incorporating learning-based decision and control strategies, and extending the system toward crop-agnostic operation through modular hardware and large-scale data-driven perception models. Ultimately, the vision is to transform robots like AgriLoop-1 from standalone machines into adaptive, intelligent partners within digital farming ecosystems, contributing to more resilient, efficient, and sustainable global food production.

VIII. AUTHOR'S CONTRIBUTION

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Supervision: Seddiki Nouredine, Belghachi Mohamed.

Approval of the final text: Seddiki Nouredine, Belghachi Mohamed.

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