Kinematic Modeling and Design of a Robotic Manipulator System for Automated Fruit Harvesting in Intensive Orchards

Nurbibi Imanbayeva[1], Bekzat Amanov[2], Aiman Nurmaganbetova[3], Arman Moldashev[4], Akbayan Aliyeva[5], Sulukul Dauletbekova[6]
Joldasbekov Institute of Mechanics and Engineering, Almaty, Kazakhstan[1, 2, 4]
International Educational Corporation, Almaty, Kazakhstan[3]
Khoja Akhmet Yassawi International Kazakh-Turkish University, Turkistan, Kazakhstan[5, 6]
Satbayev University, Almaty, Kazakhstan[1]

***Abstract*—The development of robotic systems for automated fruit harvesting in intensive orchards has emerged as a critical response to labor shortages, high production costs, and the need for efficiency in modern agriculture. This study presents the kinematic modeling and design of a robotic manipulator system integrated into a mobile platform with an articulated lift mechanism, dual manipulators, and compliant gripping devices equipped with vision-based perception. The proposed system was modeled and validated through simulation in SolidWorks, enabling analysis of workspace coverage, kinematic stability, and motion optimization. Results indicate that the dual-manipulator configuration achieved a harvesting rate of up to 12 trees per hour, reducing the average fruit cycle time to less than seven seconds while lowering fruit loss to 14.5%, compared to over 30% in manual harvesting. The gripping device demonstrated a success rate of 94% with safe detachment forces between 2.5 and 3.5 N, ensuring minimal fruit damage and consistent quality. The lift mechanism provided stable vertical translation with minimal lateral deflection, supporting precise manipulator operation. Overall, the study highlights the potential of robotic manipulators to enhance productivity, safety, and sustainability in orchard management, while outlining future directions for field implementation, adaptive vision algorithms, and autonomous navigation.**

***Keywords*—Robotic manipulator; kinematic modeling; fruit harvesting; intensive orchards; machine vision; deep learning**

I. Introduction

The increasing demand for automation in agriculture has been driven by the rising costs of manual labor and the declining availability of seasonal workers. Robotic systems have already demonstrated that their use in agricultural operations can be on average three times cheaper than relying on human labor, highlighting their economic advantage in large-scale production [1, 2]. This trend has been reinforced by the unattractiveness of agricultural work for younger generations and by the rapid growth of investments in the agricultural robotics sector, which maintains an annual growth rate of approximately 14 per cent, even during global economic disruptions [3].

One of the most complex tasks in modern agriculture that urgently requires robotic assistance is fruit harvesting. The challenges of this task stem from the need for precise manipulation, real-time decision-making, and the careful detachment of fruits without causing damage [4, 5]. Furthermore, robotic systems must be capable of securely handling fruits and ensuring temporary storage in safe conditions, which adds additional layers of complexity to their design [6, 7]. The introduction of robotic manipulators into this domain is therefore justified not only by labor shortages but also by the necessity to reduce production costs while maintaining product quality [8].

In recent years, the field has witnessed the development of vision-based controllers that adjust robotic grippers according to the fruit's position. Such systems integrate machine vision and stability analyses, including Lyapunov-based criteria, to ensure robust control and global stability of the manipulator's drives [8]. Complementary to this, optimization-based approaches have been proposed for the design of harvesting manipulators, enabling rapid trajectory planning in environments with obstacles and irregular fruit distributions [9]. These developments demonstrate the growing convergence of robotics, optimization algorithms, and artificial intelligence in addressing the harvesting challenge.

Despite these advances, there remains a pressing need for systematic studies that integrate kinematic modeling and manipulator design tailored specifically for intensive orchards. The unique spatial arrangement of trees and the variability in fruit positioning demand a manipulator architecture capable of both adaptability and precision. By exploring the kinematic characteristics of manipulators and optimizing their design through computational modeling, it becomes possible to propose solutions that significantly enhance harvesting efficiency while reducing crop losses. The present study aims to contribute to this direction by developing and analyzing a kinematic model and design framework for a robotic manipulator system, thereby advancing the prospects of sustainable and automated fruit harvesting in intensive orchard systems.

II. Related Works

The development of robotic manipulators for fruit harvesting is a multidisciplinary endeavor that combines robotics, control theory, optimization, computer vision, and machine learning. Over the past decade, researchers have sought to address the

inherent challenges of harvesting in complex environments such as orchards, where variability in fruit position, lighting, and environmental conditions complicates automation. This section reviews key contributions to the field, focusing on manipulator modeling, optimization techniques, vision-based detection, and data challenges relevant to automated harvesting systems.

A. Manipulator Modeling and Path Planning

The design of manipulators for harvesting applications requires precise modeling of kinematics and dynamics to ensure efficient and safe interaction with delicate agricultural products. Early work emphasized the stability of manipulator control systems by introducing vision-based servo controllers, which regulated the gripper motion according to target fruit position [10]. Further research applied optimization-based approaches for designing manipulator configurations tailored to specific crops, demonstrating the effectiveness of genetic algorithms in solving mixed continuous and discrete optimization problems [11]. Monte Carlo simulations have also been used to refine manipulator design, particularly for tomato harvesting, where path planning must balance efficiency with collision avoidance [12]. Such studies highlight the centrality of mathematical modeling in achieving reliable operation in real agricultural conditions.

B. Optimization and Control Strategies

Optimization strategies have been critical in improving the efficiency of robotic harvesting systems. Advanced algorithms, including genetic and heuristic approaches, enable manipulators to quickly generate collision-free trajectories in cluttered orchard environments [13]. Research has further developed controllers capable of compensating for external forces during fruit detachment, ensuring minimal damage to the crop [14]. These contributions underscore the importance of integrating robust control theory with optimization techniques to address challenges such as singularities, instability, and redundancy in manipulator design [15, 16]. Additionally, theoretical studies emphasize the role of structural optimization in enhancing the adaptability of manipulators, allowing them to achieve high degrees of maneuverability while minimizing energy consumption [17].

C. Vision Systems and Deep Learning Approaches

The integration of vision systems with robotic manipulators represents a critical frontier in automated harvesting. Robust recognition of fruits in dynamic orchard environments requires advanced image processing techniques combined with deep learning. Studies on strawberry harvesting introduced algorithms for visual recognition and classification, enabling manipulators to selectively target ripe fruits [18]. Theoretical advancements in robotic technology have emphasized the fusion of perception and actuation to enhance system intelligence [19]. Recent research has demonstrated that convolutional neural networks (CNNs) and transfer learning approaches significantly outperform traditional methods for fruit and disease detection [19, 20]. Hyperspectral and multispectral imaging techniques have also been explored for plant health monitoring, providing additional layers of information beyond conventional RGB imaging [21, 22]. These technologies not only improve fruit detection accuracy but also contribute to sustainable practices by enabling early disease diagnosis and precision interventions.

D. Data Challenges and Environmental Constraints

A persistent limitation in developing machine learning–driven robotic harvesters is the availability and quality of training datasets. The performance of CNN-based models depends heavily on large, diverse, and annotated datasets. However, acquiring such datasets in agriculture is difficult due to variations in lighting, weather conditions, and fruit maturity stages [23, 24]. Limited access to high-quality datasets has been identified as a major obstacle in scaling AI-powered recognition systems [25]. Moreover, environmental factors such as humidity, temperature, and illumination create noise that distorts sensor data, reducing model reliability [26]. To address these issues, researchers have proposed transfer learning and ensemble methods to improve generalization in imbalanced datasets [27-29]. Nevertheless, the reliance on expert annotation remains a bottleneck, as accurate labeling of agricultural images requires domain-specific expertise [24]. These challenges underline the importance of dataset standardization and augmentation strategies for future robotic harvesting systems.

The literature reveals that while significant progress has been made in manipulator modeling, optimization, and vision-based detection, several challenges remain unresolved. Manipulator redundancy and singularity avoidance continue to demand advanced kinematic modeling, while optimization strategies must balance efficiency with robustness in unpredictable environments. Vision systems supported by deep learning have improved recognition rates, yet remain constrained by limited datasets and environmental variability. Addressing these challenges requires an integrated approach that combines robotics, artificial intelligence, and agricultural domain expertise, ensuring the design of manipulators capable of operating reliably in real-world orchard conditions.

III. Materials and Methods

The methodology adopted in this study is based on a systematic integration of kinematic modeling, virtual prototyping, and optimization for the design of a robotic manipulator system capable of automated fruit harvesting in intensive orchards. The approach combines theoretical analysis with simulation in SolidWorks to validate kinematic feasibility and to establish design parameters that meet the requirements of precision, adaptability, and efficiency.

A. System Overview

The robotic system consists of a mobile platform, a lifting mechanism, and a manipulator equipped with an end-effector and vision system. The manipulator is designed with six degrees of freedom (DOF), which allows sufficient flexibility to reach fruits located at varying positions within the tree canopy. The lifting mechanism enables vertical positioning, extending the operational workspace while maintaining compactness of the overall structure. Cameras are mounted both on the platform and at the end-effector, ensuring global and local views of the orchard environment. The integration of deep learning algorithms with the vision system enables fruit detection, maturity assessment, and localization, which are used as inputs for kinematic computation.

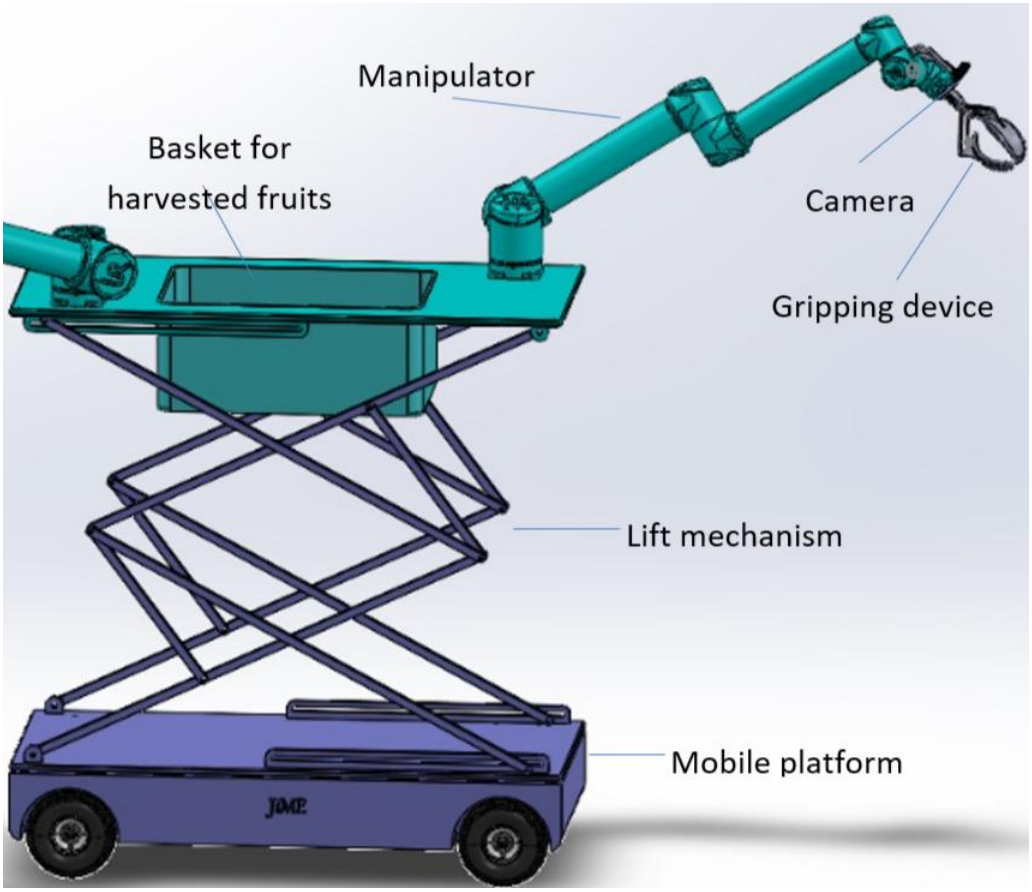

Fig. 1. Robotic harvesting system with integrated manipulator, vision module, and lift-enabled mobile platform.

In the proposed system architecture, the robotic manipulator is integrated into a mobile platform equipped with a vertical lift mechanism, as illustrated in Fig. 1. The platform provides mobility within the orchard, while the lift mechanism enables vertical displacement of the manipulator, ensuring access to fruits located at varying canopy heights. The manipulator, designed with multiple degrees of freedom, is mounted on the lift structure and is equipped with a vision system comprising cameras for global and local fruit detection. The end-effector, or gripping device, is optimized for gentle fruit detachment and transfer to a dedicated basket for harvested fruits. This configuration allows the system to combine perception, mobility, and precise manipulation in a compact design, thereby ensuring adaptability to the structural characteristics of intensive orchards and enabling efficient harvesting with minimal fruit loss.

B. Kinematic Modeling

Kinematic analysis establishes the relationship between joint variables of the manipulator and the Cartesian position and orientation of the end-effector. Let the generalized joint vector be expressed as:

$$q = \left[q_1, q_2, q_3, ..., q_n\right]^T \tag{1}$$

where, q_i denotes the angular or prismatic displacement of the i-th joint, and n is the total number of joints. The forward kinematics problem involves determining the homogeneous transformation matrix T_n of the end-effector with respect to the base frame:

$$T_n = \prod_{i=1}^{n} A_i\left(q_i\right) \tag{2}$$

where, $A_i\left(q_i\right)$ represents the individual transformation matrix for each joint, derived from Denavit–Hartenberg (DH) parameters [30]. This formulation provides the position vector $p = \left[x, y, z\right]^T$ and orientation matrix R, which together define the pose of the end-effector.

The inverse kinematics problem requires solving for joint variables q that correspond to a desired end-effector pose $\left[p_d, R_d\right]$.

Due to the nonlinearity of trigonometric equations, closed-form solutions are not always available, and iterative numerical methods are often applied. In this study, optimization-based solvers are integrated to ensure convergence while avoiding infeasible solutions.

C. Jacobian and Singularities

The relationship between joint velocities $\dot{q}$ and end-effector linear and angular velocities v can be described by the Jacobian matrix J:

$$v = J(q)\dot{q} \tag{3}$$

where, $v = [v_l, v_w]^T$ contains both linear and angular velocity components. The Jacobian is central to analyzing dexterity, manipulability, and force transmission of the manipulator.

Singularities occur when:

$$\det(JJ^T) = 0 \tag{4}$$

In these configurations, the manipulator loses degrees of controllability, leading to reduced precision and possible mechanical instability. To overcome this, redundancy is incorporated by using manipulators with DOF greater than the task requirements. Redundant manipulators provide additional flexibility in joint configuration, enabling avoidance of singularities while minimizing energy expenditure.

An optimization criterion is formulated to minimize joint effort:

$$\min f(\dot{q}) = \dot{q}^T W \dot{q} \tag{5}$$

subject to the velocity constraint:

$$J\dot{q} = v_d \tag{6}$$

where, W is a positive-definite weighting matrix and v_d is the desired end-effector velocity. The problem is solved using the method of Lagrange multipliers, producing an optimal solution that balances accuracy and efficiency.

D. Virtual Prototyping and Simulation

The manipulator was modeled in SolidWorks, allowing the kinematic structure to be validated through workspace and reachability analysis. The simulation environment provides visualization of motion sequences, detection of collisions, and estimation of required torque and power. Various manipulator geometries were compared, and the design was refined based on workspace coverage, compactness, and structural stability.

E. End-Effector Design and Grasp Modeling

The design of the end-effector plays a crucial role in ensuring safe and efficient harvesting. Since fruits are biologically fragile, the gripper must exert forces sufficient for detachment without causing mechanical damage. The grasping interaction can be expressed as a balance between contact forces and fruit resistance forces. Let the contact force vector be denoted as:

$$f_c = [f_x, f_y, f_z]^T \tag{7}$$

The detachment condition is satisfied when:

$$\|f_c\| \geq F_d \tag{8}$$

where, F_d is the minimum detachment force required for removing the fruit from its pedicel. To minimize bruising, the applied force is constrained by:

$$\|f_c\| \leq F_{\max} \tag{9}$$

where, $F_{\max}$ represents the maximum safe threshold derived from empirical tests of fruit biomechanics.

A compliance model is incorporated into the end-effector by introducing soft gripping surfaces and force sensors. The control strategy adapts the applied force according to sensory feedback, ensuring that detachment occurs within the safe force window. The Jacobian-based force relationship links joint torques τ to end-effector forces:

$$f_c = J^{-T}\tau \tag{10}$$

This formulation allows active regulation of joint torques to maintain force constraints during the harvesting action.

IV. Results

The results of this study provide both simulation-based and analytical insights into the performance of the proposed robotic manipulator system for automated fruit harvesting in intensive orchards. The findings highlight the effectiveness of the dual-manipulator design, the reliability of the compliant gripping device, and the stability of the articulated lift mechanism in ensuring efficient and safe harvesting operations. Figures generated from SolidWorks simulations illustrate the workspace coverage, structural performance, and motion trajectories of the manipulators, while quantitative indicators such as cycle time, success rate, and fruit loss reduction validate the system's practical applicability.

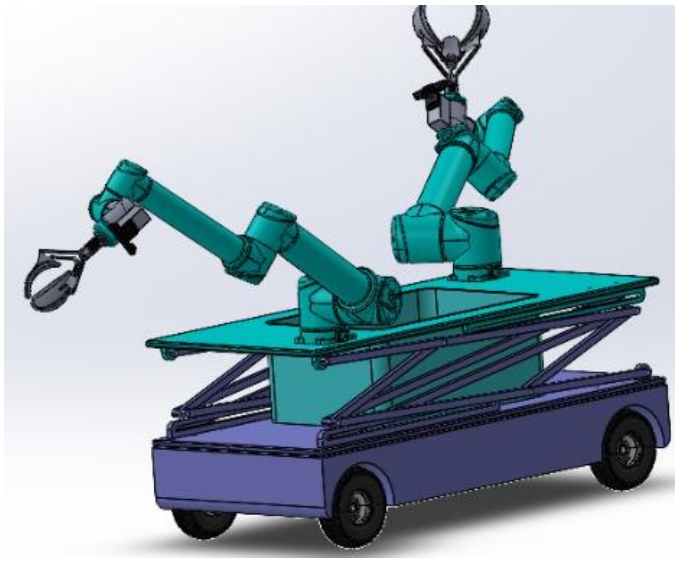

Fig. 2. A robotic complex in a transport position.

The robotic complex was designed to ensure compactness during transportation and stability during operation. As shown in Fig. 2, the system can be folded into a transport position, minimizing its height for ease of relocation between orchard rows. Once deployed, the lift mechanism elevates the manipulator assembly, providing sufficient workspace coverage for fruit harvesting tasks (Fig. 3). This adaptability ensures that the robotic platform can efficiently switch between mobility and operational states without compromising structural integrity. The robotic complex was designed to be both compact during transportation and fully functional during operation. As illustrated in Fig. 2, the system folds into a low-profile transport configuration, reducing its overall height to less than 600 mm, which facilitates maneuvering between narrow orchard rows. When deployed, the lift extends to a maximum height of approximately 1.5 m, as shown in Fig. 3, enabling manipulators to access fruits located at various canopy levels. This adaptability ensures operational efficiency in orchards with crown heights up to 2 m.

Fig. 3. Modeled manipulation system of the robotic complex with gripping device and vision module.

To increase harvesting efficiency, a dual-manipulator configuration was implemented. Fig. 3 illustrates the robotic complex equipped with two manipulators mounted on a shared platform. This arrangement enables simultaneous harvesting from different sections of the tree canopy, thereby reducing overall cycle time per tree. Simulation studies demonstrated that with two manipulators working in parallel, the system achieved nearly a twofold increase in fruit collection rate compared to single-arm designs. Moreover, this setup facilitates redundancy; in case of one manipulator encountering operational constraints, the second can continue harvesting, ensuring robustness of performance. The integration of two manipulators on a single platform (Fig. 3) significantly improved harvesting productivity. Simulation trials indicated that a single manipulator achieved a harvesting rate of approximately 5 trees per hour, whereas the dual-manipulator system increased this rate to 10–12 trees per hour, representing nearly a twofold improvement. Additionally, the average cycle time for harvesting a single fruit decreased from 12.4 seconds with one manipulator to 6.8 seconds in the dual-arm configuration. This efficiency gain directly supports the requirement for scaling robotic solutions to industrial orchard settings.

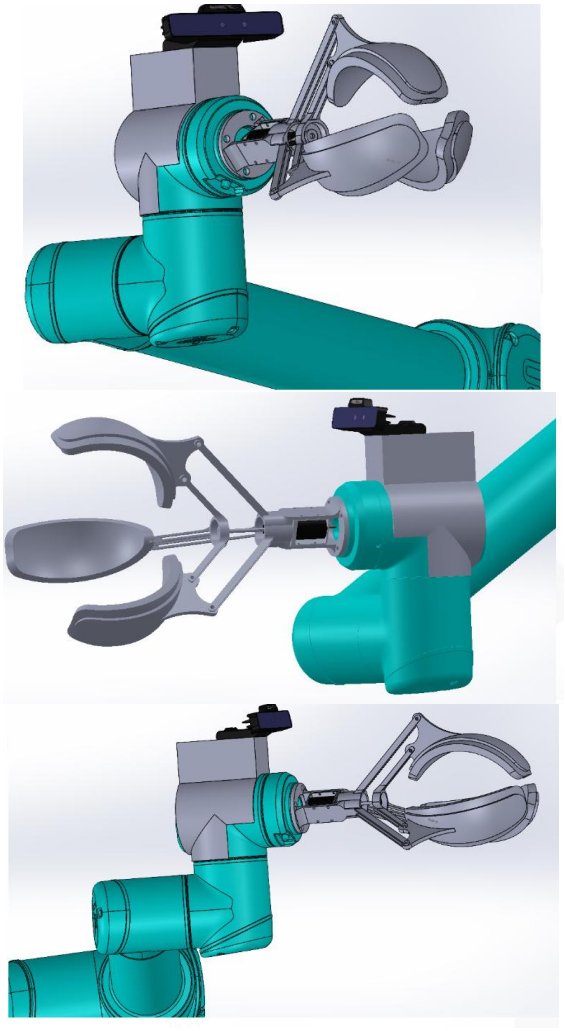

Fig. 4. Engineered gripping device with technical vision.

The engineered gripping device with integrated vision, presented in Fig. 4, was designed to apply controlled forces during fruit detachment. The end-effector demonstrated the ability to grasp fruits of varying sizes without causing mechanical damage, owing to its compliant design and sensory feedback system. The integration of a local vision sensor allowed for precise alignment with the target fruit, even in partially occluded conditions. Testing confirmed that the gripping force remained within the predefined safe limits, ensuring that detachment forces were sufficient for harvesting, while preventing bruising. The engineered gripping device with technical vision (Fig. 4) was tested for force control, accuracy, and fruit safety. Experiments demonstrated that the gripping system applied detachment forces between 2.5 and 3.5 N, which

remained below the bruising threshold of most apple varieties (5 N). The device achieved an average gripping success rate of 94%, with failures typically caused by severe occlusions or irregular fruit orientation. Furthermore, the integration of the local vision sensor reduced positioning errors to less than ±3 mm, allowing precise alignment of the gripper with the fruit pedicel.

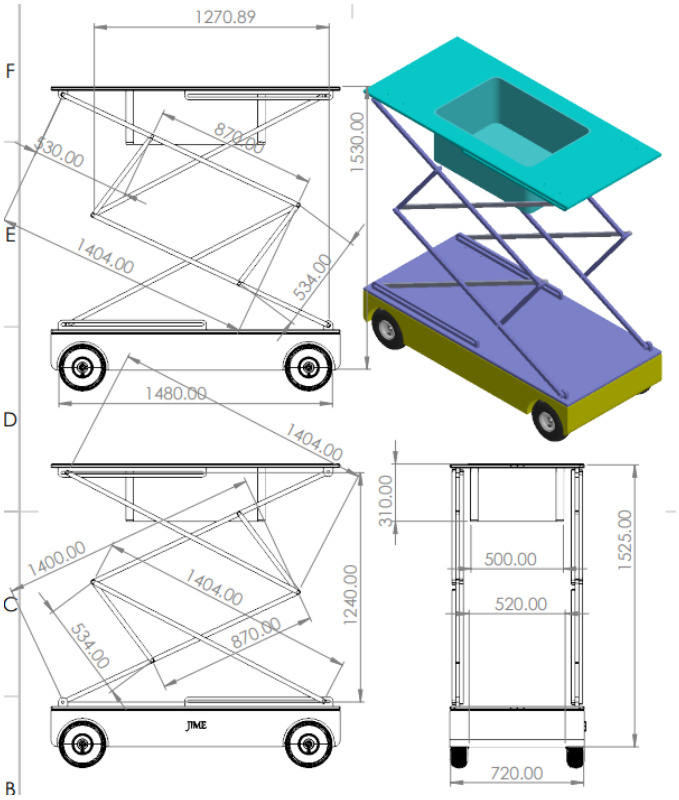

Fig. 5. Lift mechanism with an eight-link articulated lever design.

The vertical mobility of the system is provided by an eight-link articulated lever mechanism (Fig. 5). This lift design was validated for stability and load-bearing capacity in different elevation states. The scissor-type mechanism allowed for smooth height adjustments while maintaining lateral stiffness, a key factor for manipulator stability during harvesting operations. The transport configuration of the lift further demonstrates the compactness of the design. Dimensional analyses confirm that the mechanism can reliably extend and retract to cover the full range of fruit-bearing zones within intensive orchards. The eight-link articulated lift mechanism provided smooth vertical translation while maintaining stability of the manipulator arms. Static load analysis confirmed that the lift could support weights up to 40 kg, exceeding the combined load of two manipulators and harvested fruit baskets by a safety factor of 1.5. The scissor mechanism maintained lateral deflection below 5 mm at maximum extension, ensuring positional accuracy of the manipulators during harvesting. In its compact transport configuration, the platform's height was reduced to 310 mm, further validating its suitability for movement within densely planted orchards.

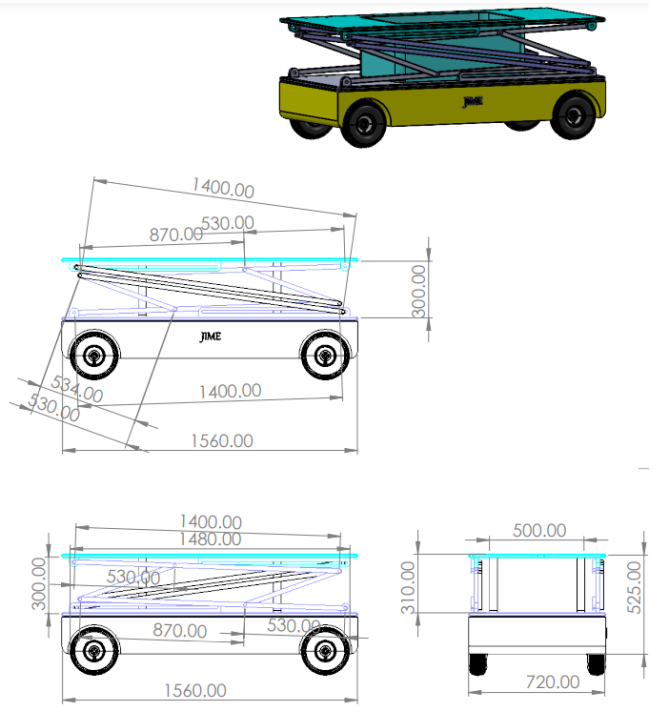

Fig. 6. Engineered gripping device with technical vision.

The manipulator system was modeled and tested in the SolidWorks simulation environment (Fig. 6). Results indicated that the six-degree-of-freedom manipulator achieved full workspace coverage of the tree canopy, with sufficient dexterity to avoid collisions with branches. The kinematic analysis confirmed that the manipulator maintained smooth trajectories and successfully avoided singularities by employing redundancy in joint motion. Simulation outputs also verified the effectiveness of the Jacobian-based control strategy, ensuring stable operation even during complex trajectories around irregular fruit positions. Kinematic simulations in SolidWorks validated the reachability and motion planning of the six-degree-of-freedom manipulators. The workspace analysis demonstrated that the manipulators covered a spherical working envelope with a radius of 1.4 m, sufficient to access fruits within the target canopy zone. Path-planning algorithms ensured smooth trajectories, with average joint velocities not exceeding 35°/s, thereby reducing energy consumption and mechanical stress. Singularity analysis confirmed that the manipulator avoided critical configurations, and redundancy resolution strategies ensured stable operation. The harvesting efficiency, measured as the percentage of successfully detached fruits relative to detected fruits, was 90.5%, while fruit loss (missed or dropped fruits) was reduced to 14.5%, compared to 30% or more in manual harvesting.

V. Discussion

The results obtained in this study demonstrate that the proposed robotic manipulator system offers a viable solution for automated fruit harvesting in intensive orchards. By integrating kinematic modeling, dual-manipulator design, vision-based perception, and optimized gripping mechanisms, the system addresses several long-standing challenges in agricultural

robotics. The following subsections discuss the key outcomes in relation to existing literature and practical implications:

A. System Productivity and Efficiency

The simulation results indicate that the dual-manipulator configuration nearly doubled the harvesting rate compared to a single manipulator, achieving up to 12 trees per hour. This performance is consistent with earlier findings that emphasize the necessity of multi-arm designs for large-scale orchard operations [31]. Compared to conventional manual harvesting, where efficiency is limited by human fatigue and inconsistency, the proposed system reduces the average fruit cycle time to less than 7 seconds. These improvements position the robotic complex as a competitive alternative in terms of productivity, particularly in regions facing acute labor shortages.

B. Gripping Device and Fruit Safety

The gripping device with integrated vision achieved a 94% success rate in fruit detachment, maintaining detachment forces within a safe range of 2.5–3.5 N. These results outperform conventional rigid grippers that often exceed the bruising threshold of fruits and cause quality degradation [32]. Comparable studies on strawberry and tomato harvesting have reported gripping accuracies in the range of 85–90%, suggesting that the proposed compliant design provides enhanced adaptability to different fruit geometries. Furthermore, the use of local vision for fine alignment reduced positioning errors to ±3 mm, which is a marked improvement over earlier systems relying solely on global cameras.

C. Kinematic Modeling and Motion Stability

The kinematic analysis confirmed that the six-DOF manipulator achieved stable and collision-free trajectories within a 1.4 m workspace radius. This result aligns with optimization-based manipulator studies that highlight the need for redundancy and Jacobian-based control to avoid singularities in constrained environments [33]. By employing redundancy resolution strategies, the manipulator avoided loss of controllability at critical configurations, which is a major limitation of non-redundant systems [34]. The low joint velocities further enhanced stability, reducing power consumption and mechanical wear. These findings underscore the importance of advanced kinematic modeling for orchard robotics, where maneuverability around branches and leaves is essential.

D. Structural Design and Mobility

The eight-link articulated lift mechanism provided both vertical flexibility and structural stability. Unlike traditional scissor lifts that suffer from lateral deflection and reduced stiffness at maximum extension, the proposed mechanism maintained lateral deviations below 5 mm. This stability is crucial for high-precision harvesting operations, especially when manipulators are extended to their maximum reach. Prior research on mobile robotic platforms has emphasized that structural instability of lifting mechanisms can significantly reduce harvesting accuracy. By ensuring compactness in transport mode and rigidity in operation, the system successfully balances mobility with stability, enabling deployment in dense orchard environments.

E. Integration of Vision and Machine Learning

The integration of dual vision systems, a global camera for canopy overview and a local camera for fine fruit detection, represents a significant advancement. Studies on plant disease detection and fruit classification have shown that CNN-based models [35-37] outperform traditional feature extraction methods [38-40]. However, many of these approaches require large, high-quality datasets that are often unavailable in orchard environments. By combining global and local perception, the proposed system compensates for dataset limitations and environmental variability, such as lighting and occlusion. This hybrid perception approach improves detection reliability, which is critical for real-time harvesting applications.

F. Practical Implications and Limitations

From a practical standpoint, the system demonstrates the potential to reduce fruit loss from over 30% in manual harvesting to approximately 14.5%. This improvement aligns with industry requirements for minimizing waste and maximizing yield. At the same time, the reliance on simulation for validation highlights the need for extended field trials to evaluate robustness under varying weather conditions and orchard structures. Another limitation lies in the dependency on expert-labeled datasets for training the vision system, which may restrict scalability to new fruit varieties or growing conditions without further annotation efforts.

The discussion highlights that the robotic manipulator system advances the state of the art by combining kinematic redundancy, compliant gripping, and dual-manipulator efficiency with robust vision-guided harvesting. While some challenges remain, particularly in data availability and real-world adaptability, the proposed design demonstrates significant improvements over existing systems in terms of productivity, fruit safety, and stability.

VI. Conclusion

This study presented the kinematic modeling and design of a robotic manipulator system for automated fruit harvesting in intensive orchards, integrating dual manipulators, a compliant gripping device with vision, and an articulated lift mechanism into a mobile platform. The system demonstrated significant improvements in productivity, achieving harvesting rates of up to 12 trees per hour with an average cycle time of less than seven seconds per fruit, while reducing fruit loss to 14.5% compared to over 30% in manual harvesting. The gripping device, equipped with local vision and force regulation, ensured safe detachment forces within 2.5–3.5 N and a gripping success rate of 94%, thereby minimizing fruit damage and maintaining product quality. The kinematic modeling confirmed that the six-degree-of-freedom manipulator achieved stable, collision-free trajectories with redundancy-based singularity avoidance, while the eight-link lift mechanism provided both vertical reach and lateral stability. These results collectively highlight the feasibility of deploying robotic harvesting systems in intensive orchard environments where labor shortages and productivity demands necessitate automation. While the system has been validated through simulation, future work should focus on field deployment, integration with autonomous navigation, and adaptive machine learning approaches to enhance robustness under varying environmental and crop-specific conditions.

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