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Finite element optimization of a flexible fin-ray-based soft robotic gripper for scalable fruit harvesting and manipulation ☆

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ABSTRACT

On the path to achieving fully autonomous farming, the use of grasping devices for fruit picking and handling remains an open challenge. Current solutions are designed for specific fruits and robot manipulators, often without considering the intrinsic interaction between the gripper's fingers and the fruit. This work explores the use of fin-ray-based flexible grippers, which mimic human fruit-picking movements, for harvesting and pick-and-place operations involving medium-sized fruits. Optimal gripper characteristics were determined through a Finite Element Analysis methodology. To achieve the harvesting objective, the grippers were integrated into a vision-based system and a robotic manipulator, with testing conducted under laboratory conditions. The harvesting study focused on apples, while the manipulation task was tested with apples, oranges, and lemons. The findings indicate that while all grippers demonstrated a suitable performance, one particular design emerged as the most effective, meeting all criteria and outperforming the others in experiments and performance metrics.

1. Introduction

The field of robotics is increasingly vital in addressing real-world challenges at an unprecedented pace. The global population, estimated at 7.8 billion in 2020, is projected to reach 9.7 billion by 2050 [1]. This growth necessitates a significant increase in food production to ensure global food security, with studies indicating that global food demand will double by 2050 compared to 2009 levels [2]. To meet this rising demand, advancements in agricultural practices, such as precision agriculture, are being explored to ensure sustainable food production [3]. Within precision agriculture, automation and robotics have emerged as key technologies for reducing environmental impact while optimizing agricultural yield [4]. However, the application of robotics in agriculture, particularly in managing arboreal crops where robots must handle fruits, remains a significant challenge.

Several prior studies have explored the use of robotics and autonomous systems in agricultural applications, including seed planting and crop harvesting [5–8]. For example, [9] introduced a smartphone-controlled robot capable of automated seed planting in designated locations while authors in [10] designed an autonomous drone for seed sowing in paddy fields, with an incorporated autopilot and a global positioning system (GPS) for navigation. Additionally, Jia et al. [11] implemented an apple harvester prototype based on a machine learning approach using an RGBD camera for accurate fruit detection and localisation. The authors used a custom-built three degrees of freedom manipulator for fruit picking supported by a vacuum end-effector for gentle apple removal from the tree. Additionally, a nonlinear control scheme ensures accurate and agile manipulator movements. A similar approach for harvesting citrus fruits like oranges is presented in Yin et al. [12]. Their system employs a fully autonomous solution that leverages fused simultaneous localization and mapping (SLAM) algorithms from various sensors, achieving precise localization and navigation within the orchard. For fruit picking, the authors developed a custom-built end effector, which achieved high success rates during field testing.

Most existing robotic grippers for agricultural applications are designed for specific fruits, with solutions tailored to strawberries [13], oranges Yin et al. [12], and apples [14]. While these designs demonstrate effectiveness for their target produce, they lack adaptability for handling fruits of varying sizes, shapes, and textures, highlighting the

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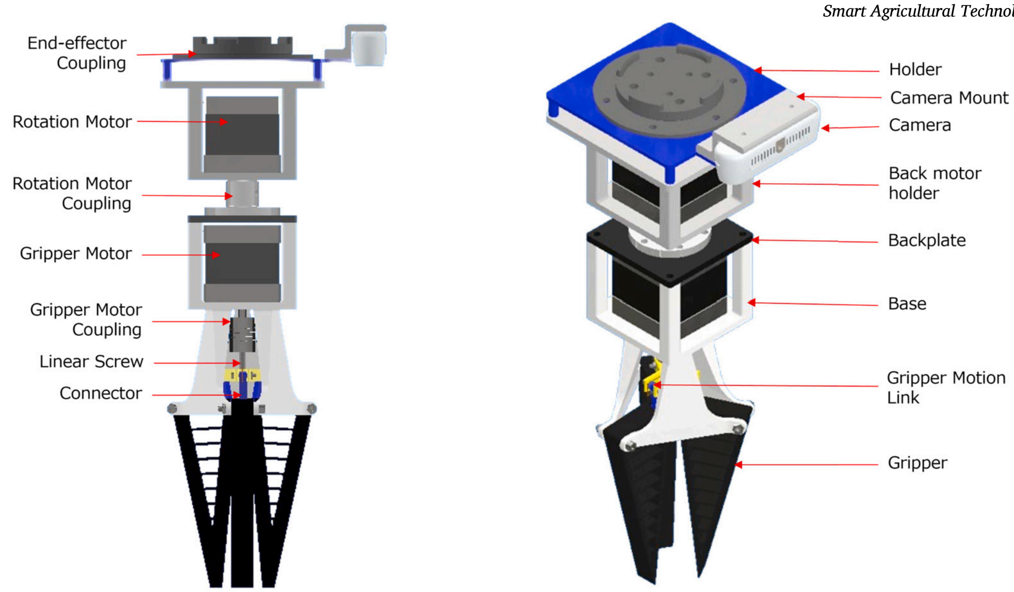


Fig. 1. Mechanical design of the proposed robot end-effector for fruit harvesting.

need for a more scalable solution capable of accommodating diverse harvesting scenarios.

As the agricultural sector increasingly relies on technology, soft robotic grippers have gained traction in agriculture, specifically for delicate tasks such as fruit harvesting, where fragility and variability of the produce are key challenges. However, most solutions lack scalability and adaptability. Current research has introduced various designs with limited applicability beyond specific tasks or fruit types [15,16].

Finite Element Analysis (FEA) has proven to be a powerful tool in optimizing soft robotic designs [17]. For instance, Wang and Hirai [18] applied FEA to soft pneumatic actuators, showing how mathematical modelling can improve deformation predictability and material performance under varying conditions. Similarly, Prasad et al. [19] used FEA to optimize the stiffness of soft grippers, providing key insights into the influence of material properties and geometry on grasp performance. These studies highlight the utility of FEA in enhancing the adaptability and efficiency of soft grippers in real-world scenarios.

The use of flexible materials in soft robotics has grown significantly, especially with the advent of advanced manufacturing techniques. Grippers based on flexible materials, like silicone or soft polymers, are particularly suited for tasks requiring adaptability and gentle handling [20], as demonstrated by Chen et al. [21] in their study on fin-ray grippers for apple harvesting. However, scalability across different types of fruits (e.g., varying sizes, textures) remains underexplored. Recent advancements in flexible materials and 3D printing techniques have opened new possibilities for designing grippers that can handle a wide variety of fruits with consistent performance [22,23]. Nevertheless, current studies often focus on single fruit types, and the flexibility of designs across multiple fruit handling tasks and operations are yet to be fully validated Elfferich et al. [24].

While prior research has demonstrated the effectiveness of soft grippers, significant limitations persist. Many existing designs focus on active systems (e.g., pneumatic actuators), which add complexity and cost, making them less suitable for scalable agricultural solutions [25]. In contrast, passive designs, such as those based on the fin-ray effect, offer simpler and potentially more scalable solutions. Pfaff et al. [26] explored the fin-ray design in robotic gripping, emphasizing its potential for handling delicate objects with minimal damage. However, this approach remains underexplored for diverse fruit types and varying conditions, underscoring a gap in scalability across different agricultural environments.

To address these challenges, the presented work focuses on the design and development of an adaptive gripper for harvesting and manipulation medium-sized fruits, such as apples, oranges, and lemons, and its integration with a robotic arm to establish a vision-based control system. This work advances beyond the state of the art by addressing key limitations in existing soft gripper designs and focusing on a scalable solution through FEA. Unlike prior research that primarily targets specific fruits or task-specific grippers, our approach employs FEA to systematically optimize the gripper design, considering both material properties and geometric configurations. This ensures adaptability across various fruit types and harvesting conditions.

The optimized fin-ray grippers are integrated into a vision-based robotic system, enhancing automation by enabling precise control during both harvesting and pick-and-place operations. We demonstrate the gripper's effectiveness not only in harvesting apples but also in handling oranges and lemons, overcoming scalability limitations noted in earlier studies such as Chen et al. [21]. Moreover, this research provides a quantitative evaluation of the gripper's performance in laboratory conditions, verified through numerical methods and experimental testing with real-world fruit samples. These advances lay the groundwork for future real-world testing and potential field deployment.

This work is organised as follows. The tools and methodology used to develop the system, as well as the architecture and control mechanism for the robot and electronics parts are discussed in Section 2. Following that, Section 3 mentions the testing protocol together with experimental results and observations. Finally, Section 4 concludes the paper by summarizing the findings and outlining potential future research directions.

2. Materials and methods

This study proposes the development of a novel robotic 3-finger gripper for fruit harvesting. The gripper design incorporates flexible materials aimed at minimising fruit damage. More specifically, the gripper mechanism utilizes 3D-printed components controlled by an Arduino-based electronic system. This combination allows for precise control and integration of sensing capabilities. Manufacture of the grippers utilizes Thermoplastic Polyurethanes (TPU). Furthermore, the system is interfaced with a robot and employs vision-based control for fruit detection and harvesting, significantly improving its accuracy and efficiency.

2.1. Mechanical design of the robot end-effector

The mechanical design of the robot end-effector, as shown in Fig. 1, features three fin-ray fingers mounted on a fixed base, forming the gripper. This base also houses the gripper motor, responsible for opening

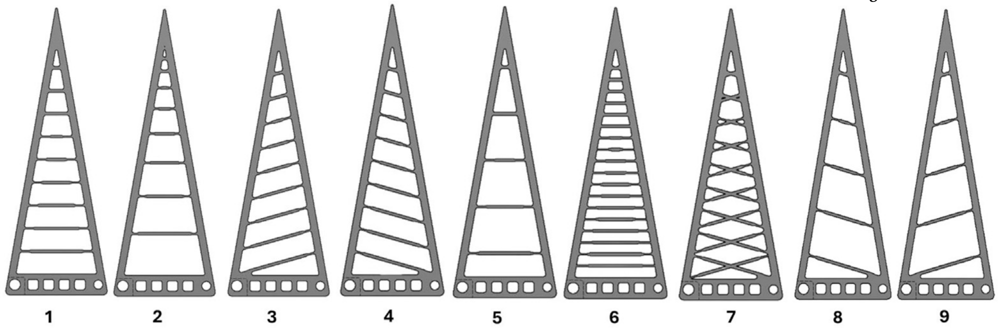


Fig. 2. Nine gripper designs.

and closing the gripper. In this design, the gripper motor coupling translates the motor's rotational motion into linear motion via a linear screw mechanism. As the motor spindle rotates, the linear screw follows suit. A dedicated gripper motion link connects to the linear screw, converting the rotary motion from the motor into the linear motion required for the grippers. Gripper links connect the movable support of each finger via the connectors. The fingers open when the motion link moves away from the motor base. Conversely, when the motion link moves towards the base, the grippers engage. The gripper motor is securely bolted to the base to prevent any unwanted movement.

This gripping mechanism is attached to the backplate, which connects it to the rotation motor using a rotation motor coupling. The rotation motor is secured in its position using the back motor holder, which is attached to the holder. This additional motor serves to mimic human fruit-picking movement during harvesting. The holder couples the developed system with that of the robot using the end-effector coupling.

To implement the vision-based autonomous control of the robot, a Realsense RGBD D435 camera is attached to the robot's end-effector, forming an eye-in-hand topology. This setup eliminates the need to recalibrate the camera-robot system whenever the robot arm position changes. The overall dimension of the gripper structure from the tool centre of the robot to the base end is 272 mm and the maximum width of the structure including the camera is 165 mm.

2.2. Various gripper designs for comparison

Building on the work of Chen et al. [21], a new gripper design was developed. This design closely follows the specifications of the reference gripper from the cited work, with minor modifications to facilitate actuation. Shown in Fig. 2 as Gripper 1, the design features nine evenly spaced cross-beams (webs) connecting two bone structures, each with a thickness of 3.5 mm and a width of 16 mm. Additionally, the gripper includes a base area for connection to both the system's base and the connectors.

In this study, Gripper 1 serves as the baseline design, against which the performance of other grippers is evaluated. In the following, various configurations of the cross-beams were explored to create different gripper variations:

- **Spacing:** Gripper 2 features decreasing cross-beam spacing towards the tip. The decreased spacing towards the end of the gripper can help the gripper to have a firm grip on the fruit and could reduce the chance of slipping during the operation.
- **Inclination:** Gripper 3 has beams inclined at 15.66 degrees towards the horizontal, while Gripper 4 has the opposite inclination. This design enables the cross beams to be equally inclined to the base while maintaining a fixed gap between the beams. The gripper 4's inclination could increase the flexibility of the gripper and could result in a lower slip, while for the gripper 3, the increased effect of sturdiness is studied
- **Number of Cross-Beams:** Gripper 5 is a variation of Gripper 1 with five beams (reduced from nine). Gripper 6 doubles the number of beams to eighteen. These designs intend to study the effect of varying cross-beams on the gripper. An increased number of cross-beams could allow the gripper to adjust better to the asymmetric surface of the fruit while reducing the structural integrity of the gripper during grasping.
- **Combination:** Gripper 7 combines the inclined beams of Gripper 3 with the opposing inclination of Gripper 4. This design is indented to combine the key advantages of inclined beams, however the increased number of cross beams could significantly reduce the flexibility of the gripper.
- **Modified Inclined Designs:** Gripper 8 reduces the number of beams in the inclined Gripper 4 design to five. Similarly, Gripper 9 reduces the beams in the inclined Gripper 3 design to five. These designs target to combine the effect of inclination with the number of cross-beams that were considered in the previous designs.

Each gripper design possesses unique characteristics, providing valuable insights for optimizing the gripper for fruit harvesting and manipulation tasks. FEA methods were then employed to analyze these designs, guiding the selection of grippers for further testing in various real-world scenarios. Fig. 2 illustrates the nine gripper designs studied in this work.

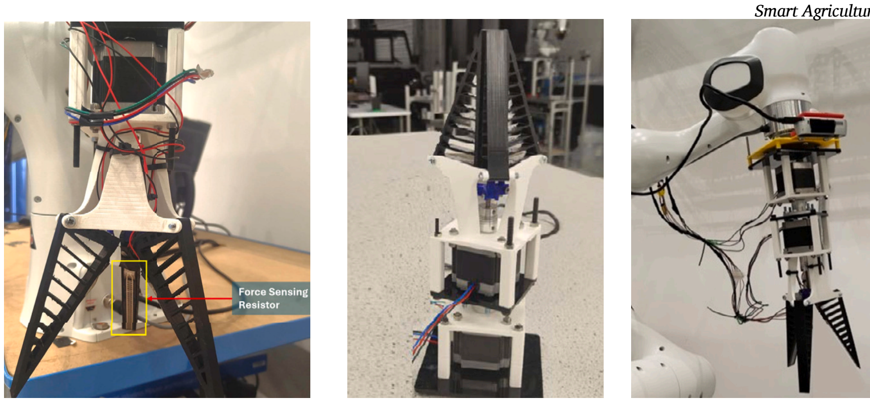
2.3. Manufacturing and assembly

Rapid roboting is one of the key technologies in robotics where fast prototyping of robotic components is performed using rapid manufacturing technologies, light programming language, and modular open electronic hardware [27]. In this work, a similar methodology is followed to develop the components mentioned in the design into reality.

This work utilizes two main manufacturing methods: 3D printing and laser cutting. For 3D printing, Fused Deposition Modelling (FDM) is used to create 3D parts by sequentially printing layers of plastic material. For the grippers requiring flexibility, 95A TPU is the chosen material. The backplate which supports the motor is developed using laser cutting of 5 mm acrylic sheets.

The components are assembled to form a functional gripper. Mechanical fasteners secure the connection between the rapidly prototyped components. Additionally, original equipment manufacturer (OEM) components, including the linear screw, gripper motor coupling, and rotation motor coupling, are integrated into the assembly. The electric motors as well as the force sensors are also integrated during this assembly. Force sensing resistor (FSR) are placed on the inner side of the gripper as shown in Fig. 3(a), ensuring contact with the fruit and enabling precise force detection during grasping. Fig. 3(b) depicts the complete gripper assembly, highlighting its mechanical complexity and design while Fig. 3(c) illustrates the integrated robot system as a whole, showcasing the gripper's functionality within the larger robotic setup.

The electrical components were interconnected according to the circuit diagram depicted in Fig. 4. The TB6600 motor drivers were controlled via pulse, direction, and enable pins using an Arduino microcontroller. Due to project constraints, the motors were powered by



(a) FSR on the gripper. (b) Gripper assembly. (c) Integrated system.

Fig. 3. Proposed robotic end-effector after component assembly.

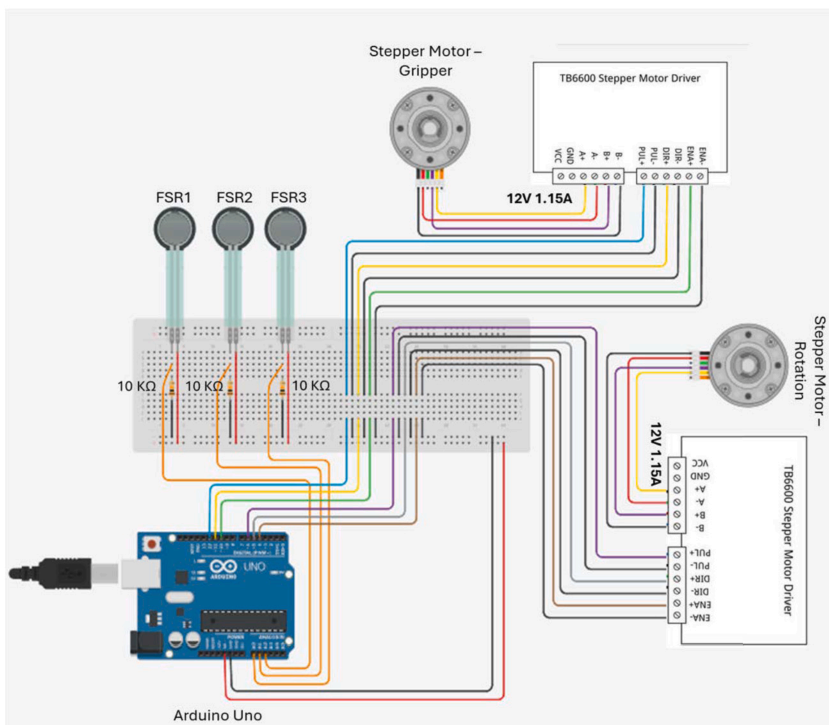


Fig. 4. Circuit diagram for the gripper control.

a benchtop power supply delivering 12 V and 1.5 A. For future field trials, this can be readily replaced with a battery power source. Force-sensing resistors were connected to the Arduino controller's analog input pins. To optimize sensitivity and provide a bridge for the feedback signal, a 10 kΩ resistor was utilized in conjunction with each sensor. The Arduino microcontroller was interfaced with a computer running the Robot Operating System (ROS) for robot control. Logical communication was established using the Arduino IDE and the rosserial protocol.

2.4. Machine vision for real-time fruit detection

The machine vision system facilitates both fruit identification and robotic control for precise positioning for fruit picking. The system is designed to handle medium-size fruits and was tested on three different fruits for pick-and-place operation – apples, oranges, and lemons. However, for the initial harvesting experiment, the apple is chosen as the target object. In the current implementation, an Intel RealSense Depth Camera D435 is used for fruit detection and position estimation. The camera is mounted on the robot as discussed in the mechanical design section, achieving an eye-in-hand configuration for the robotic arm.

To enable fruit detection, the vision algorithm utilizes YOLO-v5, implemented on ROS Noetic using the ROS Wrapper for the D435 camera. When triggered by the controller, the camera topic publishes both depth and RGB data for processing. The object detection model identifies the fruit's position and send this information to the robot controller for trajectory planning and manipulation.

The YOLOv5 model, pre-trained on the MS COCO dataset [28], was further enhanced through custom training using data collected from our lab setup. Fig. 5 shows three sample images from the custom training dataset. The custom dataset was carefully designed to simulate operational scenarios, consisting of 160 training, 120 validation, and 50 testing images. This approach ensures that the model is finely tuned to detect specific types of fruits encountered during the examined real-world operations. This training has enabled the robot to detect different

Fig. 5. Sample images from the augmented training dataset of YOLOv5 model.

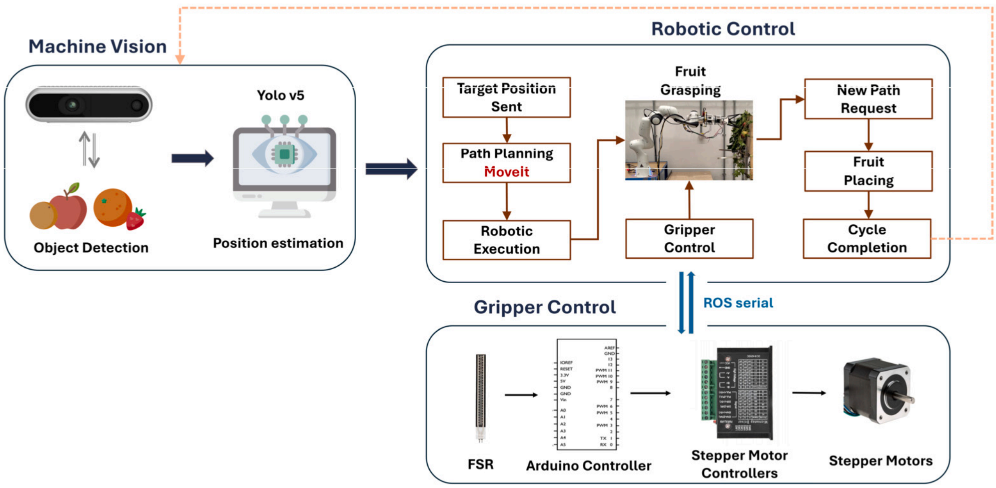


Fig. 6. Autonomous fruit gripping system control workflow pipeline.

fruits for the pick and place operation, which is also used for transfer learning in the detection of apples in laboratory experiments replicating a fruit harvesting task.

2.5. Robot planning and control

The robotic system leverages a combination of software tools to achieve precise control and motion planning. Libfranka functions[1] as the low-level controller, directly managing the Franka Panda robot's joints for high-precision movement. Franka ROS acts as an intermediary layer, enabling the integration of various Robot Operating System (ROS) packages with the robot. The MoveIt package [29] serves as the motion planner, guiding the robot's arm to reach designated points within its workspace. Finally, the ROS framework facilitates the seamless integration of additional ROS-compatible packages for enhanced functionality. The motion planner used in the system is the MoveIt Pilz Industrial Motion Planner, which plans and implements linear motion to reach the goal position. In addition to these packages, the Franka controller module is updated with the moment of inertia and centre of mass values of the gripper obtained from the 3D modelling software. These values are then used by the MoveIt packages to plan the path during manipulation.

To implement the vision-based manipulation system, the camera module integrated with the robot needs to be calibrated with the custom robotic end-effector. The MoveIt hand-eye calibration package is utilized for camera calibration. This package generates a calibration file specific to the setup, which aids the vision system in coordinating with the robot. In this process, checkerboards are used as markers and placed within the robot's workspace and field of view. Images are taken from different camera positions for these markers, which are then used by the calibration package to generate the calibration file.

The gripper control workflow pipeline, illustrated in Fig. 6, follows a coordinated sequence of actions. First, the robot transitions to a designated home position. Here, the machine vision module (YoloV5[2]) actively detects the target fruit. Upon successful detection, the target position is transmitted to the robot's ROS framework, triggering path planning through the MoveIt. Once a feasible path is established, the robot executes the plan to reach the desired location for picking the fruit. Visualization tools like Rviz allow for monitoring the planned trajectory and the robot's real-world movement. Additionally, Rviz displays the machine vision output, including the bounding box around the identified fruit.

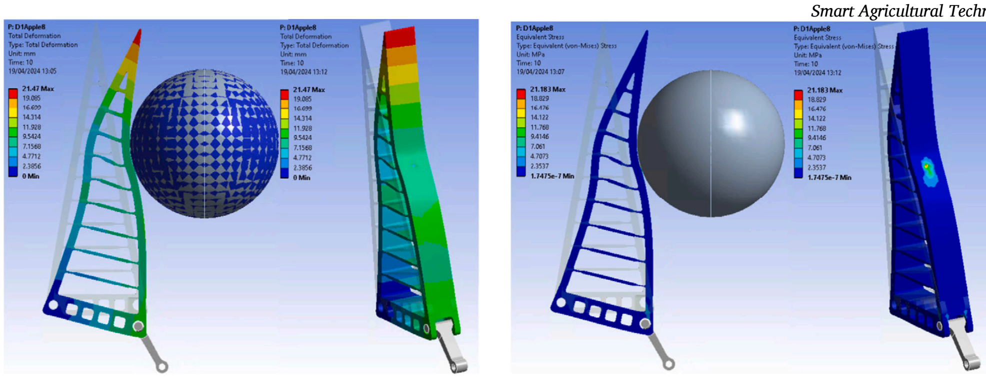
Following the execution of the motion plan, the robot communicates with the Arduino controller. This communication facilitates gripper and rotation motor control via the stepper motor drivers, while also enabling the retrieval of force sensor data. Once the fruit is grasped and removed, feedback travels back to the robot through the same serial connection. The robot then requests a new path from MoveIt, guiding the robot end-effector towards a fruit placing location to deliver the fruit. Upon reaching the destination, the gripper opens via Arduino control, and the robot returns to the home position, ready to repeat the cycle.

3. Experimental results

The developed gripper is designed to adaptively handle fruits during harvesting as well as in fruit pick-and-place movements, mimicking human behaviour in the fruit-picking task. To assess their validity and repeatability in relevant setups, the nine grippers were initially evaluated through simulation with stress analysis. The three best performers from the FEA were then manufactured and tested in two real-world ex-

[1] https://frankaemika.github.io/docs/libfranka.html.

[2] https://github.com/ultralytics/yolov5.



(a) Deformation Plot

(b) Equivalent Stress Plot

Fig. 7. Indicative results of FEA for Gripper 1.

periments. The conducted experiments and their results are discussed in the following subsections.

3.1. Stress analysis of the grasping ability

The key factor influencing optimal gripper characteristics is its behaviour during interaction with the fruit. To investigate these characteristics, the gripper designs were subjected to FEA using Ansys Mechanical software.[3] FEA results simulate the fruit-picking task, providing theoretical validation for the established design criteria.

In the analysis conducted, a scenario where the gripper interact with the apple is replicated in the simulation environment. For the study, a mean fruit size of 70.3 mm [30] is used to model the apple, and the mechanical properties such as elastic modulus of 5.0 MPa and Poisson's ratio of 0.35 [31] were used. The gripper was modelled with the mechanical properties of TPU-95A material with an elastic modulus of 29 MPa and poisson's ratio of 0.36 as indicated by the manufacturer. The connectors are designed with PLA material, as per the specifications given by the manufacturer. The position of the fruit is constrained for the study and the connector is linked with the gripper using revolute joints. The connection point opposite to the connector joint is fixed using a revolute joint, replicating the actual fixture to the base. Then a structural analysis is performed by moving the connector joint to the linear screw in the vertical direction opposite to the fruit, which is the motion resulting in the engagement of the gripper with the fruit.

FEA simulation examines three crucial factors influencing gripper performance: deformation, equivalent stress, and strain energy density. The deformation signify how the gripper creates contact with the fruit, a relatively large end-point deformation indicates the end is bending more towards the fruit, increasing the area of contact and reducing the chance of slip. The equivalent stresses indicate the structural integrity of the gripper, it should be within the maximum permissible limit indicated by the manufacturer. The strain energy density is an indication of damage caused by the gripper on the fruit. Strain energy is targeted to be kept below 12 mJ to keep the developed stresses per square millimetre area below 12 MPa [32] to avoid permanent damage to the fruit by gripper. Along with the FEA, other factors such as time taken for the 3D printing and the material used are considered to choose the best-performing gripper. An indicative example of the results of the deformation and equivalent stress analysis plot is illustrated in Fig. 7.

Table 1 summarizes the results of finite element analysis and other manufacturing factors considered for all nine grippers. The observed values of stress, deformation, and strain energy vary significantly across the grippers, which are crucial factors in selecting the gripper with the optimum characteristics.

More specifically, as shown in the table, Gripper 8 exhibits the maximum deformation, while Gripper 7 experiences the minimum. Notably, grippers 1, 4, and 8, despite having the highest deformation values, also demonstrate equivalent von-Mises stresses below 29 MPa, indicating structural stability. Grippers 5 and 9 exhibit stresses exceeding the allowable limit of 29 MPa for TPU material, suggesting these designs may experience permanent deformation under the loading conditions of this study. In contrast, Gripper 7 demonstrates the lowest stress level alongside a negligible strain energy of 1.3793 mJ. This behaviour suggests that Gripper 7 functions almost like a rigid body despite being constructed from a flexible material. Similar to the previous analysis, grippers 1, 4, and 8 exhibit stable structural integrity based on their equivalent stress values. Among these, Gripper 4 experiences the lowest stress, reaching 18.493 MPa.

Strain energy exhibits significant variations across the gripper designs. Gripper 7 demonstrates the minimum value, while Gripper 9 exhibits the maximum. As highlighted in Table 1, Grippers 1, 4, and 8 possess strain energy values ranging from 7 mJ to 12 mJ. This range is considered sufficient to create a stable grasp on the fruit without causing damage. Conversely, Grippers 5, 6, and 9 exhibit very high strain energy values, rendering them unsuitable for fruit picking due to the potential for fruit damage.

The material used for the grippers varies from 18.96 g to 24.99 g per gripper. The minimum material usage is beneficial for production and reduces the cost. Gripper 5, 8 and Gripper 9 use the minimum amount of material, while Gripper 7 uses the maximum. This can be attributed to the smaller number of cross beams for the former ones and the maximum number of cross beams for the latter.

Accordingly, based on the FEA results, Grippers 1, 4, and 8 emerged as potential candidates for the adaptable gripper for fruit handling. These designs exhibited favourable characteristics across all the metrics evaluated in the study: deformation, stress, strain energy, as well as print time and quantity of material needed. Consequently, these three grippers were selected for further evaluation through real-world lab testing integrated with robot vision-based control.

3.2. Experimental setup

The gripper's capability to harvest and safely handle different fruits was evaluated in a constrained lab environment. Fruit harvesting capabilities were analyzed by experimenting with a replica of the harvesting scenario (Fig. 8), while fruit handling capabilities were tested for pick and place operations on a flat surface with a variety of fruits. The setup included the robot affixed to a table, fruits attached to a board to simulate harvesting, and green vegetation to constrain visibility. Pick and place operations were tested on the table shown in the experimental setup. The controller and power supply units were connected to the gripper through the wires routed along the robot's surface.

[3] https://www.ansys.com/463 products/structures/ansys-mechanical.

Table 1
FEA results for the studied grippers. The rows highlighted in grey indicate the grippers that performed the best during the analysis. These grippers were selected for further testing to evaluate their accuracy in lab experiments.

Gripper	Deformation (mm)	Equivalent Stresses (MPa)	Strain Energy (mJ)	Print Time (mins)	Material used (g)
Gripper 1	21.47	21.183	9.238	220	20.69
Gripper 2	20.884	14.027	6.8915	205	19.36
Gripper 3	20.116	12.828	8.2132	225	21.18
Gripper 4	21.375	18.493	7.8612	223	21.14
Gripper 5	13.715	29.382	21.464	197	18.96
Gripper 6	12.753	16.045	21.368	271	24.99
Gripper 7	10.658	10.163	1.3793	309	25.12
Gripper 8	21.965	28.262	11.051	200	19.13
Gripper 9	14.851	30.878	37.018	200	19.19

Fig. 8. Experimental setup.

Table 2
Experiment I - Slip behaviour.

	FSR1	FSR2	FSR3	Slip (3/3)	Success
Gripper 1	554.67	870.17	3.58	1	Yes
Gripper 4	720.46	919.77	0.69	1	Yes
Gripper 8	798.67	688.13	793.63	0	Yes

3.3. *Experiment I: fruit harvesting*

In this experiment, the robot detects the position of the fruit and move to a picking position, where the gripper is engaged and a rotation motion is applied to the fruit, mimicking human picking behaviour (Fig. 9). According to Li et al. [33], the mean grasping force to detach the stem of the apple from the branch is about 5.05 N and the grasping pressure using the three-finger grasping method is 0.24 MPa for the harvesting of the fruit without any significant damage. Once the fruit is detached, the harvested fruit is transferred to a placement position, where it is released by disengaging the gripper.

The slip behaviour of the grippers during fruit harvesting was evaluated by analyzing the FSR data presented in Table 2. Physical validation of slip was also conducted, assigning a score of 0 (no slip) to 3 (all fingers slipped) for each attempt. Additionally, the success rate of the harvesting task was recorded. Apple was used as the targeted fruit in this experiment and for all the physical properties of the fruit remained at 113 grams and a diameter of 68.25 mm.

The data collected during the experiment 1 is summarised in Table 2. Results of this experiment indicate that the drop in FSR readings can be correlated to the observed slip in the fingers and the Grippers 1 and 4 experienced slip on one finger during specific trials. In contrast, Gripper 8 demonstrated no instances of slipping throughout the experiment making it most suitable for fruit harvesting operations.

3.4. *Experiment II: fruit manipulation*

The second set of experiments evaluates the pick and place capabilities of the grippers during the handling of apples, oranges and lemons, tested in a lab environment. These fruits vary in size as well as texture. In this experiment, the fruits are arranged on the table as shown in Fig. 10. At the beginning of the experiment, the robot control is activated and the robot moves to a home position above the fruits on the table. Based on the fruit selection made by the user, the robot navigates to the picking position above the desired fruit, where the gripper is activated to grasp the fruit. Then, the robot grasps the fruit and places it to a pre-defined position on the table, where the gripper eventually releases the fruit. The experiment utilized fruits with varying diameters: apples (69.07 mm - 77.56 mm), oranges (66.61 mm - 73.5 mm), and lemons (55.44 mm - 58.40 mm).

Fig. 11 presents data on the slip behaviour of the grippers during Experiment 2, a total of nine finger slips were considered during this study which involved three fingers per trial of fruit and three trials were conducted per fruit, to obtain more data for the validation of results. The results indicate that Gripper 1 experienced significant slip events, particularly when handling apples and lemons. In the case of lemons, two fingers of Gripper 1 exhibited slip conditions in all trials.

It is worth noting here that in both experimental cases the model's precision in detecting target fruits, achieves prediction accuracy exceeding 0.8 consistently and ensures robustness in detection in every iteration of the trials. The real-time detection demonstration together with indicative results from the conducted experiments of both experiments are showcased in the supplementary video.

4. Discussion

The findings from this study highlight the promising potential of the optimized flexible fin-ray-based soft gripper for scalable fruit harvesting and manipulation. The rigorous finite element optimization process not only refined the mechanical design but also validated the gripper's capabilities across a range of fruit shapes and sizes, making it suitable for commercial applications. The adaptability of the gripper to handle diverse fruit types under varying conditions is crucial for its commercial viability, ensuring effective performance in real-world agricultural environments.

The selected three grippers were tested for their capabilities in fruit harvesting and fruit manipulation tasks. Experiment I focused on harvesting reveals that Gripper 8 showed no signs of slippage during the experiment. In contrast, both Gripper 1 and Gripper 4 exhibited sliding movements on at least one finger. This observation is further supported

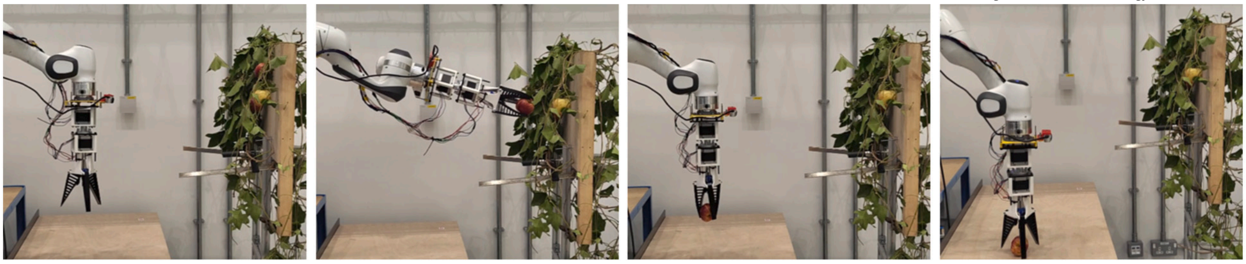


Fig. 9. Experiment I - Snapshots from the experimental procedure.

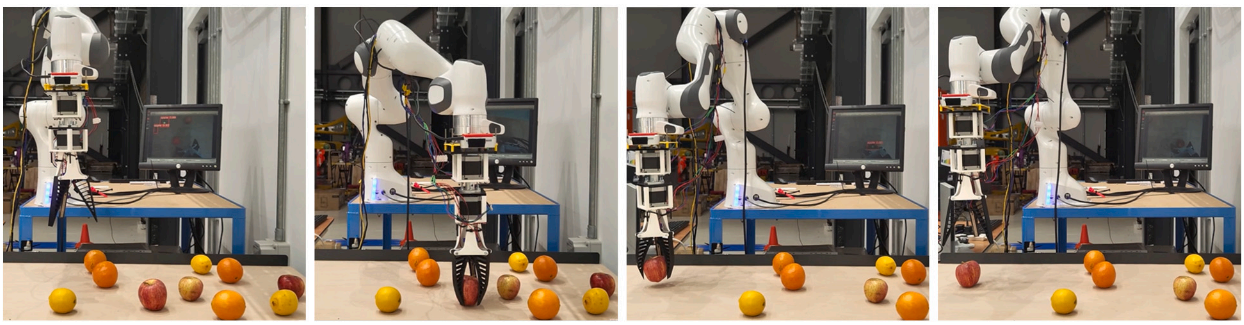


Fig. 10. Experiment II - Snapshots from the experimental procedure.

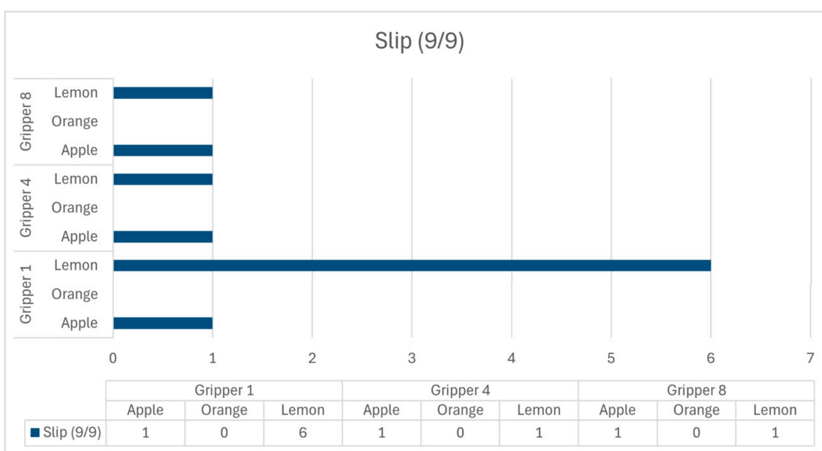


Fig. 11. Slip variation during Experiment II.

by the data presented in Table 2, where abnormal drops in FSR3 values are evident for both handles.

Experiment II revealed a more pronounced distinction in terms of slip behaviour. The plot in Fig. 11 demonstrates a significantly high slip value for Gripper 1 when handling lemons. Notably, all grippers experienced at least one slip event when manipulating apples and lemons, while none encountered any slippage during orange manipulation. These results indicate that while all grippers can handle a variety of fruits, their performance may vary depending on the fruit type, emphasizing the importance of comprehensive testing to ensure reliability across different agricultural contexts. This suggests that Gripper 1 may not be suitable for handling fruits like lemons, while Grippers 4 and 8 remain potential candidates.

Based on the combined insights from real-world testing and production considerations, the studied grippers can be ranked as follows:

1. **Gripper 8:** This gripper exhibited exceptional performance in both FEA simulations and real-world testing, with minimal slip observed during fruit handling. Its capacity to maintain grip without slippage under varying conditions positions it as a robust solution for large-scale agricultural operations. Furthermore, Gripper 8 boasts the lowest material consumption and production time, among the three, leading to significant material and cost savings during production.
2. **Gripper 4:** Gripper 4 exhibited slip during real-world testing however it was capable of handling small citrus fruits like lemons making it better than gripper 1, while the slip observations in experiment 1 ranks the gripper below Gripper 8.
3. **Gripper 1:** Gripper 1 indicated higher slip values in both experiments 1 and 2. The very high slip observations in Experiment II indicates the limitation of this gripper in handling small fruits.

Overall, Gripper 8 emerges as the most favourable option due to its exceptional performance, minimal slip, and production efficiency. The conducted results from both simulations and real-world tests position it as a noteworthy advancement in flexible gripping solutions, paving the way for further exploration and development in the field. The low slip characteristics observed in both experiments, along with its efficient print time and material usage, highlight its potential as a promising candidate for advancing agricultural technology. The gripper's scalability and adaptability across different fruit types further enhance its applicability to various agricultural tasks. These qualities not only boost its functionality but also make it a practical choice for a wide range of fruit handling scenarios. With minor modifications, the design principles outlined in this project could be adapted for smaller fruit types, such as berries and other delicate produce.

5. Conclusion

This study successfully developed a versatile robotic gripper that effectively mimics the dexterity and efficiency of human fruit harvesting. Through a systematic exploration of nine innovative design concepts, we employed finite element analysis (FEA) as a crucial tool in refining the gripper designs, allowing us to evaluate their mechanical performance and predict operational effectiveness under various conditions. The combination of FEA simulations and real-world testing led to the identification of Gripper 8 as the optimal solution, showcasing superior stability and minimal fruit slippage during grasping and manipulation tasks. The complete robotic system, equipped with Gripper 8 and vision-based fruit detection, achieved autonomous fruit picking and harvesting, successfully replicating human harvesting behaviour.

Our research advances existing work by comprehensively comparing multiple gripper designs and testing the top contenders in controlled settings with real fruits. The findings from the experimental evaluations indicate that Gripper 8 significantly outperformed other prototypes, underscoring its potential for reliable fruit handling. The rigorous metrics derived from both FEA and empirical testing provided valuable insights into the performance characteristics of each gripper, emphasizing the critical importance of aligning FEA results with experimental outcomes to ensure the reliability of our models.

Despite the achievements of our system, there are avenues for further exploration and improvement. Future work could involve enhancing the system's robustness by testing a wider range of fruits and vegetables. Additionally, testing should transition from the lab to real-field orchards for a more realistic evaluation. Future investigations could further improve the predictive accuracy of our models by integrating environmental variables into FEA simulations. Factors such as wind forces, temperature fluctuations, humidity, and branch interference could be modelled to better reflect real-world conditions, offering a more comprehensive understanding of their impact on gripper performance. This could be used to scale the presented model into other delicate fruits beyond the ones considered in the current study. Lastly, the application of machine learning techniques to the analysis of sensor data offers the potential to enhance gripper adaptability and enable the implementation of dynamic, real-time gripping strategies. This approach has the potential to improve picking efficiency and reduce fruit damage.

CRediT authorship contribution statement

Finny Varghese: Writing – original draft, Visualization, Validation, Software, Methodology. **Fernando Auat Cheein:** Writing – review & editing, Supervision, Conceptualization. **Maria Koskinopoulou:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.atech.2025.100899.

Data availability

No data was used for the research described in the article.

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