

Design, Modeling and Control of a Manipulator with Bio-Inspired Soft Robotic Gripper

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A Final Year Design Project (FYDP) submitted to the Department of Electrical and Electronics Engineering in partial fulfillment of the requirements for the degree of Bachelor of Science in Electrical and Electronic Engineering

Department of Electrical and Electronic Engineering
BRAC University
January 2026

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January 2026

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Declaration:

1. We declare with this writing that the work contained in this report, namely, in the college of final year project in design at the Department of Electrical and Electronic Engineering, BRAC University is our own original work.
2. The report has not been submitted any time earlier, either in its entirety or in parts, to compete or receive any other degree or diploma at any other institution. The sources of information and support have also been addressed appropriately in the report.
3. We are aware of the implications of any academic dishonesty and of the fact that this report is fully bound by the university code of ethical and academic conduct.
4. We also testify that the project follows the applicable codes, standards, and regulations as needed in this sector and manufacturing operation.

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Ethics Statement

Following the ethical guideline, our paper has overall 8% similarity excluding the references, with references the similarity is 14%.

Abstract:

Safe manipulation of delicate and irregularly shaped objects remains a major challenge for conventional rigid robotic systems due to their limited compliance and adaptability during physical interaction. To address this issue, this project presents a soft robotic manipulation system that integrates a 4-degree-of-freedom (4-DoF) rigid manipulator with a bio-inspired soft gripper, enabling adaptive grasping while supporting both manual and autonomous control modes. The system is developed using a structured, model-based design approach, beginning with theoretical kinematic and dynamic analysis, along with payload torque calculations to guide actuator selection and mechanical configuration. Based on these analyses, the manipulator and gripper are designed and evaluated in Autodesk Fusion 360, including static stress and motion studies, and subsequently fabricated using 3D printing. For modeling and control, a URDF-based robot description is implemented in a ROS2 and MoveIt2 environment, enabling collision-aware motion planning, workspace analysis, and repeatable end-effector positioning in both simulation and hardware. Numerical workspace sampling shows that the manipulator achieves an asymmetric reachable volume of approximately 0.77 m³ under joint and self-collision constraints. Autonomous perception is achieved using a vision-based object detection pipeline, where four deep learning models - YOLOv11-m, Faster R-CNN, RF-DETR, and RTMDet-m, are trained and evaluated on an 11-class manipulation dataset. Among these, YOLOv11-m provides the best overall balance of accuracy and efficiency, achieving 94.7% precision, 94.3% recall, and a mAP@0.50:0.95 of 0.86. The complete perception, planning, control pipeline is validated through simulation and real-world experiments using a ROS2 distributed architecture. Control performance is evaluated across randomized target poses, in simulation autonomous control achieves a mean positioning accuracy of 98.99% with an average execution time of 4.06s, compared to 70.08% accuracy and 46.72s for manual control. Physical experiments on fragile objects demonstrate grasp success rates of 33% in fully autonomous mode with an average execution time of 23s and 66% positioning accuracy under manual teleoperation with an average execution time of 51s. The results confirm the feasibility of the proposed soft robotic manipulation system while highlighting current hardware and actuation limitations. This project provides a practical foundation for low-cost soft robotic manipulators and offers clear opportunities for future improvement in autonomous performance, making it suitable for applications in industrial automation, agriculture, and service robotics where safe and compliant interaction is required.

Keywords: Robotic Manipulation, Soft Robotic Gripper, Object Detection, Motion Planning, Autonomous Control.

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Chapter 1: Introduction

1.1 Introduction

1.1.1 Problem Statement

Soft robotics are developing to overcome a well-known, yet relatively basic shortcoming of traditional robots: most available arms and grippers have been designed with rigid links, and hard interfaces designed to touch objects roughly, which is effective when items are rigid, homogenous, and well formed [7], [18], [20], [32], [35]. In most real-world environments, however, the items that must be manipulated are far otherwise; they encompass delicate fruits or farm items, uneven 3D-printed components, biological samples, and even tiny living beings, all of which can be easily bruised, deformed, or damaged when handled too hard or at the incorrect locations [18], [20], [30], [36], [45], [46], [53]. Such a mismatch between hard machinery and soft objects implies that a vast category of items could still be hard to entrust to automation without compromising either quality or safety, or both [35], [41], [58], [59], [60].

In the recent years, researchers have suggested an impressive range of soft and adaptive grippers based on compliant structures, bio-inspired geometries, and adaptability of stiffness, which simply wrap around irregular shapes and distribute contact forces more safely over that surface [7], [15], [18], [20], [28], [31], [32], [35], [46], [57], [60], [63], [69], [75], [80]. It has been demonstrated that using these grippers, tasks like harvesting fruits, handling of plants, binder-jet part manipulation, and bio-medical sample manipulation can be performed much more responsively and dependably than traditional rigid end-effectors, combined with appropriate sensing and control [18], [20], [30], [36], [46], [53], [61], [75]. Simultaneously, comparative studies and reviews indicate that most of such soft solutions are complicated and expensive requiring advanced materials, multi-stage fabrication, sensitive actuation, or task-oriented designs, which renders them difficult to be broadly implemented, especially where budgets, maintainability, and standardization are important factors [16], [18], [21], [35], [39], [43], [55], [69], [70]. The market and technology reports also observe that market is still skeptical despite the increasing interests on soft robotics because products in market seem too costly, inaccessible to integrate, and yet not as developed as standard rigid gripper technologies [17], [40], [62], [70].

The project sets a soft robotic arm and adaptive gripper as one viable way of filling that gap, with a goal of providing a system that can easily work with delicate and irregularly shaped objects without damaging them, at the same time fitting the industry acceptance criteria. The design will focus on simple and robust soft architectures, an actuation and control system, and compatibility with other robotic systems and modular frameworks, such that users can expand or adapt existing systems rather than upgrade systems altogether or invest in highly specialized and high-priced soft robotic infrastructures.

1.1.2 Background Study

Robotic manipulators are mechanical arms that consist of several rigid links, joined together by joints, powered by actuators to move an end-effector about its desired positions and orientations in space [1], [21], [33], [37], [39], [41]. These types of manipulators are able to follow task-space paths and provide forces or torques in a controlled manner by solving forward and inverse kinematics allowing operations like pick-and-place, assembly, welding, and sorting materials in an industry (or service) setting [1], [21], [33], [37], [39], [41], [42]. A gripper, also known as the end-effector in robotic manipulation, is involved in direct contact with the object itself, and different designs, such as parallel jaws, multi-finger hands, suction cups, and tendon-driven fingers, have been developed to handle objects with various geometries and mechanical properties [7], [20], [32], [35], [36], [41], [53].

The traditional grippers used in industry are commonly hard and consist of metals or firm polymers with well-known geometries of fingers and high structural rigidity to achieve consistent and high-force manipulation of standardized objects such as machined parts, bottles, or boxes [20], [32], [35], [36], [41], [62]. Hard contact surfaces and limited compliance are tolerable or even desirable in such applications since the workpieces are tough, their geometry is predictable, and tight tolerances are needed to help ensure that the workpieces are placed precisely [20], [32], [35], [41]. Nonetheless, when deformable, delicate or irregular shaped objects, such as fruits, nursery plants, delicate 3D-printed components, or biomedical samples, are manipulated with the same form of rigid gripper, localized contacts and concentrated forces can readily result in slipping, bruising and cracking or other damages, and the grip may be unstable when the shape of the object does not match the geometry of the gripper well [18], [20], [30], [36], [45], [46], [53]. Such structural incompatibility between rigid end-effectors and delicate products poses an obstacle to automated execution of most tasks that require sensitivity as much as mass and precision [35], [41], [58], [59], [60].

Soft robotics would provide a different paradigm, incorporating compliant materials and deformable architectures in manipulators and grippers so that they can adjust their shape based on the object instead of forcing the object to fit the tool [9], [10], [16], [18], [28], [31], [34]. Soft robotic parts are commonly engineered of elastomeric silicones, soft polymers or flexible composite arrays, layered into continuum like fingers or bodies which are able to bend, twist, and stretch under actuation, expanding the contact area and naturally redistributing forces along the object surface [18], [20], [30], [31], [36], [46], [75]. Several designs of soft grippers have been developed, such as PneuNet fingers with inner chambers able to bend under pressure, hybrid soft-critical grippers fitted with soft fingers on stiff frames, variable-stiffness fingers using particle jamming or layered cores, bio-inspired grippers based on human fingers, or other biological appendages, [7], [15], [18], [20], [28], [31], [32], [35], [36], [46], [53], [57]. Such grippers have shown the capability to hold fruits, vegetables, baked goods, additively manufactured components, household objects, and

biomedical objects with less harm and greater strength to shape variation when compared to traditional rigid end-effectors [18], [20], [30], [36], [45], [46], [53], [61], [69], [75].

The concept of SpiRobs, logarithmic spiral-shaped robots with multi-purpose grasping at all scales, is among the geometry-driven soft designs that offer a specific structural concept to an adaptable gripper [73]. Rather than straight or just curved fingers, SpiRobs possess a logarithmic spiral geometry as the primary structural motif, such that as the spiral spins around an object, the length of the spiral comes into contact in a scale-invariant manner, meaning that the identical design can wrap a variety of sizes with similar behavior [73]. Such a rotating spiral nature allows the structure to roll around an object and produces distributed contact along the spiral instead of a small number of discrete hard contacts, which contributes to reduction of local stress and easier stabilization of fragile or irregular shaped objects [18], [31], [36], [46], [53], [69], [73]. In the case when such a spiral is used in a compliant body, the geometry and softness can work together so that the structure becomes able to bend to fit as it winds round smoothly, needing no complicated joint co-ordination or a large number of independent actuators [21], [35], [39], [73]. The principle of SpiRobs is thus considered the central structural inspiration in this project: it is conceived that the gripper fingers will be realized as compliant objects of spirals that have the ability to surround objects of all sizes with a single, unified morphological design [18], [35], [46], [69], [73].

In reality, to control manipulators and soft grippers various control and perception strategies are employed. One system category employs purely autonomous control based on inverse kinematics, sometimes with learned models of robot motion, [1], [5], [6], [21], [33], [37], [39], [71]. Under these systems, a desired position and orientation of the gripper are fed into an algorithm which then computes the appropriate angles of each joint such that the arm can attain the desired pose [1], [21], [33], [37]. Previous work is based on mathematical and soft-computing algorithms that compute this joint-angle calculation with standard industrial robotic arms [1], [5], [6], [21], [33], [37], [49], [52], [56], [71], [81], although more recent work applies deep learning or optimization algorithms to compute the same mapping even when the number of possible settle positions of the joints is large or when the robot faces other motion constraints [11], [13], [14], [37], [49], [52], [In these inverse-kinematics-based controllers, a compliant gripper is capable of adjusting its shape around the object by changing to the planned paths when contact is made [18], [20], [31], [36], [46], [53]. These control schemes are commonly coupled with vision and image processing to identify target objects, estimate object pose and object type and then proceed to grasp them, particularly in unstructured scenes like agricultural scenes or a mixed manufacturing bin [12], [18], [20], [30], [31], [36], [53], [60], [61], [69], [78], [79]. The camera systems (RGB, depth, or RGB-D) used with object detection and segmentation algorithms (including the classical image processing, convolutional neural networks, and YOLO-like detectors) enable the robot to perceive fruits, components, or other objects, calculate their position and angle, and send them as targets to the automotive inverse kinematics block [12], [18], [20], [30], [31], [36], [53], [60], [78], [79]. A vision-based tactile estimation or marker tracking of the gripper surface is also applied in certain soft gripper systems to estimate the contact conditions and

modify the grasp to enhance safety and reliability when handling delicate objects [9], [16], [18], [20], [30], [46], [53], [61], [75].

Manual or semi-manual control is also another popular type of system where human operators control the arm and gripper by manipulating joysticks, teaching pendants or teleoperation interfaces [41], [42], [45], [62]. Such operator-in-the-loop configurations do not provide complete autonomy, although they are very flexible: the user can adopt new object types or strange conditions without retraining models or redesigning motion plans, even in part structured environments, in a matter of seconds [41], [42], [45], [62]. In combination with a soft gripper, manual control integrates the compliance of the gripper to achieve more ease of control on the operator and is also capable of safely interacting with delicate or irregular shaped objects even in cases where object pose or properties are poorly known [18], [20], [31], [36], [46], [53].

The increased industrial attention given to soft and adaptive manipulators is closely connected with the general economic trends in robotics [62]. International news on robotic arms predicts a significant growth in the arm markets and revenues are expected to be increasing exponentially during the second half of this decade as additional factories, warehouses and service companies implement automated handling systems [40], [70]. Comparable studies on the concept of soft robotics explicitly note that there is a growing demand to develop technologies capable of handling more

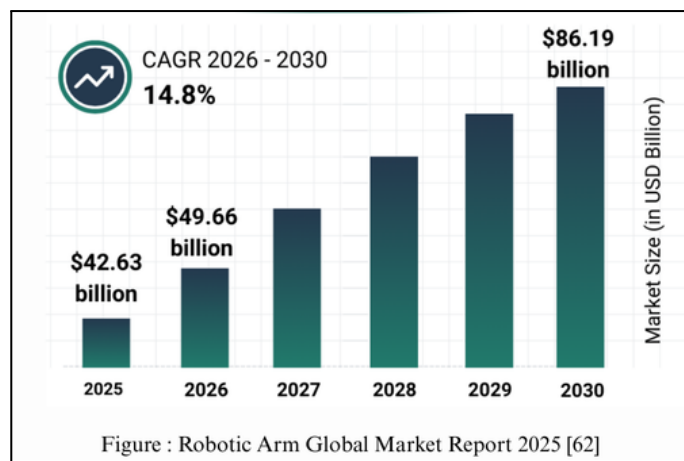


Figure: Robotic Arm Global Market Report [62] varied and delicate goods, with manufacturers pursuing lower costs of labor, enhanced consistency, and the need to solve shortages in skilled manual labor and, at the same time, to preserve quality of products [17], [23], [40], [58], [59], [60], [62], [70], [71]. These considerations imply that cost-effective soft arms and grippers that are reliable, easy to integrate, and able to fit existing industrial setups can be used to reduce the entry-level barrier to smaller and medium-sized firms and allow them to enjoy the same automation trends as reported on the world markets including the Robotic Arm Global Market Report 2025.

In this scenario, the project develops a 4-DoF soft robotic arm added with an adaptive, bio-inspired type of gripper that extends previous spiral-based and tentacle-based soft gripper virtual models to more viable, industrial-based applications. An adaptive manipulator and soft robotic arm that would allow carrying the delicate and geometry-focused grasping abilities of models like SpiRobs to real-world industry applications. The goal is to design conforming spiral-shaped gripper structures that can safely manipulate fragile and irregular

shaped objects on a large scale, and make the arm-gripper system mechanically simple, inexpensive and easily serviced. Simultaneously, the manipulator and its control architecture are to be compatible with regular industrial methods, including inverse-kinematics-based motion planning, object-location by camera, and operator-in-the-loop control, such that the given system can be deployed in even the current production line and does not need any new infrastructure to operate.

1.1.3 Literature Review

A number of soft gripper have already been created, including underactuated hands with soft fingers, multi-bend, variable-stiffness segment bending grippers, crop-specific harvesting tools, and hybrid soft-rigid ones [7], [15], [18], [20], [28], [31], [32], [35], [36], [43], [46], [53], [57], [60], [61], [63], [69], [75], [80]. Such designs demonstrate that compliant fingers are more successful and cause less damages than rigid grippers in grasping fruits, vegetables, baked products, 3D-printed components, household items, and biomedical samples [18], [20], [30], [36], [45], [46], [53], [61], [69], [75]. The disadvantage is that most of these grippers incorporate tricky internal action, multi-material, molding, particle jamming or dense sensing devices, thus they are more challenging to manufacture, costly, and not appealing to simple modular tools used daily in industry [16], [18], [21], [35], [39], [43], [55], [69], [70].

The other shortcoming is that several soft grippers work or are designed in a highly specific group of objects or working environments. An end effector that has been optimized to work with one type of fruit, a single style of stem geometry, or a thin size range can sometimes require significant redesign and test when applied to a new product, even with 3D printed parts [7], [18], [20], [28], [30], [31], [36], [45], [46], [53], [57], [61], [69], [75], [78]. The surveys of flexible gripping systems and hybrid systems indicate that simple, geometry-directed designs are still unavailable that can operate reliably in a broad size and irregular-shaped repertoire and remain simple to produce [35], [40], [43], [55], [69], and [70]. Other concepts that have developed in this direction include spiral inspired concepts like SpiRobs, which demonstrate that logarithmic forms with a spiral shape can be wound round different sized pieces of geometry with a single similar shape and distort around them in a distributed contact manner [21], [35], [39], [73]. These experiments, however, are primarily looking at the geometry of spirals itself, and not constructing a complete, low cost soft arm-gripper system including a performed control system [21], [35], [39], [73].

On the control side, there exists deep literature on inverse-kinematics algorithms, learning-based kinematic models, and vision-guided object detection and pose estimation that can run on embedded hardware [1], [5], [6], [11], [13], [14], [21], [33], [37], [38], [39], [40], [43], [55], [69], [70]. And at the same time many advanced soft gripper prototypes do not necessarily interoperate with such simple controllers and do This leads to a distinct lack of systems that combine three components: (i) a mechanically simple, 3D-printable geometries of soft grips that operate over a useful size space; (ii) a multi-joint arm to position such grips; and (iii) autonomous inverse-kinematics/vision-based control and operator-in-the-loop

control on available embedded hardware [18], [20], [28], [31], [35], [36], [41], [46], [53], [69], [71]

This project fits within such a gap. It extends previous soft gripper designs through a spiral engineered compliant tentacle design which can be manufactured using conventional 3D printing and mounted to a 4 degree-of-freedom arm. At the system level the goal of this project is to integrate this soft robotic manipulator and gripper with inverse-kinematics motion planning, camera-based workspace and object localization, and a control mode to produce a soft arm-gripper system that is flexible yet still mechanically straightforward and timely compatible with convenient industrial control procedures.

1.1.4 Relevance to Current and Future Industry

The focus of this project is to develop a soft robotic manipulator that can perform real time precision in dynamic and unstructured environments. The general idea is to introduce a system that can be capable of handling delicate and irregular shaped objects with not only accuracy and security but versatility too which may be applied in many of the processes such as automation in manufactures, warehouse tasks and agriculture. The soft robot manipulator offers a one-fit solution to various industries that require fineness and customization in their operation and precision. The key areas of application where the technology can contribute a lot include the following:

Table 1 : Relevance to the Current and Future Industry

Application Area	Description	Key Benefits
Industrial Automation	In industrial settings, robotic manipulators can be used for handling delicate components in manufacturing, assembly, or packaging processes, where traditional grippers fail.	1. High precision in handling delicate parts 2. Adaptability to irregularly shaped items 3. Enhanced safety for fragile materials
Precision Manufacturing	In precision manufacturing, soft robotic arms can handle small, delicate components in industries like electronics, automotive, and medical device manufacturing.	1. High precision for fine assembly 2. Safe handling of fragile and small components 3. Flexibility for different product types
Warehouse Operations	In warehouses, soft robotic manipulators can be used for sorting, picking, and packing fragile or irregular shaped items, especially in e-commerce fulfillment centers.	1. Reduced risk of damage during handling 2. Improved operational efficiency
Agriculture	Soft robotic manipulators can assist with harvesting, sorting, and handling crops, particularly delicate or irregularly shaped ones. This includes fruits, vegetables, and other agricultural products.	1. Gentle handling of crops 2. Increased efficiency in harvesting 3. Adaptability to different crop shapes and sizes

1.2 Objectives, Specifications, Requirements, and Constraints

1.2.1 Project Objectives

- **Handling fragile and irregular shaped objects:** To handle fragile and irregularly shaped objects by developing a soft robotic arm–gripper system that can manipulate small, delicate, and non-uniform items safely under controlled laboratory conditions.
- **Design and control of a 4-DoF manipulator:** To design and implement the kinematics and control of a 4-DoF manipulator that can position the soft gripper within a practical workspace using standard inverse-kinematics-based methods.
- **Design of a bio-inspired soft robotic gripper:** To design a bio-inspired soft robotic gripper with spiral-shaped compliant fingers that can be fabricated by 3D printing and mounted on a modular arm, enabling conforming grasps while keeping the overall system simple and cost-effective
- **System testing and performance assessment:** To experimentally test the system on a chosen set (of size variety and fragility) of objects (different shapes, sizes and fragility) and measure the practical indicators of grip success rate, retention in slow motion and minimal observable damage.

1.2.2 Functional and Nonfunctional Requirements

Table 2 : Functional Requirements

Functional Requirement	Description
Workspace mobility	The manipulator arm must provide enough combined translational and rotational motion so that the end-effector can reach and orient objects within a typical benchtop workspace used for laboratory testing.
Payload capacity	The manipulator and gripper together should safely lift and manipulate objects up to around 400 gm, assuming the object fits within the gripper and motions are performed at moderate speeds to maintain stability
Adaptive grasping	The soft gripper should conform to a range of object shapes and surface profiles, providing compliant, distributed contact so that irregular and fragile items can be held with reduced risk of damage, even when exact geometries are not known in advance
Coordinated motion and control	The manipulator and gripper should operate as a coordinated system. The overall control behaviour should ensure smooth, predictable motion of the arm and timely activation of the gripper so that object approach and grasping can be performed in a consistent and repeatable manner.

Table 3 : Non-Functional Requirements

Non-Functional Requirement	Description
Weight and Portability	The manipulator and gripper system should remain reasonably lightweight so that it can be mounted on typical laboratory benches or simple frames without special lifting equipment, and can be relocated by one or two people when needed
Reliability and Safety	The system must perform reliably in various environmental conditions with fail-safe features to prevent accidents or damage.
Structural robustness	Adequate rigidity while maintaining low overall weight
Scalability and Modularity	The mechanical and control design should allow individual components (such as the gripper, links, or control modules) to be replaced or extended without redesigning the entire system, making it easier to adapt the prototype for different experiments, future upgrades, or application-specific studies

1.2.3 Conflicting Requirements and Constraints

Table 4 : Conflicting Requirement and Constraints

Conflicting Requirement	Description
Payload Capacity vs. Manipulator Weight and DoF	Heavier actuators, structural elements, and additional joints can increase potential payload and motion capability but also add overall weight and inertia, which may reduce positioning accuracy, responsiveness, and safety margins when handling objects near the intended payload limit
Budget Constraints vs. Quality Assurance	Higher-performance components such as precise actuators, durable flexible materials, and reliable electronics typically increase total system cost. Working within a limited budget may require trade-offs in accuracy, lifetime, or robustness, so a balance is needed between acceptable performance and affordability for a prototype aimed at future industrial-style uses
Simplicity of design vs. future scalability	A simpler mechanical and control design is easier to build, debug, and maintain in a student project, but may restrict future upgrades or adaptation to larger workspaces and heavier tasks, such as those in agricultural or warehouse-related scenarios. Designing for modularity and scalability can reduce this limitation but usually adds extra interfaces, structure, and design effort in the current prototype

1.2.4 Technical Specifications

To reach the technical and non-technical requirements mentioned earlier, the design approach requires specific components.

Table 5 : Technical Specifications

SubSystems	Subsystem Requirements	Components	Specification
Soft Robotic Gripper	3D printed tentacle	Filament	TPU 95A 1.75 mm
	Cable or Tether		Nylon cable
	Motor	Servo	- Digital servo with Magnetic Encoder - Stall: Torque 40Kg.cm - Rotation: 360° - Operating Voltage: 5-8.4V - Dtall current: 3.5A@7V
	Microprocessor	Raspberry Pi 5	- Processor: Broadcom BCM2712 (Quad-core Cortex-A72; ARM v8-A, 64-bit) - Clock Speed: 2.4 GHz - RAM: 8 GB LPDDR4-3200 SDRAM - Storage: microSD card for OS and data storage - Operating Voltage: 5V - Wi-Fi: Dual-band 802.11 b/g/n/ac (2.4 GHz & 5 GHz)
	Microcontroller	Arduino Mega	54 Digital I/O terminals 16 MHz crystal clock. - Operating voltage: 6 ~ 12v.
	Power Source	ADC	- Output Voltage: 0–24 V DC (adjustable) - Max Output Current: 20 A - Rated Power: 480 W - Input Voltage: AC 110–220 V, 47–63 Hz
4-DoF Manipulator	3D Printed Body/Chassis	Filament	PLA+ 1.75 mm
	Motor	Servo	- Stall: Torque 380 kg·cm (Holding: 340 kg·cm) - Rotation: adjustable up to 300° - Operating Voltage: 12-24 V DC (7 V min, 30 V max) - Speed (24 V): 0.5 s/60° - Dimensions: 95 × 60 × 110 mm
	Controller	Joystick	Connection Type: wired
Object Detection & Localization	Camera	RGBD Camera	High-resolution depth (1280×720 at 90 FPS) and 2MP RGB imaging.

1.3 Applicable Codes and Standards

Table 6 : Applicable Codes

Code / Regulation	Standard Name	Description	Project Alignment/ Implementation
ISO 10218-1/2:2025	Robotics - Safety Requirements	Safety for mechanical design, integration, and emergency stops in robots	Motion / payload limits, emergency stop, inspection, regulated power
ISO/TR 20218-1:2018	Robot End-Effector Safety Guidance	Guidance for safe design of grippers / end-effectors	Soft gripper modular, manual override, non-hazardous operation
ISO 13482:2014	Safety for Personal / Service Robots	Service robot safety in non-industrial scenarios	Safe service / education deployment protocols
ISO 22166-1	Modular / Sustainable Robotic Design	Guidelines for modular, sustainable robot design	Recyclable materials, modular repair, waste reduction
ICT Act (2006/09/13)	Bangladesh Information Security Laws	Laws governing data protection, legal software usage, and IT system security in Bangladesh	All project data is securely managed; only licensed / free software is used; hardware / software access is controlled; documentation and regular audits are maintained;

1.4 Summary of the Proposed Project

The presented project is focused on creating a soft robotic gripper-manipulator device to safely manage small, delicate, and irregular objects in highly controlled laboratory settings. The essence of the concept is to incorporate a tentacle-inspired soft gripper together with a 4-DoF articulated arm to allow the entire system to adjust its contact of the various shapes and surface qualities of an object and still be feasible to operate and optimize in a standard laboratory or industrial setting. The flexible nature of the gripper body and fingers are achieved with the assistance of 3D printing, particularly with flexible materials that reproduce the tentacle-like morphology of the body and the fingers, which enables the fingers to encircle non-uniform objects and redistribute contact forces across more areas, and thus minimise the risk of visible damage during the grasping process.

Another benefit of the project is to apply this behaviour with the help of a compact, low-DOF manipulator so that the soft gripper can be positioned in a small yet convenient workspace in place of trying to design a complicated, high-precision industrial robot. The arm and gripper are jointly designed to ensure that the kinematics, payload (approximately 400 g) and reach

are capable of dealing with standard laboratory pick-and-place operations at the expense of having a conventional inverse-kinematics-based autonomous and operator-in-the-loop manual control approach and motion. The object detection pipeline presented in this paper based on YOLO allows the system to find target objects in real-time and exhibit autonomous grasping capabilities.

Mechanical parts are manufactured through 3D printing with commercial PLA+ and TPU filaments, actuation and control hardware is made out of off-the-shelf motors, drivers, and raspberry pi hardware which are both found in the Bangladesh market. The system suggested provides a viable means of connecting 3D printing soft structures and a modular 4DoF robotic arm with familiar perception and control mechanisms in a single platform. It is made to operate similarly to the robotic practice currently in use, with the added benefit of being able to work with fragile and irregular objects with a much safer approach via using a soft adaptive gripper.

1.5 Conclusion

Altogether, the project offers a logical way of dealing with fragile and irregular shaped objects by combining a tentacle-inspired soft gripper with a 4DoF articulated manipulator and a simple vision pipeline. The soft TPU gripper structure design is 3D-printed and offers adaptable non-uniform contact with low pressure, and the PLA+ arm and joints offer rigidity and positioning ability needed in the chosen laboratory environment. Meanwhile, the system architecture is geared toward 4 degrees of freedom, autonomous control based on an inverse kinematics as well as operator based manual control and a YOLO-based detector that are sufficient to perform safe and repeatable operations on objects with masses of up to approximately 400 g.

Using 3D printing to fabricate, soft compliant fingers, off-the-shelf actuators and controllers which are available in the market in Bangladesh allow the proposed design to be a viable soft-robotic platform that eventually can be adapted into light industrial environment and also used in research and small scale experimental activities. It fulfills the primary goals of the project: it develops a working 4DoF adaptive manipulator coupled with a bio-inspired soft gripper that proves how safely fragile and irregular shaped objects can be handled, and confirms the potential of 3D-printed tentacle-like structures as a way to develop a suitable grasp.

Chapter 2: Project Design Approach

2.1 Introduction

The development of the soft robotic manipulator and gripper system is directly connected to the way the arm will be controlled in practice. Here, the project of interest is one where non-uniform and delicate objects are manipulated, although the prototype to be used has to be realistic in terms of cost implications and complexities in hardware and development. These limitations imply that the control method should facilitate not only the exploratory tests but also the experiments that are both more detailed and repeatable without making use of the sophisticated and costly types of equipment.

To meet these requirements, the design strategies applied in this case are premised on two complementary operation approaches rather than on a fixed single control approach. One of them has a human operator in the loop, whereas the other attempts to partially automatize the movement and grip. Such a combination enables the same mechanical platform to be tested on different usage conditions and shows how soft robotic manipulation can move back and forth between more basic teleoperation and more autonomous behaviour in a gradual, achievable manner.

2.2 Control Methods

The soft robotic gripper-manipulator system has two principal control methods that are to be used to operate the robot:

1. **Manual Operation:** When manually operated, the operator turns the manipulator by means of an external controller, and has a real-time camera view of the workspace displayed on a monitor. The gripper is placed by the user with respect to the target object, and the grasping act is triggered according to the visual judgment. This is based on the human decision-making approach and is applicable in situations where tasks are diverse or not completely structured.
2. **Automatic Operation:** In automatic mode, the system captures camera images to find or identify target objects in the workstation and compute appropriate commands to the manipulator and gripper to effect an approach and grasp. The goal is to minimize user effort and obtain more repeatable motions of objects that come within the assumed conditions of the control algorithm.

These strategies have been selected since they are two realistic extremes that are both practical to be implemented using the available resources. The attractiveness of manual operation in this prototype is that it does not involve much complicated control electronics or software, but the system can still do significant manipulation, because the operator can counterbalance modeling errors, poor sensing or unpredictable object behavior with visual judgment and experience.

Automatic work, however, is added to investigate the extent to which the system can be pushed to the scope of self-directed movements and a single grasp working with primitive vision and control algorithms. Although it may not be within the scope of the project to have full industrial autonomy, even an extremely basic automatic mode can show that the same mechanical and gripper design can be used to repeatedly produce motions towards observed objects. A combination of these two methods would create a useful testbed: manual control would offer strength and flexibility, whereas automatic control would explore the opportunities of more structured, semi-autonomous control in future applications, such as repetitive pick-and-place assignments in small warehouses or in farm sorting systems.

2.3 Design Approaches

In order to meet the technical requirement, two approaches to design are derived. They both have block diagrams and flowcharts to describe the working flow and system architecture:

2.3.1 Design Approach 1 : Manual Control

This provides the option of operating the manipulator and the gripper directly with human control and can be used in applications that require human control and decision-making flexibility. Operators control the manipulator manually through an interface and have the ability to control the manipulator in a responsive and precise way in conditions that demand human judgment extensively.

Block Diagram for Manual Control:

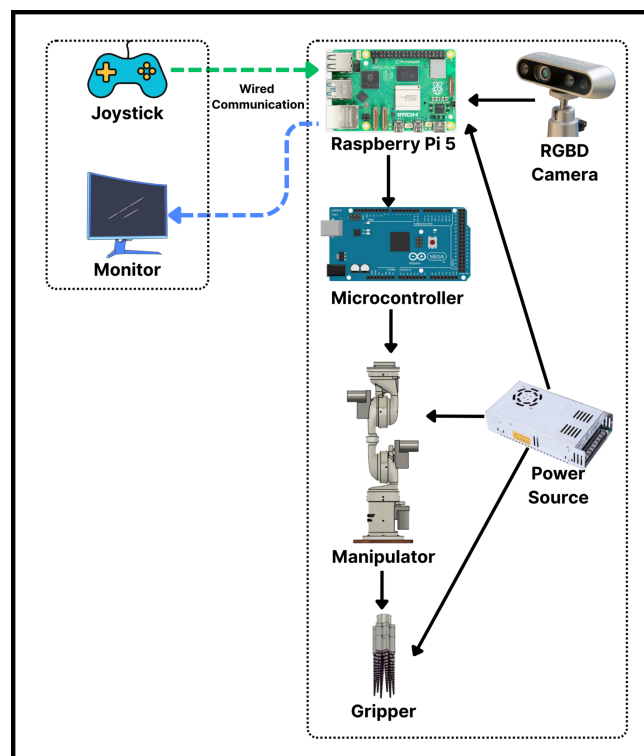


Figure 1 : Block Diagram of Manual Control Manipulation

Flowchart for Manual Control:

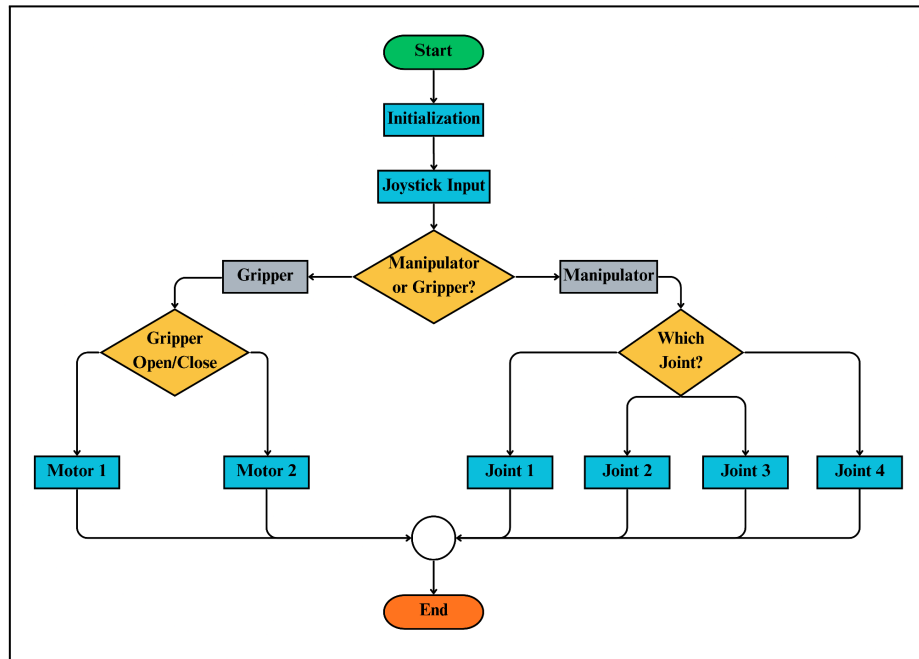


Figure 2 : Working Flowchart of Manual Control

Manual Operation Workflow

The manual control manipulation system starts its operation through an initialization period during which the Raspberry Pi 5 microprocessor establishes links with the joystick, RGBD camera, motors, and all connected joints of the manipulator and gripper. The system sets both the manipulator and gripper to their designated safe default positions, which establish the conditions for dependable system performance.

The joystick serves as the main control device that users operate to handle manual system operations. The joystick enables users to control the system through their movements, which the microprocessor processes to execute their commands. The RGBD camera continuously collects visual data from both the workspace and the robotic arm, which the operator can monitor through a display that presents real-time visual feed.

The microcontroller assesses joystick commands to identify which control mode should be used based on whether the user wants to operate manipulator joints or gripper functions. The joystick input for gripper control is established when the user selects the gripper control option to choose between the opening and closing actions. The microcontroller generates appropriate control signals to control the gripper motors Motor 1 and Motor 2 to provide precise movement for the gripper. The gripper uses force control to ensure it has the ability to grasp the object while also releasing the object when required.

The microcontroller selects which joint or actuator to control using the joystick input when the user selects the manipulator control mode. The manipulator receives motion control to move to different positions using incremental movement. The operator can continuously monitor these movements through the live camera feed.

The control system maintains its operation through an endless loop that enables the operator to switch between gripper control and manipulator motion control at any time. The operator uses discrete joystick inputs together with real-time visual feedback to control the end-effector movement which includes positioning, target alignment, grasping operations, and manipulator repositioning.

The design system uses manual control through joystick operation to establish teleoperation mode which does not depend on autonomous systems for perception, sensing, or motion planning. The system functions as a baseline control method which enables assessment of both mechanical operation and soft gripper performance testing during system evaluation and operator development.

2.3.2 Design Approach 2 : Autonomous Control

This design uses autonomous movement implemented on the basis of vision-based sensing and inverse kinematics. The system recognizes objects through image processing, and then through the use of inverse kinematics corrects the position automatically and then determines the grip force required automatically without need of human operator. It enhances the effectiveness and dependability of automating the industrial setup since it could be adapted instantly to the characteristics of the objects.

Block Diagram for Autonomous Control:

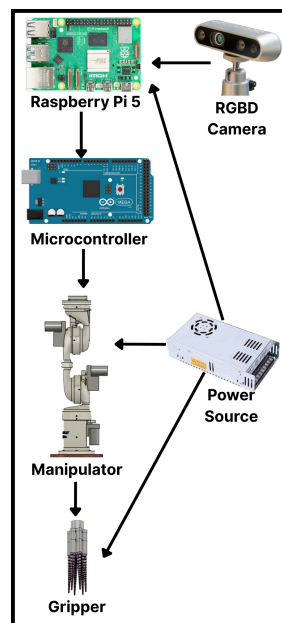


Figure 3 : Block Diagram for Autonomous Control Manipulation

Flowchart for Autonomous Control:

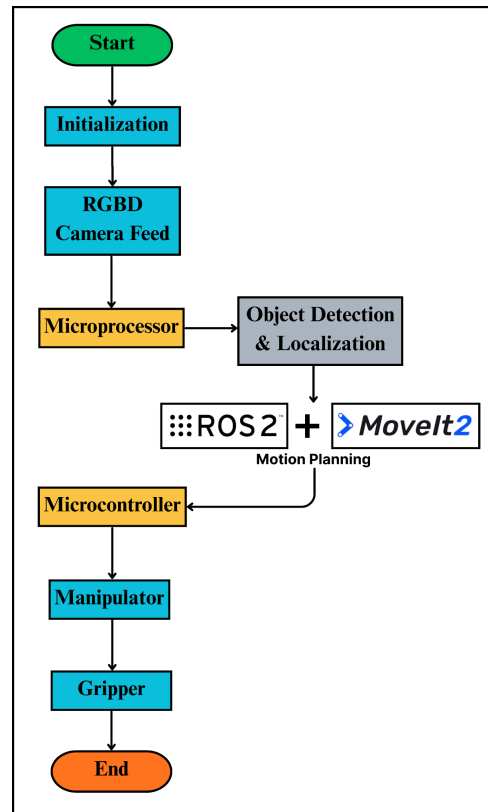


Figure 4 : Working Flow Chart for Autonomous Control

Autonomous Operation Workflow

The autonomous control manipulation approach starts its system operation process with an initialization phase which requires the Raspberry Pi 5 to function as the main microprocessor and conduct system tests. The system establishes communication links with the RGBD camera, microcontroller unit (Arduino Mega), and all actuator interfaces. The operator can direct the manipulator to its designated home position during system startup to establish a dependable method for motion planning that uses an identified reference position.

The RGBD camera starts to record visual and depth data of the workspace after the system finishes the initialization process. The camera feed is transmitted to the Raspberry Pi 5, where it acts as a primary sensory input for autonomous operation. The use of depth information together with RGB image data enables measurement of distances and 3D perception of the scene.

The Raspberry Pi 5 executes machine learning-based object detection and localization algorithms during its high-level processing stage. The algorithms track target objects within the workspace while determining their distance to the camera. The depth component of the

RGBD data helps compute the camera-object distance, which enables representation of object position in a basic 3D workspace coordinate system.

The system first integrates detected object pose data into a ROS 2 software framework which functions as the main system link for both inter-module communication and complete system operation. The system uses MoveIt 2 as its motion planning tool and inverse kinematics calculation tool. MoveIt 2 uses the target object location to determine an end-effector position that meets kinematic requirements and joint restrictions and collision avoidance rules for the manipulator. RViz provides users with a visual display of planned trajectories which allows them to monitor and troubleshoot all stages of perception and planning and motion execution processes.

The Raspberry Pi 5 sends trajectory commands to the Arduino Mega microcontroller after the system creates a valid motion plan which controls all aspects of the robotic system's functions. The microcontroller uses the incoming trajectory data or joint commands to generate accurate motor control signals which operate each actuator of the manipulator. The system designates the microprocessor to perform all demanding activities which include perception and planning and decision-making activities while the microcontroller handles all time-sensitive motor control requirements.

The manipulator system improves its ability to track objects through ongoing camera frame updates which help it determine the position of targets while tracking their movement. The microprocessor sends a signal to activate the gripper after the end-effector successfully reaches the required grasp position. The Arduino Mega operates the gripper control system which closes the soft gripper through established motion patterns that protect fragile objects.

The system determines task completion after a grasp attempt by assessing actual task performance and receiving information from internal systems about completed motion paths and gripper movements. The workflow ends when a grasp succeeds, but it continues to the next steps of object lifting and placement which follow. The system restarts the perception–planning–execution cycle after a grasp attempt fails, using new visual information to develop better control methods.

This design method establishes an entire automatic manipulation system which depends on perception to operate, utilizing RGBD imaging and machine learning object detection with ROS 2 connections and MoveIt 2 pathfinding and distributed system control from a Raspberry Pi 5 and Arduino Mega combination. The system supports independent robotic manipulation through its ability to build multiple operational units which function without needing human assistance.

2.4 Design Analysis

Table 7 : Design Comparison

Aspect	Manual Operation (Joystick + Camera View)	Automatic Operation (Vision + IK)
User Effort and Flexibility	High flexibility, as the user can adapt to unexpected situations, irregular objects, or partial occlusions using judgment and experience; suitable for exploratory testing and one-off tasks	Lower continuous user effort once set up, since the system can repeat the same motion pattern for similar objects; flexibility is limited by the vision and IK algorithms and their tuning
Implementation Complexity	Relatively simple to implement, since the microcontroller mainly needs to map joystick inputs to motor commands and maintain safe limits; easier to debug and modify during development	More complex, because it requires image processing, object localization, coordinate mapping, and IK computation inside the microprocessor; debugging can be harder when multiple software stages interact
Repeatability and Speed	Repeatability depends on the operator; performance can vary from trial to trial, and long, repetitive tasks may become slow or tiring for the user	Can provide more repeatable motion for structured tasks, as the same detection and motion pipeline can be reused; speed is limited by processing time and the accuracy of the detection and IK stages
Robustness to Uncertainty	More tolerant of imperfect models or partial visibility, because the user can correct for errors in real time by watching the camera feed and adjusting commands	More sensitive to modeling errors, lighting changes, and occlusions; if detection or localization fails, the resulting motion may be inaccurate, and the system may need additional checks or retries
Hardware and Resource Requirements	Works with modest processing resources, since no heavy vision or IK computation is required; suitable for simpler microcontrollers and basic lab setups	Needs more processing capability and memory to run the vision and IK routines on the microprocessor; timing and resource management become more critical to keep the system responsive
Suitability for Future Applications	Well suited for scenarios where a trained operator is always present, such as laboratory experiments, training setups, or low-volume tasks; provides a good baseline for testing new gripper designs	Provides a starting point for future semi-autonomous or autonomous applications, such as repetitive pick-and-place in small warehouses or agricultural sorting, provided that algorithms are refined and hardware is upgraded as needed

2.5 Conclusion

With the analysis presented in this chapter, it can be said that the decision on whether to use manual or autonomous control of the soft robotic manipulator cannot be based on the results of the simulation only. Cost of hardware, computation capability, effort of implementation and the expertise needed to sustain the system are factors that are very essential and determine whether the control strategy is indeed practical to be used in the real- world field. Specifically, autonomous operation requires increasingly sophisticated processing powers,

closer attention to algorithm tuning, and more resistance to sensing and environmental uncertainties which might not be well represented in simulation.

Simultaneously, the manual, teleoperation-oriented model has evident simplicity, flexibility and debugging simplicity benefits, particularly when dealing with a limited budget and a small platform of microcontrollers. With viable operator control, an experienced operator can be able to adjust to a situation with unforeseen events, to correct modeling failures and to cope with irregular object forms, to an extent less repeatable than autonomous pipeline motions designed by an expert.

As such, the ultimate design selection should be based on balancing the advantages of greater autonomy and increased complexity, cost and expertise, as opposed to focusing on the actual theoretical performance. Even though a more autonomous approach can be more effective in the long-term performance at the structured and repetitive tasks, a more predominantly manual or semi-autonomous approach can be considered more appropriate in the present stage of the development because of its lesser complexity and stronger capability to resolve the practical problems. Through these trade-offs, a balanced setup will be chosen that fits within the constraints of the project, but still allows the possibility to upgrade to a more autonomous state in the future.

Chapter 3: Use of Modern Engineering and IT Tools

3.1 Introduction

This chapter shows the contemporary engineering and information technologies that can be used to design, visualize, and validate the manipulator and gripper system of soft robotics. Software with the capability to interface with ROS2 and clearly visualize 3D robot movement and sensor behavior as well as enabling fast mechanical design and iteration in a university laboratory environment was needed in the project. Some of the tools were analyzed based on their ease of use, simulation, capabilities of integrating with hardware, cost, and learning curve. On this assessment, RViz was chosen as the main visualization and debugging tool of ROS2 robots, whereas Fusion 360 became the major 3D modelling solution of manipulator and gripper parts. The other software such as MATLAB and Gazebo was conceptually reviewed as one of the environments to use advanced control and full-physics simulation but was not incorporated in the current implementation.

3.2 Selection of Modern Engineering / IT Tools

Table 8 : Softwares for Simulation

Criteria	MATLAB	RViz-ROS	Gazebo
Ease of Use	Beginner-friendly, strong documentation, widely used in academia	User-friendly for visualization; fast to set up	Moderate setup; steeper learning curve
Simulation Power	Excellent for kinematics, mathematical modeling, visualization (Simulink, Robotics Toolbox)	Basic physics and visualization; no full dynamics	Advanced 3D physics, sensors, and environment sim
Flexibility	Best suited for control, algorithm development, data analysis	Highly flexible for complex robot-environment sim	Visualization focused; limited simulation flexibility
Integration with Hardware	Limited, needs extra toolboxes/interfaces	Visualization interface through ROS, indirect hardware integration	Strong integration via ROS
Real-Time Capabilities	Mostly offline; some real-time features via toolboxes	Real-time visualization and parameter updates	Supports real-time physics and sensor simulation
Learning Curve	Moderate for simple sim; steep for complex robotics systems	Easiest to learn; good for quick visualization	Steep learning curve; requires robotics familiarity
Visualization	Advanced plotting, simulations,	3D visualization of robot	Detailed environment

& Analysis Tools	data analysis	states and sensors	and sensor visualization
Why We Chose It	Planned for future trajectory optimization and control algorithms	Primary tool currently for visualizing and debugging	Considered for future full-system simulation

Based on the comparison table and our project requirements, we chose RViz as our primary simulation and visualization tool. RViz offers a user-friendly interface for real-time visualization of robot states and sensor data, which fits our current needs effectively with minimal setup and strong ROS integration. While MATLAB provides powerful tools for algorithm development, kinematics, and control system prototyping, its simulation environment is best suited for offline analysis and future trajectory planning. Although Gazebo is widely regarded as an industry-standard simulator capable of detailed physics-based robot and environment simulation, we have not yet integrated it into our workflow due to its steeper learning curve and setup complexity. Gazebo remains a strong candidate for future stages of the project requiring full-system simulation and hardware-in-the-loop testing.

Table 9 : Softwares for CAD Design

Criteria	Fusion 360	SolidWorks	TinkerCAD (or FreeCAD)
Ease of Use	Intuitive, cloud-based, good collaboration tools	Professional, steep learning curve, very precise	Simple, great for beginners, less powerful
Modeling Power	Strong parametric modeling, simulation, assemblies	Advanced assemblies, simulation, industry standard	Basic modeling only
Cost	Free for students/educators, affordable plans	Expensive, licensed	Free and open-source
Integration	Good export options (STEP, STL), integrates with CAM and simulation tools	Excellent for engineering workflows	Good for learning, not suited for complex assemblies
Collaboration & Cloud Access	Excellent cloud integration, real-time collaboration, easy sharing of files/projects online.	Primarily local files, but supports collaboration via PDM (Product Data Management) systems; cloud add-ons are available but less seamless.	TinkerCAD is cloud-based with simple sharing; FreeCAD is local file-based, limited collaboration
Simulation & Motion	Includes built-in simulation and basic motion analysis tools for	Advanced simulation and motion analysis features	Very limited or no simulation/motion

Analysis	assemblies.	(FEA, CFD, etc.).	analysis capabilities.
Why We Chose It	We use Fusion 360 for all manipulator and claw designs due to its balance of power and ease of use	Considered, but licensing and learning curve were factors	Good for basic designs, not chosen for this project

Our decision to use Fusion 360 as a primary 3D design interface was based on user-friendly interface, good modeling capabilities and accessibility to students. It enables us to rapidly prototype manipulator and claw designs, and export models quickly, to simulate with ROS simulations.

3.3 Use of Modern Engineering and IT tools

Fusion 360 for Mechanical Design and Fabrication

All mechanical components of the soft robotic manipulator and gripper were designed by use of Fusion 360 as the main CAD platform. The arm and bracket and base framework together with the soft-gripper mounting tool were modeled in terms of parameters, thus allowing dimensions and clearances to be changed in a short amount of time as the kinematic and structural design was changed. The designs were finalized after which the parts and assemblies could be exported out as STL files and made on BanBU lab FDM 3D printers, using PLA to make rigid structures and TPU to make compliant tentacles, thus forming an entire pipeline between the digital design and physical prototype.



ROS2 and RViz for Simulation and Validation

The Fusion 360 models had been translated into a ROS-compatible robot description (URDF/xacro) and added to the ROS2 workspace before any hardware was made. With RViz, we were able to visualize the manipulator in three-dimension in addition to checking the correctness of link frame and joint constraints and noting the end-effector motion upon different joint commands, making sure that the kinematic behavior was within the requirements of the project.



ROS2 and MoveIt for Control

ROS 2 acts as the middleware that facilitates modular and real-time communication of the perception, planning, and control nodes of the robotic system. It provides a framework that can be utilized for autonomous operations. Being part of the



ROS 2 family, MoveIt acts as the framework that offers motion planning and manipulation functionality. It can be utilized for kinematic modeling, collision checking, and execution of joint-space as well as Cartesian-space motions. The 4-DOF robotic arm is modeled as a URDF representation, allowing MoveIt to be utilized for performing operations such as inverse kinematics and path planning.

3.4 Conclusion

The toolchain of this project shows that contemporary open-source and student-friendly software can be useful in developing a soft robotic system without using the complex commercial simulation suites. RViz was used as the main visualization, and it was possible to inspect the state of the joints, transform link and sensor topics in real-time, in the ROS ecosystem, which simplified verification and debugging of the manipulator kinematics and control flows significantly. In terms of its mechanical aspects, Fusion 360 offered an effective platform to do the parametric modeling, assembly design and export of geometries that are 3D printable as well as the ability to create design-fabricate-test cycles on both rigid links and soft gripper structures very quickly at no extra software expense to us.

Chapter 4: Optimization of Multiple Design and Finding the Optimal Solution

4.1 Introduction

For the development of the soft robotic manipulator and gripper, two design approaches are considered: manual control and autonomous control. In this chapter, these two approaches are first evaluated in simulation on the same 4-DoF manipulator model to determine which provides more accurate and repeatable end-effector positioning. After selecting the optimal approach, the chapter explains how the chosen control method guides the mechanical and kinematic design, the selection of electrical and electronic components, and the definition of the complete system architecture that will later be realised in hardware

4.2 Optimization of Multiple Design Approach

4.2.1 Simulation of Two Design Approaches

There are a total of 4 joints in the manipulator. For the comparison between the two design approaches, we considered the tip of the 4 DoF manipulator as the end-effector.

Manipulator Description in RViz Simulation:

There are a total of 4 joints in the manipulator. The first 3 joints from the base to tip are the manipulator's core joints for manipulation. The remaining joint is the tip of the manipulator which is considered as the end-effector to show gripping purposes in the simulation.

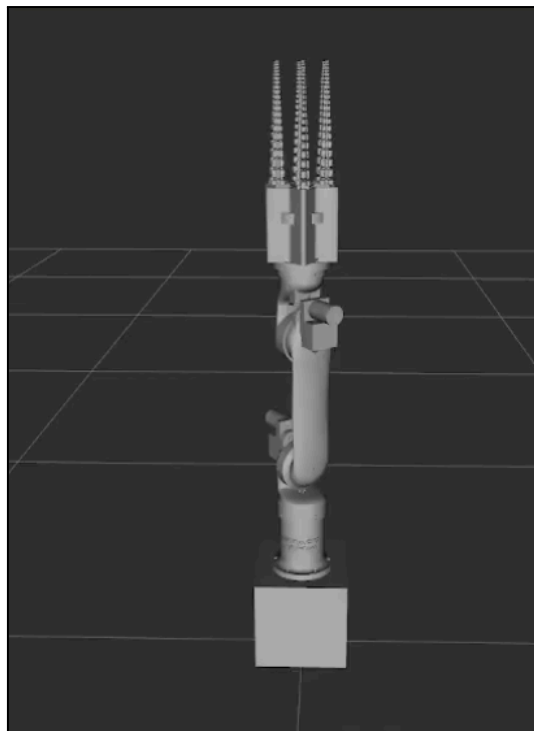


Figure 5 : 4-DoF Manipulator in RViz

Design Approach 1: Manual Control

Simulation Procedure:

1. A “Joint-State-Publisher-GUI” is present to control the movement of the 4 joints of the manipulator.
2. The (x,y,z) cartesian coordinate of the target position is set in a .py file. The target position’s coordinate can be changed for each test simulation.
3. User can use the GUI to control the manipulator's joint positions to reach the target position.
4. At the end of the process, the terminal shows the following parameters :
 - i) **Final position** : The (x,y,z) position reached by the end-effector of the manipulator.
 - ii) **Position Error** : How much deviated the current position of the end-effector is from the target position.
 - iii) **Position Accuracy (%)**
 - iv) **Execution Time**
 - v) **Simulation Status** (an error threshold has been set to measure the status)

Step 1: Setting the target position in the bottom terminal

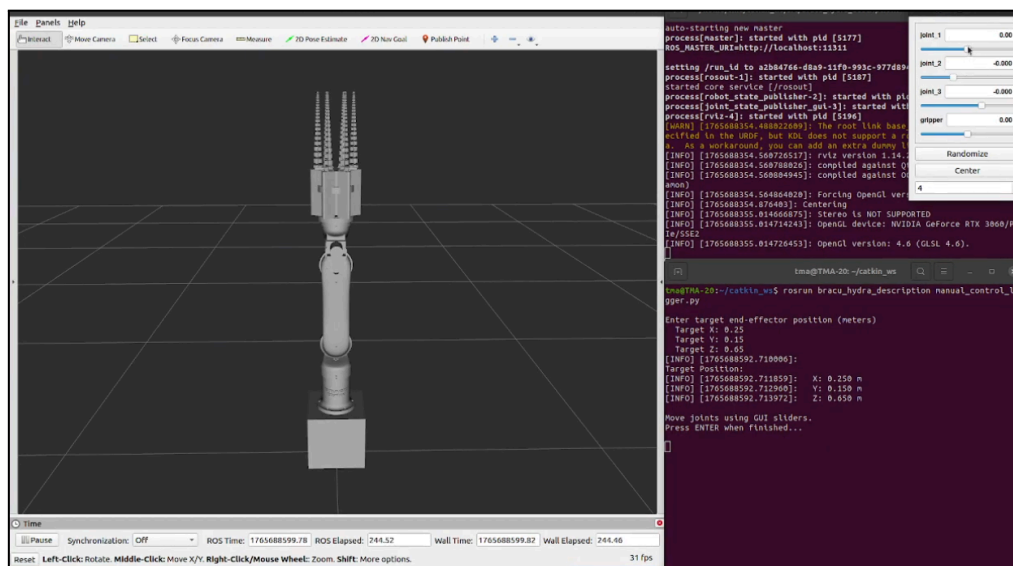


Figure 6 : Target Position Set

Step 2: Changing the joint angles to reach the desired position using Joint-State-publisher GUI

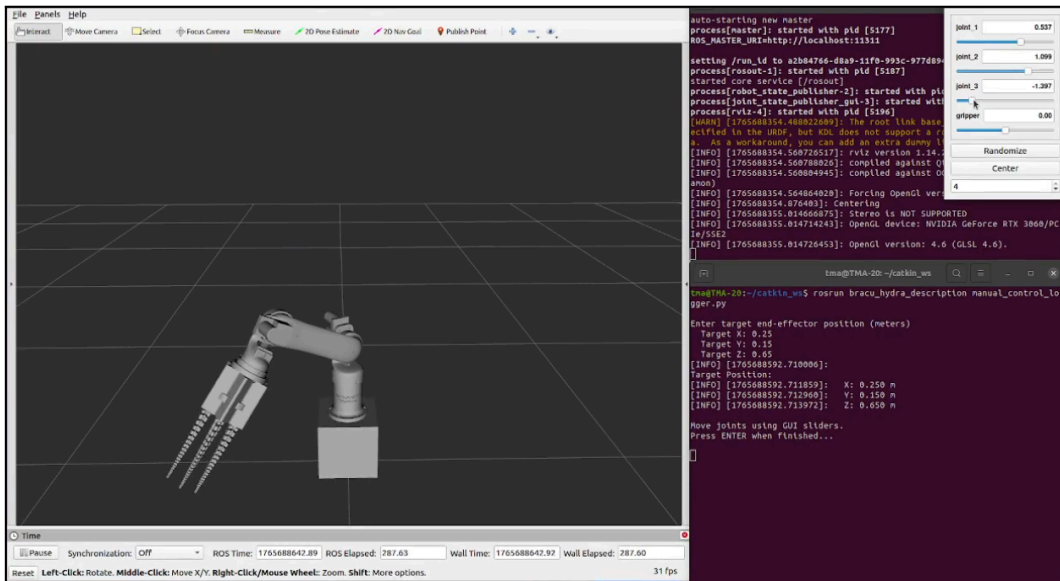


Figure 7 : Using Joint-State-Publisher-GUI to Control Joint Angles (in Radian)

Step 3: Ending simulation and displaying the parameters

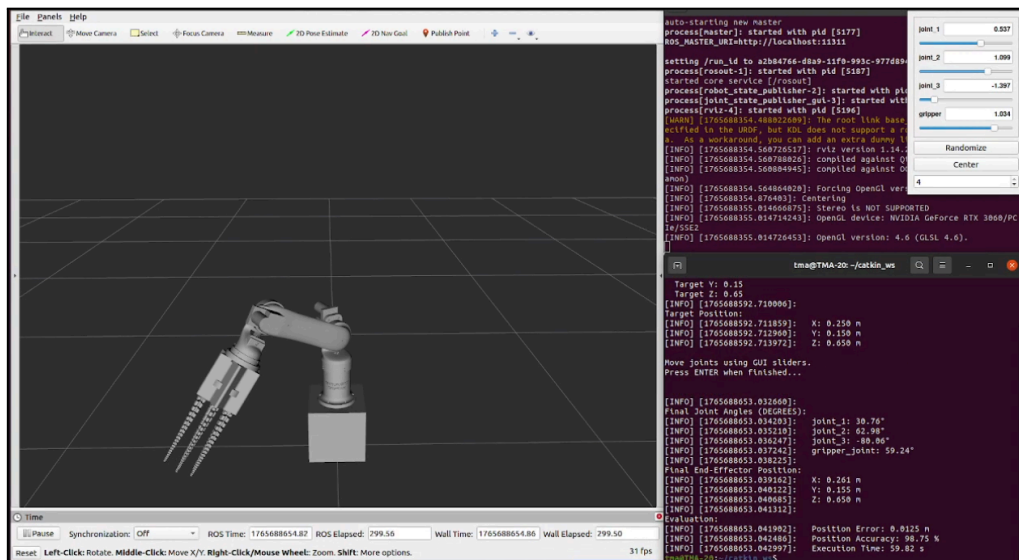


Figure 8 : Displaying Parameters in the Bottom Terminal after Terminating Simulation

```

[INFO] [1765689350.007664]:
Final Joint Angles (DEGREES):
[INFO] [1765689350.009206]:    joint_1: 24.07°
[INFO] [1765689350.010433]:    joint_2: 72.77°
[INFO] [1765689350.011605]:    joint_3: -71.29°
[INFO] [1765689350.012803]:    gripper_joint: 51.39°
[INFO] [1765689350.013961]:
Final End-Effector Position:
[INFO] [1765689350.015064]:    X: 0.228 m
[INFO] [1765689350.016136]:    Y: 0.102 m
[INFO] [1765689350.016983]:    Z: 0.718 m
[INFO] [1765689350.017614]:
Evaluation:
[INFO] [1765689350.017998]:    Position Error: 0.0864 m
[INFO] [1765689350.018363]:    Position Accuracy: 91.36 %
[INFO] [1765689350.018681]:    Execution Time: 25.81 s

```

Figure 9 : Snippet of the Parameters of Manual Controlled Simulation

Design Approach 2: Autonomous Control

Simulation Procedure:

1. The (x,y,z) cartesian coordinate of the target position can be set in the user prompt of the terminal. The target position's coordinate can be changed for each test simulation.
2. After that, the manipulator will move its joints automatically to reach the target position.
3. After executing, the terminal shows the following parameters same as Manual Control approach:
 - i) **Final position** : The (x,y,z) position reached by the end-effector of the manipulator.
 - ii) **Position Error** : How much deviated the current position of the end-effector is from the target position.
 - iii) **Position Accuracy (%)**
 - iv) **Execution Time**
 - v) **Simulation Status** (an error threshold has been set to measure the status)

Step 1: Setting the target position in the terminal

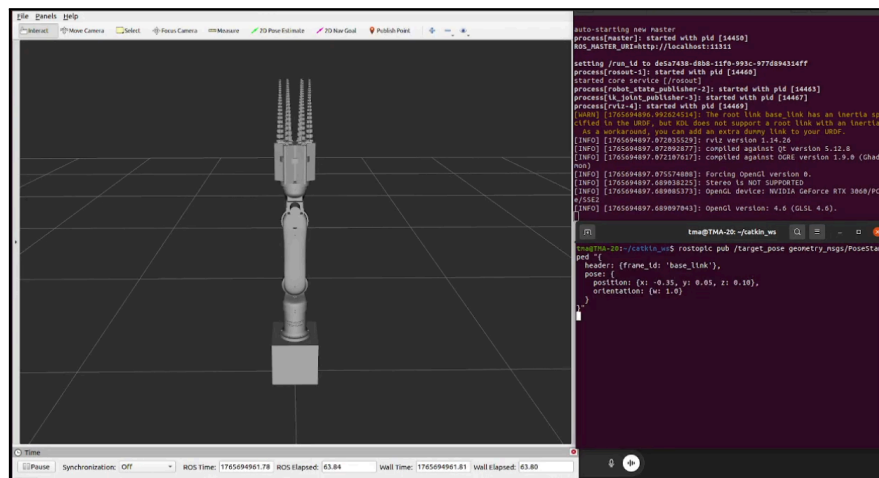


Figure 10 : Target Position Set

Step 2: Executing the simulation

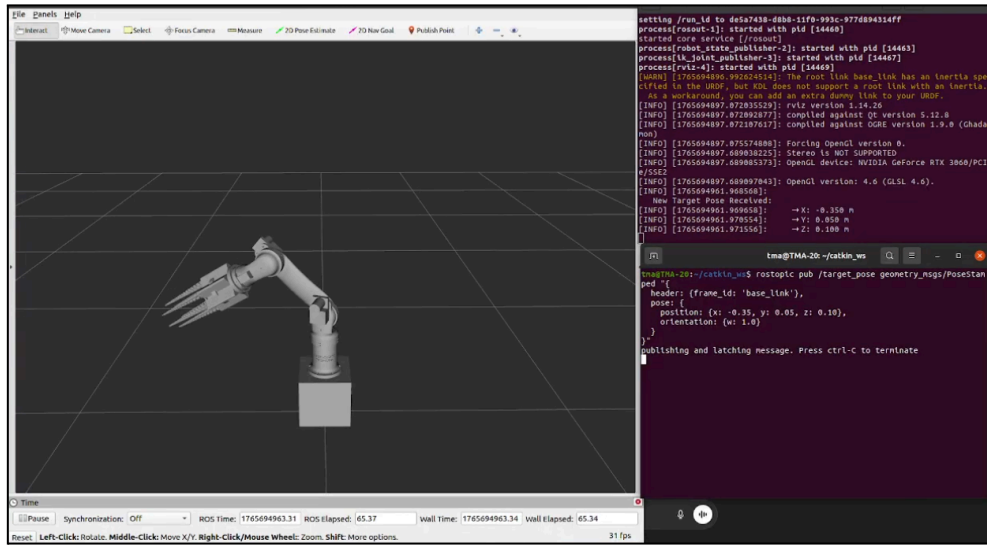


Figure 11 : Simulation Executed

Step 3: Displaying the parameters

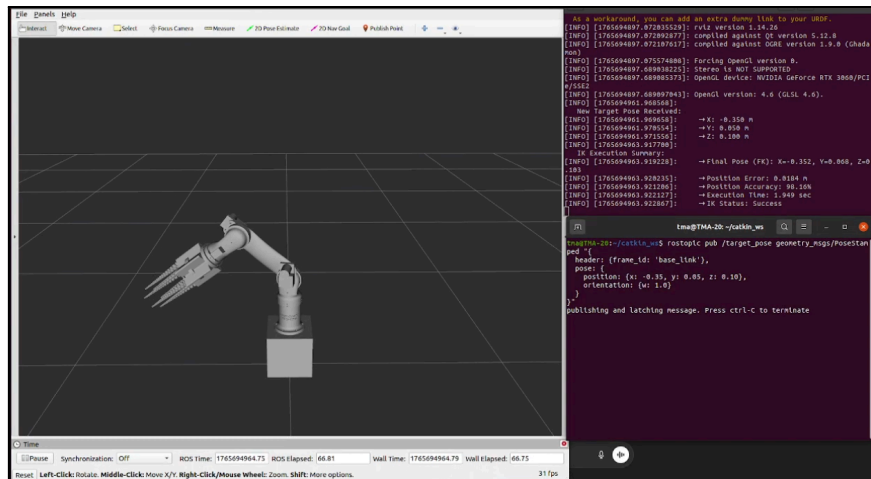


Figure 12 : Parameters Displayed in the Top Terminal After Successful Execution

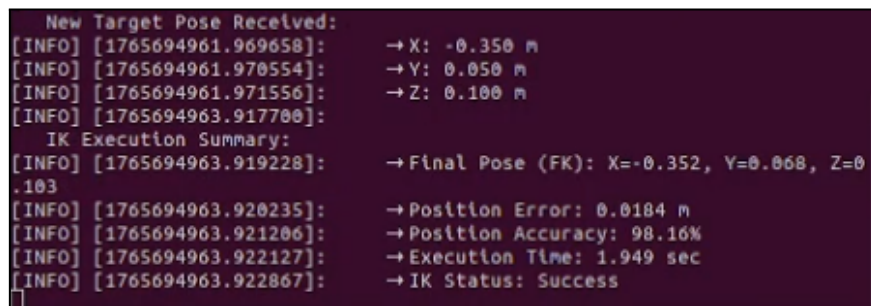


Figure 13 : Snippet of the Parameters of Autonomous Controlled Simulation

Workspace Simulation

To uncover the area that the soft robotic manipulator can actually reach before producing hardware, a special workspace simulation was performed in ROS2 and RViz on the 4-DoF model of our arm. The aim was to sample the entire range of end-effector poses within the joint limits numerically and to visualise the workspace thus ensuring that the mechanical dimensions and the joint ranges were compared with the tasks to be performed. This general accessible area is shown in the RViz perspective of the arm with a coloured point cloud (Fig. 14).

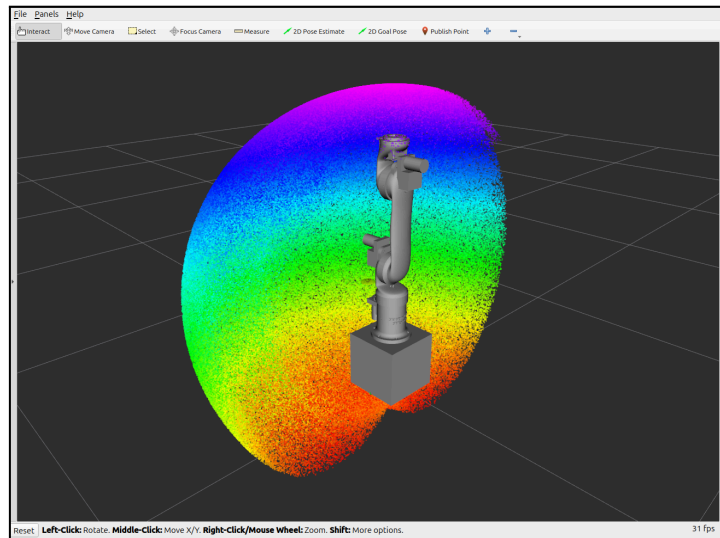


Figure 14 : Workspace of the Manipulator

The first step involved the creation of a Python tool: it was a tool that swept the four joint variables throughout their valid ranges and calculated the resulting end-effector positions using forward kinematics. The code is executed within a terminal, and it repeatedly samples the combinations in joint space and its result is printed as the number of considered configurations grows. RViz is set up to subscribe to this topic and visualise the information as a coloured point cloud around the 3D visualisation of the manipulator. The workspace is easily visualised by adjusting the settings of the PointCloud2 settings, i.e. size of the points, openness/opacity, an axis based colour like a rainbow, making it look like an operational site the end-effector is allowed to use.

In the visualisation, it could be seen that the reachable space is an asymmetric dome in front of the robot base and sparse or absent points are near the base of the robot and behind the arm where self-collision and joint-limit constraints limit the motion. Based on the same data set, the workspace volume was measured and the total number of sampled points are recorded in the terminal output of Fig. 15 That is indicative of the fact that with the chosen link lengths and joint limits the soft manipulator offers a generous range to the intended work without exceeding its small operational volume of 0.7695 m^3 .


```

tma@tma:~/ros2_ws/src/bracu_hydra_ik_control/tools$ gedit hydra_workspace_generate.py
^C
tma@tma:~/ros2_ws/src/bracu_hydra_ik_control/tools$ cd ~/ros2_ws/src/bracu_hydra_ik_control/tools
python3 hydra_workspace_generate.py
Sampling true workspace (joint-space driven)...
0/300000
50000/300000
100000/300000
150000/300000
200000/300000
250000/300000

Workspace volume ≈ 0.7695 m³
DONE
tma@tma:~/ros2_ws/src/bracu_hydra_ik_control/tools$ 

```

Figure 15 : Terminal Output of the Computed Workspace Volume (0.7695 m³)

4.2.2 Performance Evaluation of the Developed Solution

Parameters for Performance Comparison

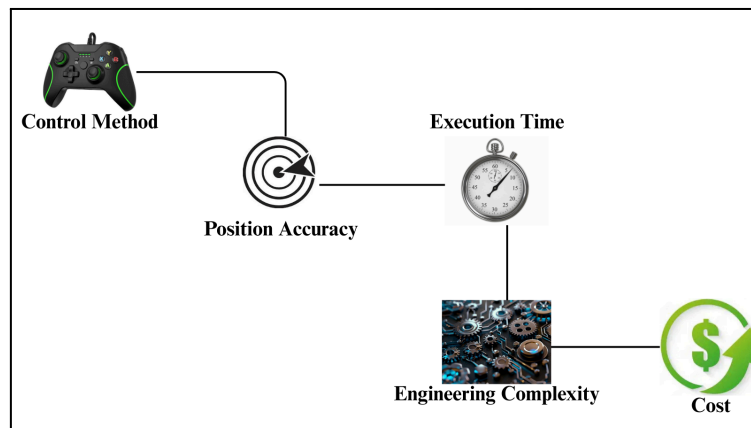


Figure 16 : Performance Evaluation Parameters

To evaluate and select the optimal control approach for the manipulator, key parameters were considered:

- **Control Method:** Distinguishes between manual and autonomous operation.
- **Accuracy:** Measuring the precision of object manipulation.
- **Execution Time:** Evaluating the time need to complete the task.
- **Engineering Complexity:** Accounts for system integration and design challenges.
- **Cost:** Considers overall development and operational expenses.

These criteria provide a clear, structured basis for comparing the simulated manual and autonomous control methods.

Multiple Test Case Evaluation:

We have performed a total of 10 test simulations for both design approaches. The target positions for the 10 different cases are chosen randomly and run upon these. For comparison, the average values of “Position Accuracy” and “Execution Time” have been taken.

Position Accuracy:

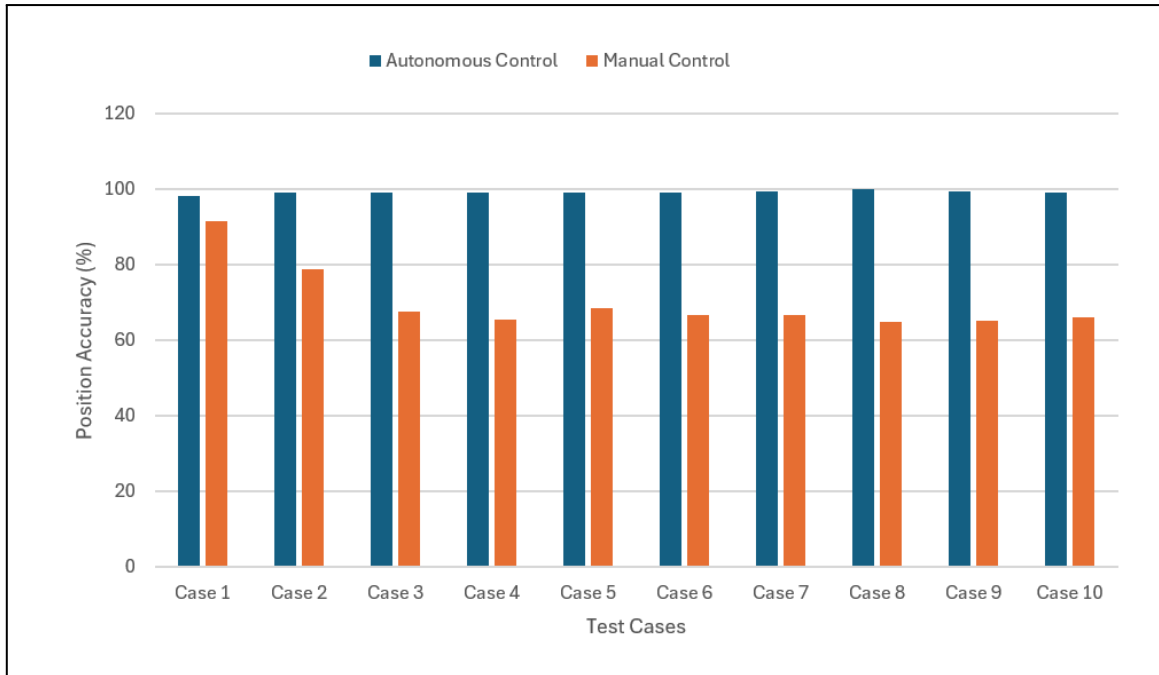


Figure 17 : Test Cases vs Position Accuracy Plot for both Design Approaches

Average Position Accuracy for Manual Control

$$= \frac{91.36 + 78.7 + 67.58 + 65.5 + 68.51 + 66.6 + 66.63 + 64.8 + 65.17 + 65.98}{10}$$

$$= 70.083 \%$$

Average Position Accuracy for Autonomous Control

$$= \frac{98.06 + 99.05 + 99 + 99.18 + 99.04 + 99.09 + 99.29 + 99.84 + 99.30 + 99.12}{10}$$

$$= 98.997 \%$$

The Test Cases vs Position Accuracy plot shows that the average position accuracy we got for Manual Control Manipulation is less than 80% for all cases, whereas, it is more than 95% margin for all cases for Autonomous Control Manipulation. So for multiple test cases, the 2nd Design Approach of Autonomous Control Manipulation gives better position accuracy.

Execution Time:

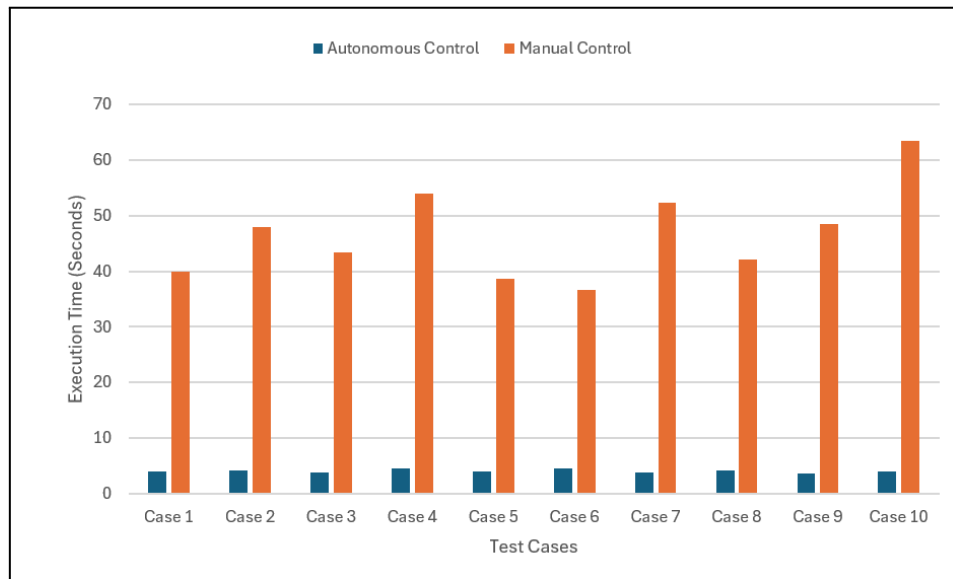


Figure 18 : Test Cases vs Execution Time Plot for both Design Approaches

Average Execution Time for Manual Control

$$= \frac{40+48.05+43.5+54+38.63+36.57+52.32+42.22+48.45+63.45}{10}$$

$$= 46.719 \text{ seconds}$$

Average Execution Time for Autonomous Control

$$= \frac{4.022+4.15+3.86+4.45+3.95+4.6+3.74+4.22+3.58+4.01}{10}$$

$$= 4.058 \text{ seconds}$$

The Test Cases vs Execution Time plot shows that Manual Control Manipulation takes more than 35 seconds to complete simulation for all test cases. On the other hand, Autonomous Control Manipulation takes a very short time (mostly 3 to 5 seconds of margin) for all test cases. So for multiple test cases, the 2nd Design Approach of Autonomous Control Manipulation gives better execution time.

Table 10 : Average Performance

Parameters (Average)	Approach 1 (Manual Control)	Approach 2 (Autonomous Control)	Better Approach
Position Accuracy	70.08 %	98.997 %	Approach 2
Execution Time	46.719 seconds	4.058 seconds	Approach 2

4.2.3 Identifying the Optimal Solution:

Table 11 : Performance Evaluation

Criteria	Approach 1 (Manual Control)	Approach 2 (Autonomous Control)	Better Approach
Human Involvement	Required continuously	Not required	Approach 2
Accuracy	Depends on Operator's skill	Sensor-driven and Calculative precision	Approach 2
Engineering Complexity	Low	High	Approach 1
Cost	Almost equal	Almost equal	Draw
Working Efficiency	Slower for repetitive tasks	Faster and more consistent	Approach 2
Error Handling	Prone to human error	Can use feedback to correct	Approach 2

From the both types of comparisons above, we can prompt the decision that the 2nd design approach of **Autonomous Control Manipulation** is the best approach to proceed with.

4.3 Design and Calculation

The core manipulator is optimally configured with multi-degree-of-freedom motion to meet the requirements of automation in industrial applications, with high-precision stepper or servo motors. This guarantees precise motion control required in sorting, assembling, and handling objects with a strict payload capacity of 400gm.

4.3.1 Manipulator Design

The manipulator is fabricated as a modular design based on the advanced articulated robotic arms, and it uses only servo motors to move every joint. The body of the manipulator is therefore made up largely of PLA, which is easy to fabricate with 3D printing and lightweight construction, but the logical use of carbon fiber rods makes sure that the mechanical performances requirements are met.

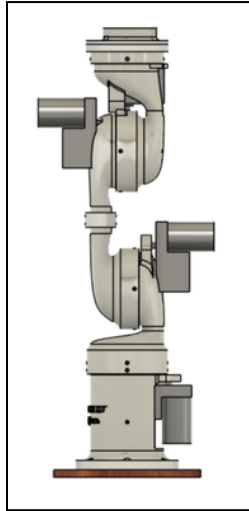
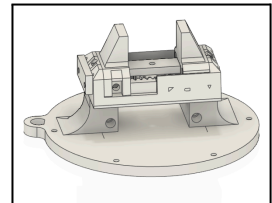


Figure 19 : CAD Design of the 4-DoF Manipulator in Fusion360

4.3.2 Gripper Design

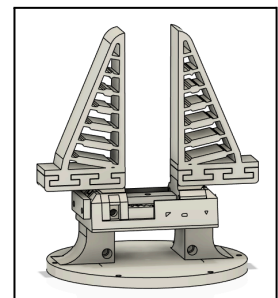
1. Two-Finger Rigid Claw:

This claw uses two rigid fingers whose geometry is best suited to the grip of regular-shaped and smaller objects. It's easy design makes it easy to hold and of particular focus in automation environments where precision and reliability are needed in operations.



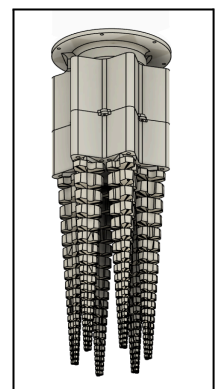
2. Two-Finger Soft Claw:

Attaching TPU based two soft fingers to the gripper instead of rigid fingers makes the gripping process more adaptive, enabling more secure control over irregular objects. The soft fingers can bend according to the shape and size of the objects which ensures balanced gripping force distribution and enhances better gripping stability while handling diverse objects.



3. Bio-Inspired Soft Robotic Gripper:

The bio-inspired soft robotic gripper is designed with six identical soft tentacles, which is capable of gripping delicate or irregular-shaped objects with ease. Two different servo motors can be used inside the controller of this gripper to control open and close of the gripping mechanism. The fragmented design of the each tentacle and their combination allow the grip to adapt dynamically to the shape of the object in best possible way, and is therefore preferred in industry and agriculture with delicate items or produce.



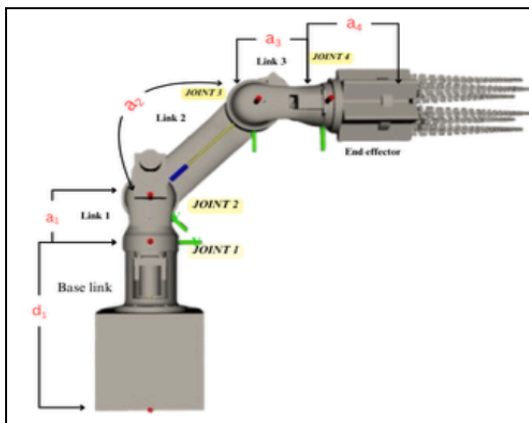
This adaptive manipulator, with a suite of replaceable claws, is built using only stepper motors and can be used to provide flexibility and assured automation in warehouse, industrial, and agricultural applications.

Table 12 : Gripper Design Comparison

Gripper Type	Number of Fingers	Design Characteristics	Suitability	Advantages	Limitations
Two-Finger Rigid Claw	2	Simple compliant fingers suited for regular, small sized objects	Basic industrial tasks requiring precision	Simple design; reliable for symmetric objects; easy control	Limited adaptability to irregular shapes
Two-Finger Soft Claw	2	Can be made by replacing with rigid fingers for enhanced grip on asymmetric and irregular objects	Moderately complex environments where flexibility is required	Improved stability and grip security for varied shapes	Round or oval shaped objects can be slipped out while gripping
Bio-Inspired Soft Robotic Gripper	6 Tentacles	Soft, highly flexible design inspired by biological tentacles; adapts to object shape	Complex, unstructured environments (agriculture, fragile goods)	Maximum adaptability; gentle, secure grasp on delicate objects	Higher mechanical complexity; advanced control required

The design that will be used in the project is the Bio-Inspired Soft Robotic Gripper. This selection is based on the fact that it has several soft and flexible fingers which can dynamically adapt to the shape of many objects. This flexibility ensures that it is particularly applicable in the work with sensitive and multiple-shape objects in the industrial and farming setting. The delicate holding nature of the tentacle claw also makes manipulation of delicate objects much safer, which is more advantageous than the two-finger and three-finger claws as they are generally simpler and more precise.

4.3.3 Kinematics



$$\text{Base Link} = l_0 = 356\text{mm} = 0.356\text{m},$$

$$\text{Link 1} = l_1 = 90\text{mm} = 0.090\text{m},$$

$$\text{Link 2} = l_2 = 187\text{mm} = 0.187\text{m},$$

$$\text{Link 3} = l_3 = 222\text{mm} = 0.222\text{m},$$

$$\text{Link 4} = l_4 = 179\text{mm} = 0.179\text{m}$$

DH Table:

Joints	α	a	d	θ
1	$-\frac{\pi}{2}$	0	0.356	$\frac{\pi}{6}$
2	0	0.187	0	$-\frac{\pi}{4}$
3	$\frac{\pi}{2}$	0.222	0	$\frac{\pi}{4}$
4	$-\frac{\pi}{2}$	0.179	0	0

Homogenous Transformation Matrix:

$$\begin{aligned}
 T_1 &= \begin{bmatrix} \cos \theta_1 & -\sin \theta_1 \cdot \cos \alpha_1 & \sin \theta_1 \cdot \sin \alpha_1 & a_1 \cdot \cos \theta_1 \\ \sin \theta_1 & \cos \theta_1 \cdot \cos \alpha_1 & -\cos \theta_1 \cdot \sin \alpha_1 & a_1 \cdot \sin \theta_1 \\ 0 & \sin \alpha_1 & \cos \alpha_1 & d_1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \\
 &= \begin{bmatrix} \cos \frac{\pi}{6} & -\sin \frac{\pi}{6} \cdot \cos(-\frac{\pi}{2}) & \sin \frac{\pi}{6} \cdot \sin(-\frac{\pi}{2}) & 0 \\ \sin \frac{\pi}{6} & \cos \frac{\pi}{6} \cdot \cos(-\frac{\pi}{2}) & -\cos \frac{\pi}{6} \cdot \sin(-\frac{\pi}{2}) & 0 \\ 0 & \sin(-\frac{\pi}{2}) & \cos(-\frac{\pi}{2}) & 0.356 \\ 0 & 0 & 0 & 1 \end{bmatrix} \\
 &= \begin{bmatrix} \frac{\sqrt{3}}{2} & 0 & -\frac{1}{2} & 0 \\ \frac{1}{2} & 0 & \frac{\sqrt{3}}{2} & 0 \\ 0 & -1 & 0 & 0.356 \\ 0 & 0 & 0 & 1 \end{bmatrix}
 \end{aligned}$$

$$\begin{aligned}
T_2 &= \begin{bmatrix} \cos \theta_2 & -\sin \theta_2 \cdot \cos \alpha_2 & \sin \theta_2 \cdot \sin \alpha_2 & a_2 \cdot \cos \theta_2 \\ \sin \theta_2 & \cos \theta_2 \cdot \cos \alpha_2 & -\cos \theta_2 \cdot \sin \alpha_2 & a_2 \cdot \sin \theta_2 \\ 0 & \sin \alpha_2 & \cos \alpha_2 & d_2 \\ 0 & 0 & 0 & 2 \end{bmatrix} \\
&= \begin{bmatrix} \cos(-\frac{\pi}{4}) & -\sin(-\frac{\pi}{4}) \cdot \cos 0 & \sin(-\frac{\pi}{4}) \cdot \sin 0 & 0.187 \cdot \cos(-\frac{\pi}{4}) \\ \sin(-\frac{\pi}{4}) & \cos(-\frac{\pi}{4}) \cdot \cos 0 & -\cos(-\frac{\pi}{4}) \cdot \sin 0 & 0.187 \cdot \sin(-\frac{\pi}{4}) \\ 0 & \sin 0 & \cos 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \\
&= \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 & 0.1323 \\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 & -0.1323 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \\
T_3 &= \begin{bmatrix} \cos \theta_3 & -\sin \theta_3 \cdot \cos \alpha_3 & \sin \theta_3 \cdot \sin \alpha_3 & a_3 \cdot \cos \theta_3 \\ \sin \theta_3 & \cos \theta_3 \cdot \cos \alpha_3 & -\cos \theta_3 \cdot \sin \alpha_3 & a_3 \cdot \sin \theta_3 \\ 0 & \sin \alpha_3 & \cos \alpha_3 & d_3 \\ 0 & 0 & 0 & 1 \end{bmatrix} \\
&= \begin{bmatrix} \cos(\frac{\pi}{4}) & -\sin(\frac{\pi}{4}) \cdot \cos 0 & \sin(\frac{\pi}{4}) \cdot \sin 0 & 0.222 \cdot \cos(\frac{\pi}{4}) \\ \sin(\frac{\pi}{4}) & \cos(\frac{\pi}{4}) \cdot \cos 0 & -\cos(\frac{\pi}{4}) \cdot \sin 0 & 0.222 \cdot \sin(\frac{\pi}{4}) \\ 0 & \sin 0 & \cos 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}
\end{aligned}$$

$$= \begin{bmatrix} \frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} & 0.1569 \\ \frac{1}{\sqrt{2}} & 0 & -\frac{1}{\sqrt{2}} & 0.1569 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$T_4 = \begin{bmatrix} \cos \theta_4 & -\sin \theta_4 \cdot \cos \alpha_4 & \sin \theta_4 \cdot \sin \alpha_4 & a_4 \cdot \cos \theta_4 \\ \sin \theta_4 & \cos \theta_4 \cdot \cos \alpha_4 & -\cos \theta_4 \cdot \sin \alpha_4 & a_4 \cdot \sin \theta_4 \\ 0 & \sin \alpha_4 & \cos \alpha_4 & d_4 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} \cos 0 & -\sin 0 \cdot \cos(-\frac{\pi}{2}) & \sin 0 \cdot \sin(-\frac{\pi}{2}) & 0.179 \cdot \cos 0 \\ \sin 0 & \cos 0 \cdot \cos(-\frac{\pi}{2}) & -\cos 0 \cdot \sin(-\frac{\pi}{2}) & 0.179 \cdot \sin 0 \\ 0 & \sin(-\frac{\pi}{2}) & \cos(-\frac{\pi}{2}) & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0 & 0 & 0.179 \\ 0 & 0 & 1 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

So final transformation matrix:

$$T = T_1 \cdot T_2 \cdot T_3 \cdot T_4$$

Now,

$$T_{12} = T_1 \times T_2$$

$$= \begin{bmatrix} \frac{\sqrt{3}}{2} & 0 & -\frac{1}{2} & 0 \\ \frac{1}{2} & 0 & \frac{\sqrt{3}}{2} & 0 \\ 0 & -1 & 0 & 0.356 \\ 0 & 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 & 0.1323 \\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 & -0.1323 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} \frac{\sqrt{3}}{2} \times \frac{1}{\sqrt{2}} + 0 & \frac{\sqrt{3}}{2} \times \frac{1}{\sqrt{2}} + 0 & \frac{\sqrt{3}}{2} \times 0 + (-\frac{1}{2}) \times 1 & 0.1146 \\ \frac{1}{2} \times \frac{1}{\sqrt{2}} + 0 & \frac{1}{2} \times \frac{1}{\sqrt{2}} + 0 & 0 + (-1) \times 0 + \frac{\sqrt{3}}{2} & 0.06615 \\ 0 + \frac{1}{\sqrt{2}} + 0 & 0 - \frac{1}{\sqrt{2}} + 0 & 0 & 0.4883 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 0.6123 & 0.6123 & -0.5 & 0.1146 \\ 0.35355 & 0.35355 & 0.866 & 0.06615 \\ 0.7071 & -0.7071 & 0 & 0.4883 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$T_{123} = T_{12} \times T_3$$

$$= \begin{bmatrix} 0.866 & -0.5 & 0 & 0.3068 \\ 0.5 & 0.866 & 0 & 0.1771 \\ 0 & 0 & 1 & 0.4882 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$T_{1234} = T_{123} \times T_4$$

$$= \begin{bmatrix} 0.866 & 0 & 0 & 0.3068 \\ 0.5 & 0 & 0 & 0.1771 \\ 0 & -1 & 1 & 0.4882 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

We know that the forward kinematics should be - (P_x, P_y, P_z)

$$P_x \rightarrow T_{14}$$

$$P_y \rightarrow T_{24}$$

$$P_z \rightarrow T_{34}$$

So according to our transformation matrix

$$P_x = 0.4618m$$

$$P_y = 0.2666m$$

$$P_z = 0.4882m$$

Jacobian Calculation

The Jacobian matrix J for 4 DoF arm with revolute joints is a matrix

$$J_i = \begin{bmatrix} z_{i-1} \times (p_e - p_{i-1}) \\ z_{i-1} \end{bmatrix}$$

For 4-DoF

$$J = \begin{bmatrix} z_0 \times (p_e - p_0) & z_1 \times (p_e - p_1) & z_2 \times (p_e - p_2) & z_3 \times (p_e - p_3) \\ z_0 & z_1 & z_2 & z_3 \end{bmatrix}$$

From previous calculation

$$T_1 = \begin{bmatrix} 0.866 & 0 & -0.5 & 0 \\ 0.5 & 0 & 0.866 & 0 \\ 0 & -1 & 0 & 0.356 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\text{So, } z_0 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \quad p_0 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

$$T_2 = \begin{bmatrix} 0.7071 & -0.7071 & 0 & 0.2094 \\ 0.7071 & 0.7071 & 0 & -0.2094 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\text{and } T_{12} = \begin{bmatrix} 0.6123 & 0.6123 & -0.5 & 0.1146 \\ 0.35355 & 0.35355 & 0.866 & 0.06615 \\ 0.7071 & -0.7071 & 0 & 0.4883 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\text{So, } z_1 = \begin{bmatrix} -0.5 \\ 0.866 \\ 0 \end{bmatrix}$$

$$p_1 = \begin{bmatrix} 0 \\ 0 \\ 0.356 \end{bmatrix}$$

$$\begin{aligned} T_{123} &= T_{12} \times T_3 \\ &= \begin{bmatrix} 0.866 & -0.5 & 0 & 0.3068 \\ 0.5 & 0.866 & 0 & 0.1771 \\ 0 & 0 & 1 & 0.4882 \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{aligned}$$

$$\text{So, } z_2 = \begin{bmatrix} -0.5 \\ 0.866 \\ 0 \end{bmatrix}$$

$$p_2 = \begin{bmatrix} 0.1145 \\ 0.0661 \\ 0.4882 \end{bmatrix}$$

$$\begin{aligned} T_{1234} &= T_{123} \times T_4 \\ &= \begin{bmatrix} 0.866 & 0 & 0 & 0.3068 \\ 0.5 & 0 & 0 & 0.1771 \\ 0 & -1 & 1 & 0.4882 \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{aligned}$$

$$\text{So, } z_3 = \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix}$$

$$p_3 = \begin{bmatrix} 0.3068 \\ 0.1771 \\ 0.4882 \end{bmatrix}$$

$$\text{So, } p_e = \begin{bmatrix} p_x \\ p_y \\ p_z \end{bmatrix} = \begin{bmatrix} 0.4618 \\ 0.2666 \\ 0.4882 \end{bmatrix}$$

For Joint 1

$$P_e - P_0 = \begin{bmatrix} 0.4618 \\ 0.2666 \\ 0.4882 \end{bmatrix}$$

$$z_0 \times (p_e - p_0) = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}^T \times (p_e - p_0)^T$$

$$= \begin{bmatrix} -0.2666 \\ 0.4618 \\ 0 \end{bmatrix}$$

$$J_1 = \begin{bmatrix} -0.2666 \\ 0.4618 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

For Joint 2

$$P_e - P_1 = \begin{bmatrix} 0.4618 \\ 0.2666 \\ 0.1322 \end{bmatrix}$$

$$\begin{aligned}
z_1 \times (p_e - p_1) &= \begin{bmatrix} -0.5 \\ 0.866 \\ 0 \end{bmatrix}^T \times (p_e - p_1)^T \\
&= \begin{bmatrix} 0.866 \times 0.1322 - 0 \\ 0 - (-0.5) \times 0.1322 \\ (-0.5) \times 0.2666 - 0.866 \times 0.4618 \end{bmatrix} \\
&= \begin{bmatrix} 0.1145 \\ 0.0661 \\ -0.5332 \end{bmatrix} \\
J_1 &= \begin{bmatrix} 0.1145 \\ 0.0661 \\ -0.5332 \\ -0.5 \\ 0.866 \\ 0 \end{bmatrix}
\end{aligned}$$

For Joint 3

$$\begin{aligned}
P_e - P_2 &= \begin{bmatrix} 0.3473 \\ 0.2005 \\ 0 \end{bmatrix} \\
z_2 \times (p_e - p_2) &= \begin{bmatrix} -0.5 \\ 0.866 \\ 0 \end{bmatrix}^T \times (p_e - p_2)^T \\
&= \begin{bmatrix} 0 \\ 0 \\ 0.4010 \end{bmatrix} \\
J_3 &= \begin{bmatrix} 0 \\ 0 \\ -0.4010 \\ -0.5 \\ 0.866 \\ 0 \end{bmatrix}
\end{aligned}$$

For Joint 4

$$P_e - P_3 = \begin{bmatrix} 0.155 \\ 0.0895 \\ 0 \end{bmatrix}$$

$$z_3 \times (p_e - p_3) = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}^T \times (p_e - p_3)^T$$

$$= \begin{bmatrix} -0.0895 \\ 0.155 \\ 0 \end{bmatrix}$$

$$J_4 = \begin{bmatrix} -0.0895 \\ 0.155 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

So, the final Jacobian matrix is as follows

$$J = \begin{bmatrix} -0.2666 & 0.1145 & 0 & -0.0895 \\ 0.4618 & 0.0661 & 0 & 0.155 \\ 0 & -0.5332 & -0.4010 & 0 \\ 0 & -0.5 & -0.5 & 0 \\ 0 & 0.866 & 0.866 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix}$$

$$J^T = \begin{bmatrix} -0.266 & 0.4618 & 0 & 0 & 0 & 1 \\ 0.1145 & 0.0661 & -0.5332 & -0.5 & 0.866 & 0 \\ 0 & 0 & -0.4010 & -0.5 & 0.866 & 0 \\ -0.0895 & 0.155 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Inverse Kinematics Calculation

We know pseudo inverse formula, angles (in radian) $\Delta q = J_v' e$

Where, $J_v' = J_v^T (J_v J_v^T)^{-1}$; $J_v = \text{linear jacobian} = z_{i-1} \times (p_e - p_{i-1})$

We have calculated, from jacobian matrix the linear jacobian matrix-

$$J_v = \begin{bmatrix} -0.2666 & 0.1145 & 0 & -0.0895 \\ 0.4618 & 0.0661 & 0 & 0.155 \\ 0 & -0.5332 & -0.4010 & 0 \end{bmatrix}$$

$$J_v' = \begin{bmatrix} -0.8421 & 1.4610 & 0.0001 \\ 6.5505 & 3.78 & 0 \\ -8.71 & -5.02 & -2.5 \\ -0.2847 & 0.48 & -0.0003 \end{bmatrix}$$

Now, end effector position $P_e = \begin{bmatrix} 0.4618 \\ 0.2666 \\ 0.4882 \end{bmatrix}$

Desired end effector position, $P_d = \begin{bmatrix} 0.6 \\ 0.3 \\ 0.55 \end{bmatrix}$

$$e = P_d - P_e$$

$$e = \begin{bmatrix} 0.1382 \\ 0.0334 \\ 0.0618 \end{bmatrix}$$

$$\text{Now, } \Delta q = \begin{bmatrix} -0.8421 & 1.4610 & 0.0001 \\ 6.5505 & 3.78 & 0 \\ -8.71 & -5.02 & -2.5 \\ -0.2847 & 0.48 & -0.0003 \end{bmatrix} \times e$$

$$\Delta q = \begin{bmatrix} -0.06762 \\ 1.0316 \\ -1.5258 \\ -0.0230 \end{bmatrix} \quad [\text{Joint angles in radians}]$$

So the Inverse kinematics values are following for the manipulator :

$$\theta_1 = -0.06762 \text{ radian}$$

$$\theta_2 = 1.0316 \text{ radian}$$

$$\theta_3 = -1.5258 \text{ radian}$$

$$\theta_4 = -0.0230 \text{ radian}$$

4.3.4 Payload Torque Calculation

Arm link masses-

$$\text{Link 1} = 1.085 \text{ Kg}$$

$$\text{Link 2} = 1.150 \text{ Kg}$$

$$\text{Link 3} = 0.785 \text{ Kg}$$

$$\text{Link 4} = 0.680 \text{ Kg}$$

Arm link lengths-

$$\text{Link 1} = l_1 = 90\text{mm} = 0.090\text{m},$$

$$\text{Link 2} = l_2 = 187\text{mm} = 0.187\text{m},$$

$$\text{Link 3} = l_3 = 222\text{mm} = 0.222\text{m},$$

$$\text{Link 4} = l_4 = 179\text{mm} = 0.179\text{m}$$

Gravity torque-

$$\tau_g = \Sigma m_i g d_i$$

Where, m_i =link mass

d_i =Perpendicular distance from joint axis to that mass's COM

Inertia torque-

$$\tau_i = \alpha \Sigma (m_i d_i^2)$$

Where, m_i =link mass

d_i =Perpendicular distance from joint axis to that mass's COM

α =Angular acceleration

Joint 1 Torque-

Center of mass calculation-

$$\text{Link COM} = \text{Joint start} + \frac{L}{2}$$

$$\text{Link 1} = d_1 = (0 + \frac{0.090}{2})m = 0.045m,$$

$$\text{Link 2} = d_2 = (0.090 + \frac{0.187}{2})m = 0.1835m,$$

$$\text{Link 3} = d_3 = (0.277 + \frac{0.222}{2})m = 0.388m,$$

$$\text{Link 4} = d_4 = (0.499 + \frac{0.179}{2})mm = 0.5885m$$

Gravity torque-

$$\begin{aligned}\tau_g &= \Sigma m_i g d_i \\ &= 9.8 \times (1.085 \times 0.045 + 1.15 \times 0.1835 + 0.785 \times 0.388 + 0.68 \times 0.5885) \\ &= 9.81 \times 0.9646 \\ &= 9.46 \text{ N-m}\end{aligned}$$

Inertia torque-

$$\begin{aligned}\tau_i &= \alpha \Sigma (m_i d_i^2) \\ &= 3 \times (1.085 \times 0.045^2 + 1.15 \times 0.1835^2 + 0.785 \times 0.388^2 + 0.68 \times 0.5885^2) \\ &= 3 \times 0.3946 \\ &= 1.183 \text{ N-m}\end{aligned}$$

Let, $\tau_{\text{friction}} = 1 \text{ N-m}$

$$\begin{aligned}\text{Now } \tau_1 &= \tau_g + \tau_i + \tau_{\text{friction}} \\ &= 9.46 + 1.183 + 1 \\ &= 11.64 \text{ N-m}\end{aligned}$$

Considering Safety factor $S = 2$

$$\begin{aligned}\tau_{J1} &= \tau_1 \times S \\ &= 11.64 \times 2 \\ &= 23.28 \text{ N-m}\end{aligned}$$

Joint 2 Torque-

Center of mass calculation-

$$\text{Link COM} = \text{Joint start} + \frac{L}{2}$$

$$\text{Link 2} = d_2 = (0 + \frac{0.187}{2})m = 0.0935m,$$

$$\text{Link 3} = d_3 = (0.187 + \frac{0.222}{2})m = 0.298m,$$

$$\text{Link 4} = d_4 = (0.409 + \frac{0.179}{2})mm = 0.4985m$$

Gravity torque-

$$\begin{aligned}\tau_g &= \Sigma m_i g d_i \\ &= 9.8 \times (1.15 \times 0.0935 + 0.785 \times 0.298 + 0.68 \times 0.4985) \\ &= 9.81 \times 0.6804 \\ &= 6.67 \text{ N-m}\end{aligned}$$

Inertia torque-

$$\begin{aligned}\tau_i &= \alpha \Sigma (m_i d_i^2) \\ &= 3 \times (1.15 \times 0.0935^2 + 0.785 \times 0.298^2 + 0.68 \times 0.4985^2) \\ &= 3 \times 0.2487 \\ &= 0.7461 \text{ N-m}\end{aligned}$$

Let, $\tau_{\text{friction}} = 1 \text{ N-m}$

$$\begin{aligned}\text{Now } \tau_2 &= \tau_g + \tau_i + \tau_{\text{friction}} \\ &= 6.67 + 0.7461 + 1 \\ &= 8.41 \text{ N-m}\end{aligned}$$

Considering Safety factor $S = 2$

$$\begin{aligned}\tau_{J2} &= \tau_2 \times S \\ &= 8.41 \times 2 \\ &= 16.83 \text{ N-m}\end{aligned}$$

Joint 3 Torque-

Center of mass calculation-

$$\text{Link COM} = \text{Joint start} + \frac{L}{2}$$

$$\text{Link 3} = d_3 = (0 + \frac{0.222}{2})m = 0.111m,$$

$$\text{Link 4} = d_4 = (0.222 + \frac{0.179}{2})mm = 0.3115m$$

Gravity torque-

$$\begin{aligned}\tau_g &= \Sigma m_i g d_i \\ &= 9.8 \times (0.785 \times 0.111 + 0.68 \times 0.3115) \\ &= 9.81 \times 0.299 \\ &= 2.93 \text{ N-m}\end{aligned}$$

Inertia torque-

$$\begin{aligned}\tau_i &= \alpha \Sigma (m_i d_i^2) \\ &= 3 \times (0.785 \times 0.111^2 + 0.68 \times 0.3115^2)\end{aligned}$$

$$=3 \times 0.1343$$

$$=0.4031 \text{ N-m}$$

Let, $\tau_{\text{friction}} = 1 \text{ N-m}$

$$\text{Now } \tau_3 = \tau_g + \tau_i + \tau_{\text{friction}}$$

$$= 2.93 + 0.4031 + 1$$

$$= 4.33 \text{ N-m}$$

Considering Safety factor $S = 2$

$$\tau_{J3} = \tau_3 \times S$$

$$= 4.33 \times 2$$

$$= 8.66 \text{ N-m}$$

Joint 4 Torque-

Center of mass calculation-

Link COM = Joint start + L2

$$\text{Link 4} = d_4 = \left(\frac{0.179}{2}\right) \text{mm} = 0.895 \text{m}$$

Gravity torque-

$$\tau_g = \Sigma m_i g d_i$$

$$= 9.81 \times 0.68 \times 0.0895$$

$$= 0.597$$

$$= 6.655 \text{ N-m}$$

Inertia torque-

$$\tau_i = \alpha \Sigma (m_i d_i^2)$$

$$= 3 \times 0.68 \times 0.0895^2$$

$$= 3 \times 0.2483$$

$$= 0.016 \text{ N-m}$$

Let, $\tau_{\text{friction}} = 0.5 \text{ N-m}$

$$\text{Now } \tau_4 = \tau_g + \tau_i + \tau_{\text{friction}}$$

$$= 0.597 + 0.016 + 0.5$$

$$= 1.113 \text{ N-m}$$

Considering Safety factor $S = 2$

$$\begin{aligned}
\tau_{J4} &= \tau_4 \times s \\
&= 1.113 \times 2 \\
&= 2.26 \text{ N-m}
\end{aligned}$$

Motor torque-

$$\tau_{out} = \tau_{motor} \times G \times \eta$$

Where, τ_{motor} = Motor torque

G = Gear ratio

$\eta = 90 \% = 0.9$

Motor torque, τ_{motor}

Joint 1 motor $\tau_{motor1} = 380 \text{ Kg-cm} = 37.3 \text{ N-m}$

Joint 2 motor $\tau_{motor2} = 380 \text{ Kg-cm} = 37.3 \text{ N-m}$

Joint 2 motor $\tau_{motor3} = 380 \text{ Kg-cm} = 37.3 \text{ N-m}$

Joint 4 motor $\tau_{motor4} = 80 \text{ Kg-cm} = 7.85 \text{ N-m}$

For Joint 1- Gear ratio, G=1.5

$$\begin{aligned}
\text{Final Motor torque } \tau_{out} &= \tau_{motor1} \times G \times \eta \\
&= 37.3 \times 1.5 \times 0.9 \\
&= 50.355 \text{ N-m}
\end{aligned}$$

For Joint 2- Gear ratio, G=2

$$\begin{aligned}
\text{Final Motor torque } \tau_{out} &= \tau_{motor1} \times G \times \eta \\
&= 37.3 \times 2 \times 0.9 \\
&= 67.14 \text{ N-m}
\end{aligned}$$

Table 13 : Torque Calculation Comparison

Joint	Calculated Torque (With Safety Factor)	Motor torque (With Gear)
1	23.28 N-m	50.355 N-m
2	16.83 N-m	67.14 N-m
3	8.66 N-m	37.3 N-m
4	2.26 N-m	7.85 N-m

The payload analysis was conducted to determine the torque at every joint of the robotic arm during the static and dynamic conditions. Each joint was added up to give the total torque, including gravitational torque, inertia torque or angular acceleration and an assumed frictional torque. Joint 1 was given a safety factor of 1.5 and Joint 2 was given a safety factor of 2 to provide consistency and to accommodate uncertainties that included variation of loads, modeling errors and mechanical losses.

It was found out that the torque requirement increases in Joint 1 because it sustains all the subsequent masses and the cargo making its moment arm the maximum. Likewise, a similar thing can be said about Joint 2 that needs a considerable torque because of the summation of the contribution of the Links 2-4. On the contrary, the Joint 3 and Joint 4 have relatively low torque demands because there are fewer links involved in their loading and effective lever arms are shorter.

The choice of the motor was justified by a comparison of the calculated torque requirements and the actual motor output torque after consideration of the gear ratio and transmission efficiency. The chosen motors in combination with the correct gear ratios and an efficiency of 90% offer an output torque that is easily higher than the needed joint torques in all the joints. This has ensured that the actuation system selected is sufficiently large and mechanically stable with significant torque margins to accommodate dynamic motion, external perturbations and long service without stalling or overheating.

On the whole, the computation of torques proves that the design of robotic arms is mechanically sound, well-balanced, and robust, providing safe performance conditions with a decrease in the case of both static and dynamic loads.

4.4 Components Selection

Power Supply

To provide power supply, a 24V switch-mode power supply (SMPS) will be employed as a principal source of power distribution of the entire robot. Simple linear supply is much less efficient, and would be very massive, and would not be able to provide high current to multiple motors without overheating and necessitating a large heat sink, which is unimportant to a bench-top soft manipulator. The 24V rating has been chosen such that the target base, shoulder and elbow motors can be driven at their nominal voltage and still leave sufficient voltage headroom to buck converters; and its power rating should be higher than the sum of the worst-case powers of all the joints and the Raspberry Pi (including a safety margin), as is common when powering a robot-arm.



Buck Converters

Based on the 24 V SMPS line a few of these buck converters will be modified into lower voltages to serve sensitive electronics and smaller actuators. The Raspberry Pi and its camera will be powered by a single, 24V-to-5V step-down converter since the Pi must be supplied at a stable 5V at a few amperes; buck converters are often used with this aim, and are even tolerable at digital electronics relatively sensitive, as long as the converter is correctly set up with a distribution capacitance line. Two additional step-down converters will be installed to form 8V rail which will drive the wrist motor and the two gripper motors which are chosen in 8V versions to save space and mass at the distal end although powered by the same 24V main bus. Separate buck converters on the controller and the distal motors are also easier to fuse and protect each branch, and thus a fault on one of the motors will not as easily disrupt the entire system.



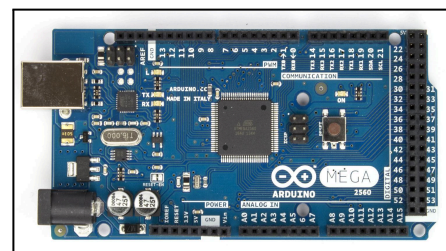
Microprocessor

A single-board computer is a Raspberry Pi 5 which will be utilized as a primary microprocessor in terms of control and perception. The reason behind the selection of the Pi is the capability to run a complete operating system, and high-level code in Python or C++, which makes it possible to implement inverse-kinematics algorithms that translate the desired end-effector pose into base, shoulder, elbow and wrist base joint angles of the soft manipulator. Meanwhile the Pi is capable of executing image-processing code (i.e. with OpenCV) to process camera images, detect things and pass the information to the kinematic controller, and already with Raspberry Pi, cameras and robotic arm have been reported to work together, indicating that its processing power is sufficient to do this system. The Pi will also be used as a send or receive of PWM or direction signals to the motor drivers, and general sensors, using the following on the Pi: the GPIO, I2C, SPI, and UART pins.



Microcontroller

In this scheme, the Raspberry Pi is used as the main microprocessor that performs the computation and decision-making functions. On the other hand, the low-level control commands are performed by the Arduino Mega 2560. These two boards are connected via a USB serial for effective communication. The Arduino



Mega 2560 is based on the ATmega2560 and runs at 5 V and 16 MHz frequencies. It provides 54 digital I/O pins, out of which 15 are PWM pins. It also provides 16 analog input pins. In addition, it comes with 256 KB flash memory, 8 KB SRAM memory, and 4 KB EEPROM memory.

Motors

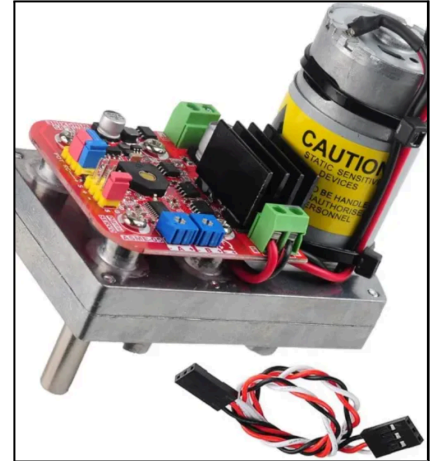
A. Base, Shoulder and Elbow Motors

On the base, shoulder and elbow joints, high-torque 24V DC gearmotors are chosen such that all main axes can be powered off an identical 24V DC bus and still have sufficient torque margins during worst-case loading of the arm. The stall torque of 380 kg. cm in the datasheet, is approximately,

$$380kg.cm = 380 \times 0.098 = 37.2Nm$$

and the given holding torque of approximately 340 kg-cm is approximately.

$$340kg.cm = 340 \times 0.098 = 33.3Nm$$



Since they are locally sourced, actuators with limited characterization data, the design is conservative and assumes that only approximately 50 per cent of the nominal actuator torque is statistically offered in continuous operation, i.e. an effective result range of approximately 16-18 Nm.

Jacobian-based analysis of axis torque, with a 0.5 kg payload, shows that the largest inertial gravity torques at the examined position are approximately 2-3 Nm at the shoulder and elbow joints, with insignificant activity at the base joint. Although margins are added to account for the link self-weights, friction and dynamic actions, the anticipated operating torques are still significantly less than this derated 16-18 N.m value, giving the chosen actuators ample safety margin. This makes it possible to make the joints capable of supporting the joint weight of links, gripper and payload in near-horizontal configurations without pushing them to their practical limits, enhancing reliability and increasing service life.

With the relatively large gearbox torque, the actuators also no longer require the constant stall current to withdraw, just to maintain position; the mechanism advantage allows the resistance to the effect of gravity to be attained with limited electrical effort on the actuators, minimizing copper losses and thermal loads to the motors and drivers. The use of 24 V supply in the operation of these joints also assists in keeping currents modest with respect to the applied mechanical power, reduces I^2R losses, enables smaller cross-sections and connector rating of cables, and enhances overall electrical efficiency of the manipulator.

B. Wrist Motor

At the wrist joint, the torque needed is smaller than in the shoulder and elbow, but nevertheless, large to rotate the end-effector load. A small metalgear servo of nominal torque 80 kg cm is employed and this has got an approximate value of

$$80kgcm = 80 \times 0.098 = 7.8Nm$$

Using the same conservative assumption in regard to the locally sourced parts, at least half of this rating (approximately 3-4 N m) is assumed as the practically available continuous torque. Nevertheless, this remains higher than the 1-2 Nm torque range of the Jacobian-based calculation of typical wrist positions with the design load, which gives a significant buffer during a dynamic movement and unexpected loading. The high gear ratio of the servo and medium supply voltage (6 to 8.4 V through a buck converter off the main DC bus) are also useful in keeping the actuator small and light yet providing adequate stiffness in the wrist.



C. Gripper Motors

In the case of the gripper, the key consideration is to develop sufficient fingertip forces in a minimal added end-effector mass. The drive of each of the gripper is a smaller metal-gear servo of 35 kg.cm and is equivalent to

$$35kgcm = 35 \times 0.098 = 3.4Nm$$

Also, under the same derating assumption, virtually 1.5 to 1.7 Nm of usable torque should be available, and this can supply certain grips on the target lightweight items without raising the mass of motion. These lighter servos on the fingertip minimize the inertia on the proximal joints and enhance the backdrivability and safety, and the metal gearbox construction typically ensures the gripping forces do not change with repeated cycles even with the conservative assumption of torque applied to the locally sourced components.



RGBD Camera

For perception tasks such as object detection, localization, and depth estimation, the system makes use of the **Intel RealSense D435i** depth camera. This device contains stereo RGB sensors coupled with an active IR projector, enabling real-time depth information up to a distance of ~10 m, with a depth resolution of 1280 x 720 pixels. A 9-axis IMU (accelerometer + gyroscope) allows motion tracking, enhancing spatial localization. This device



supports USB 3.0, hardware-synchronized depth + RGB streams, making it a popular choice in robotics and ROS-based perception systems.

4.5 Machine Learning Models for Object Detection

In this project machine learning is employed to give the autonomous control of the soft robotic manipulator and gripper solid visual perception. The object detection module recognizes and locates the objects in the workspace in such a way that the motion planner can determine the collision-free and task-suited grasps of various day-to-day objects. To allow this, four architecture models of the deep learning system are trained and tested on a standard custom training data set and evaluated on their training behavior, classification performance as well as localization.

4.5.1 Dataset Description

All the four models run on the same 11 manipulation-relevant objects-classes:

- Banana
- Bottle
- Bowl
- Box
- Capsicum
- Chips-Packet
- Egg
- Fire extinguisher ball
- Football
- Tennis-ball
- Tomato

Dataset Overview

We prepared a custom dataset with around 6900 images. This dataset shows that there is a fairly balanced distribution of various common objects, although the maximum percentage of food-related items (chips packet, egg, capsicum, tomato, banana) take the largest share. Sport equipment (football, tennis ball) and household items (bottle, bowl, box, fire extinguisher ball) offer variety, and make sure that the model is able to generalize in other spheres. The total number of around 6900 is big enough to be used to train strong object detection and classification models.

Table 14 : Dataset Class Distribution

Class Name	Image Count
Banana	762
Bottle	531
Bowl	679
Box	575
Capsicum	491
Chips-Packet	591
Egg	617
Fire extinguisher ball	750
Football	827
Tennis-ball	598
Tomato	515

Data Augmentation Techniques

The augmentation schemes augmented by the following strategies were used to obtain two outputs per sample to increase the generalization and robustness of the models:

- 1) Horizontal Flip:** Flips randomly along the horizontal axis, so that the model should learn to identify symmetric features of the image.
- 2) Rotation ($\pm 3^\circ$):** Random rotations of a range between $\pm 3^\circ$ are applied, as an approximation to slight changes in camera angle, and to enhance tolerance to rotation.
- 3) Shear ($\pm 6^\circ$ Horizontal and Vertical):** Integrate geometrical distortion by slanting the image horizontally and vertically as much as $\pm 6^\circ$ which helps the model to identify skewed representations.
- 4) Saturation Adjustment ($\pm 16\%$):** Adjustment of the degree of colors in $\pm 16\%$ so that the model can adapt to color and lighting changes.
- 5) Exposure Adjustment ($\pm 10\%$):** Can change image brightness by $\pm 10\%$ which simulates various light conditions and is better suited to work with various light conditions.
- 6) Noise Injection ($\leq 0.22\%$ pixels):** Integrate random noise at the pixel-level up to 0.22% of the image to increase resistance to small artifacts.

The shared label set will make sure that variation in the detection performance is based on the underlying architecture and training processes, not changes in the data set. The details of the training curves, confusion matrices and quantitative measurements of the training models of each of the trained models are described and explained further in the following sections.

4.5.2 YOLOv11 for Object Detection

YOLOv11 is a single-stage, real-time object detector on the soft robotic manipulation task which is trained on an 11-class dataset as the prior models. The medium configuration (YOLOv11-m) is chosen to ensure the compromise between accuracy and the costs of computations, which is why it is a reasonable choice when applied in conjunction with the autonomous manipulator and gripper.

Training and validation box loss

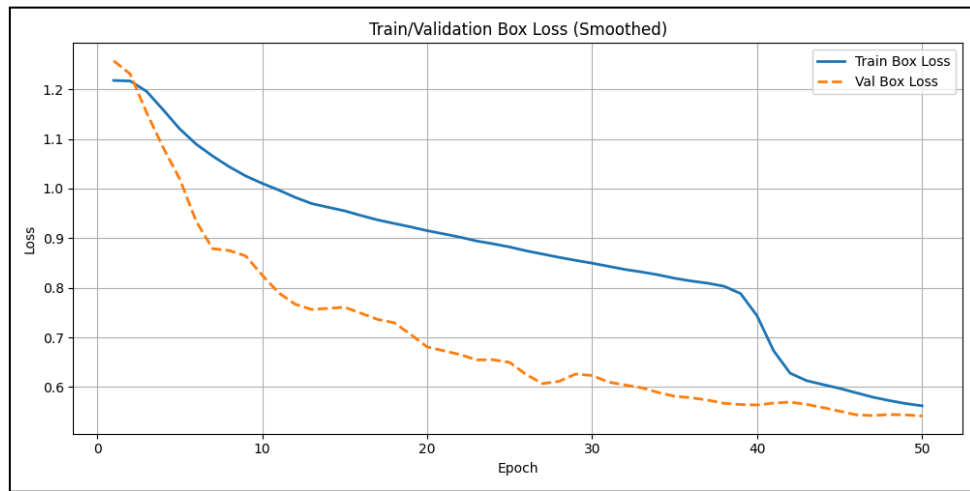


Figure 20 : Training and Validation Loss of YOLOv11 Model

Our smoothed training and validation loss curves indicate that the downward trend has been steady with 50 epochs and the loss of trainbox appears to be 0.558 with a loss of valbox appearing to be 0.540. The fact that the two curves are almost parallel is a good indication that the model is well generalizing since the model is able to produce similar levels of error on the training as well as the validation data and the model does not overfit. This logic indicates that the training program and regularization is properly tuned to the YOLOv11 model and the specified dataset.

F1–Confidence Relationship

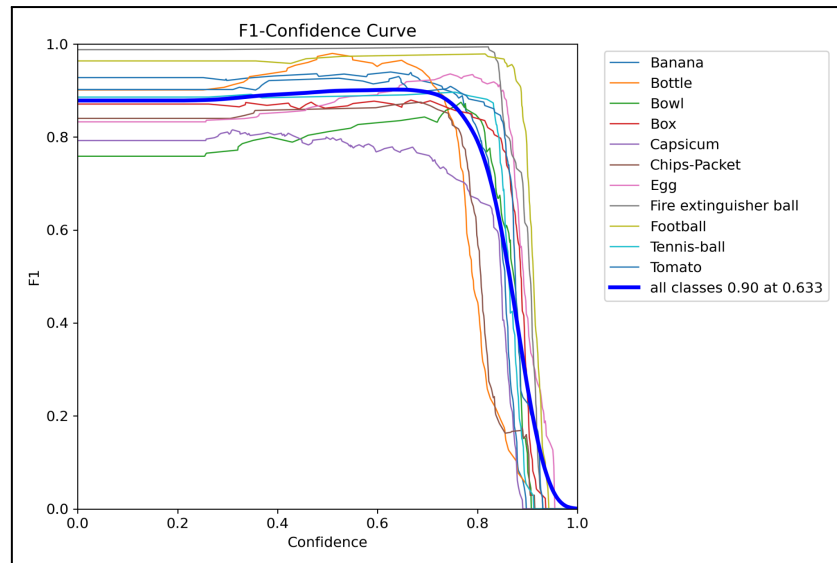


Figure 21 : F1 Confidence Curve of YOLOv11 Model

The F1-confidence curve is a curve that provides a summary of how the harmonic mean of preciseness and recall changes as one goes through the detection confidence threshold that is swept between 0 to 1. In the case of YOLOv11, the F1 score is maximized at 0.90 with a confidence value set to around 0.633 for all 11 possible classes, which means that this operating point is good in terms of strikes on failure and false positives. Practically, this threshold can be taken as default values in the perception pipeline and make sure the detector is not only sensitive to the relevant objects but also discriminatory to the false alarms.

Confusion Matrix Analysis

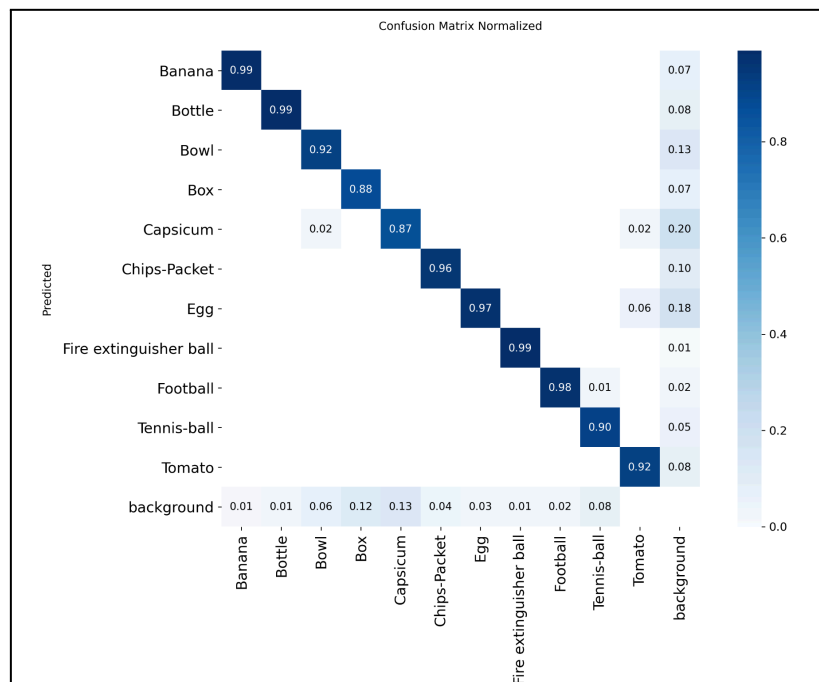


Figure 22 : Confusion Matrix of YOLOv11 Model

The normalized confusion matrix of the YOLOv11 has a very high count of diagonal values of almost all the objects including 0.99 with banana and bottle, 0.92 with bowl, 0.88, or more with box, and 0.96 or more with various other objects like egg, fire extinguisher ball, and tomato. The reason why these diagonal values are high on the diagonal shows that when YOLOv11 does a prediction, it is nearly always correct in attaching the determinant. Background-related misclassifications and off-diagonal entries are also minor, only minor breakage between visually similar categories and the background pixels being misclassified as an object are low, which minimizes the risk of spurious targets in the workspace of the manipulator.

Metric Correlations and Summary Statistics

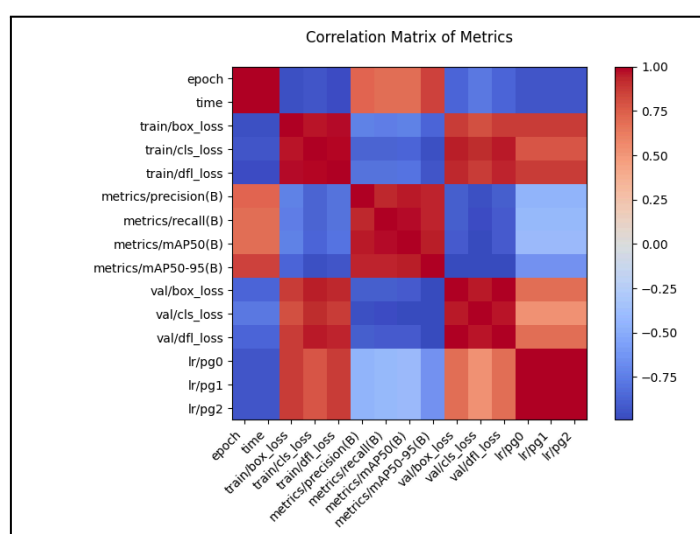


Figure 23 : Correlation Matrix of Metrics of YOLOv11 Model

The training and validation metric correlation matrix indicate that there are positive strong relationships between the changes in losses of box/cls/dfl and improvement in precision, recall and mAP, confirming that the overall optimization progress correlates positively to the improvement in detection quality.

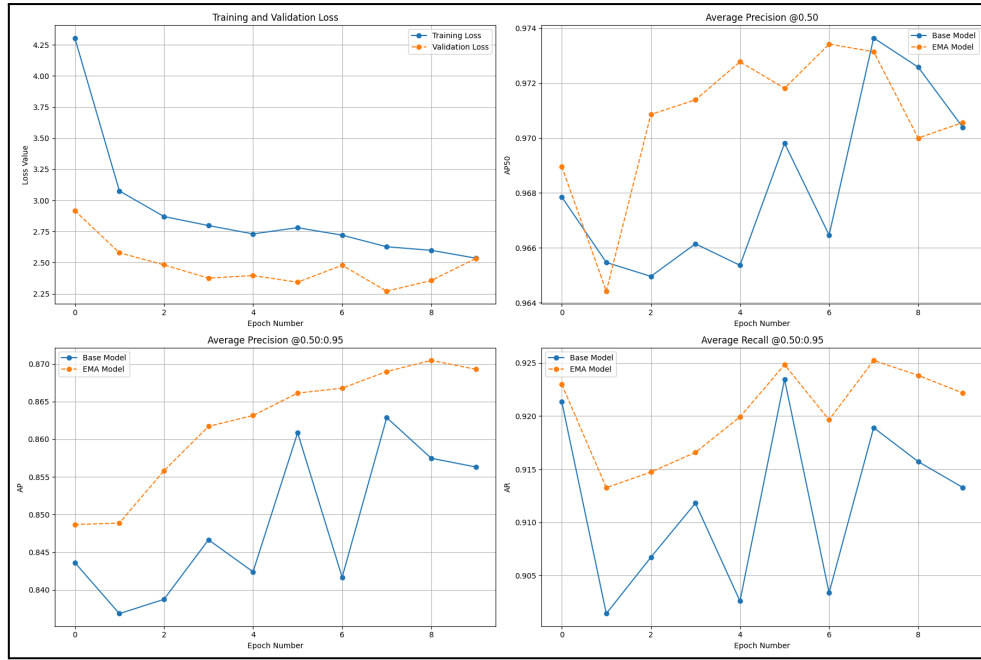


Figure 24 : a) Training and Validation Loss, b) Average Precision @0.50, c) Average Precision @0.50:0.95, d) Average Recall @0.50:0.95 of YOLOv11 Model

In the process of training, the mean IoU 0.50 (AP50) increases to approximately 0.974 corresponding to the original base model, and AP 0.50:0.95 rises to approximately 0.870 with an average recall of 0.50:0.95 of 0.925 corresponding to the EMA-smoothed case. A metrics summary ends with values of valprecision of around 0.9469, valrecall of approximately 0.9427, valmAP50 of about 0.9645, and valmAP50 of 0.8602 stating that YOLOv11 achieves high performance measured by valprecision, soft threshold and strict threshold.

4.5.3 Faster R-CNN for Object Detection

Faster R-CNN is a two stage baseline detector in the soft robotic manipulation task in which a Region Proposal Network is used to compute the candidate regions and a second stage performs classification and bounding box regression. This model is trained using 11-class dataset (banana, bottle, bowl, box, capsicum, chips-packet, egg, fire extinguisher ball, football, tennis-ball, tomato) so that localization and labeling of objects in the robot workspace is provided on an instance-level. Its training dynamics and the final detection performance are summarized by the following figures.

Training and Validation Loss

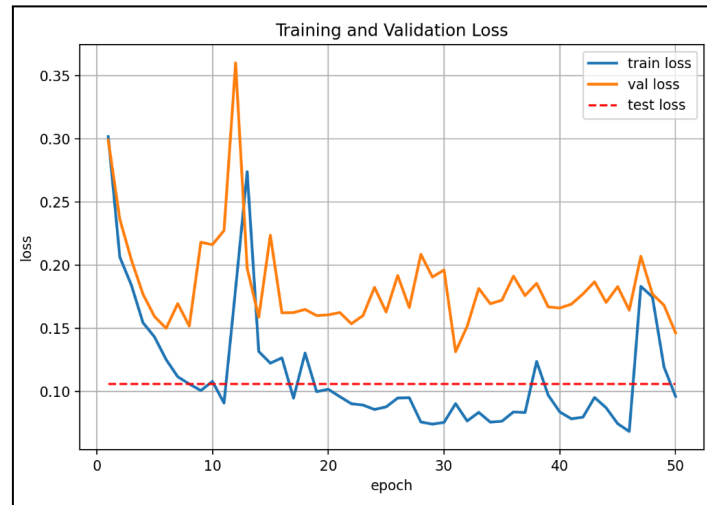


Figure 25 : Training and Validation Loss Curves

Faster R-CNN training and validation loss curves demonstrate a monotonic decline during 50 training epochs and the last training loss reaches around 0.0474 and the validation loss reaches around 0.1004. The distance between the two curves is moderate and does not increase sharply at late epochs meaning that the model does not need a severe overfitting or instability to learn meaningful features using the dataset. The behavior indicates that the scale of the problem and the selections of learning rate, batch size and regularization are sufficient, and the network has already reached a fairly stable optimum given the chosen architecture.

Confusion Matrix Analysis

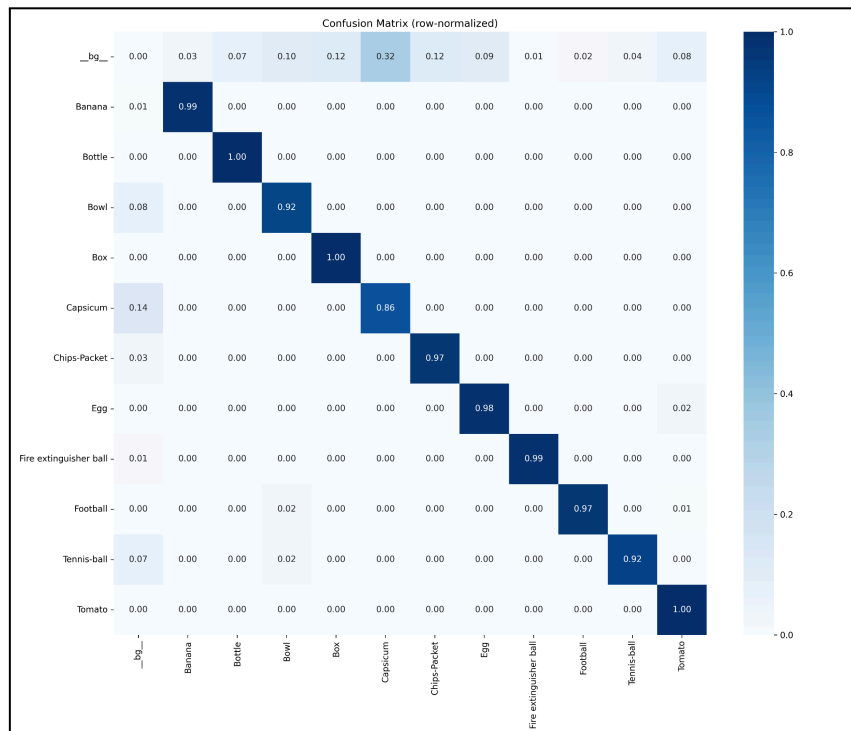


Figure 26 : Confusion Matrix of Faster R-CNN

The row-normalized confusion matrix of Faster R-CNN has high diagonal scores almost to all of the object classes which implies that once the object has been detected, it will be given the correct object label. Bottle, box, egg, fire extinguisher ball, football, tennis-ball and tomato are some classes that have almost perfect or perfect entries, which implies that there is very little confusion between them. In certain classes (bowl, capsicum, chips-packet, and tennis-ball) some of the samples leak to the background class (bg), indicating that the detector will sometimes produce no detection of instances with a high detection threshold instead of a false detection of a different object. Such a cautionary approach is safer but it emphasises the fact that region proposals and classification thresholds might overlook borderline objects within clutter, which should be thought of as a significant factor in autonomous grasping work in cluttered scenes.

Quantitative Detection Metrics

The trained Faster R-CNN model is quantitatively assessed with a reported precision (0.9630) and recall (0.9630) on a validation set, which means that the detector is not capable of generating a false positive or missing any object when used with the set-point levels of confidence. Nonetheless, the average precision at 50 (mAP) of the pixels is approximately 0.4367 and more stringent COCO-style mAP50-95 is about 0.3495 indicating that most of the detections fail to achieve tight enough bounding boxes at more severe overlap requirements of 50-95. In the case of the soft robotic manipulator, this implies that despite having a confident and consistent model in classifying objects, the localization is usually not optimal to use in planned grasp points.

4.5.4 RF-DETR for Object Detection

RF-DETR (Region-Free Detection Transformer) is utilized as an alternative version of the two-stage Faster R-CNN baseline in the soft robotic manipulation challenge based on the transformer. RF-DETR prevents region proposals in favor of components made up of fixed set of object queries to be predicted directly and refined with multi-head self-attention and cross-attention layers, which also prove useful in crowded scenes with multiple interacting objects. The same 11-class dataset is used to train the model to make localization and end-to-end detection appropriate to be used in downstream grasp planning.

Training and Validation Loss

Both the base model and the Exponential Moving Average (EMA) of the base model show steady reduction in the RF-DETR training and validation loss curves throughout the training epochs. No late-epoch divergence is detected and training and validation losses are well-correlated, which implies that the transformer-based detector can be generalised without a substantial amount of overfitting. This constant convergence behavior presupposes that the optimization values and data augmentations are right to learn the strong attention-based representation of the manipulation scenes.

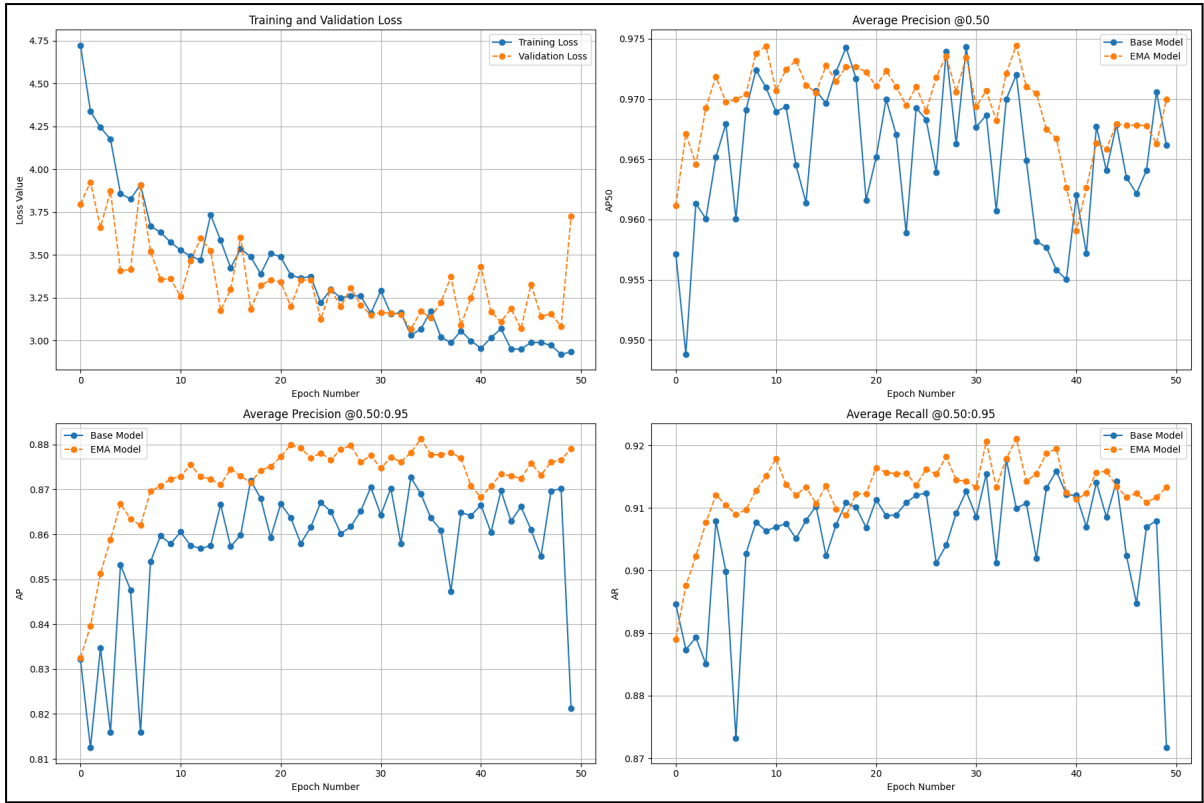


Figure 27 : a) Training and Validation Loss, b) Average Precision @0.50, c) Average Precision @0.50:0.95, d) Average Recall @0.50:0.95 of RF-DETR Model

Average Precision and Recall across Epochs

The series of average precision and average recalls vs. epoch demonstrates that RF-DETR rapidly increases its average performance in terms of detection quality but levels off once it has achieved large values of AP at 0.50 and AP at 0.50:0.95. The final mAP0.50 is about 0.965 and the stricter mAP0.50: 0.95 is about 0.847 with the respective average recall also remaining high hence confirming a high localization and a solid performance at different IoU thresholds. There is a consistent trend in the EMA model tracking or slightly exceeding the base model, meaning that a temporal smoothing of parameters aids in reducing noise and generating more consistent predictions that are advantageous to continuous robotic operation.

Confusion Matrix Analysis

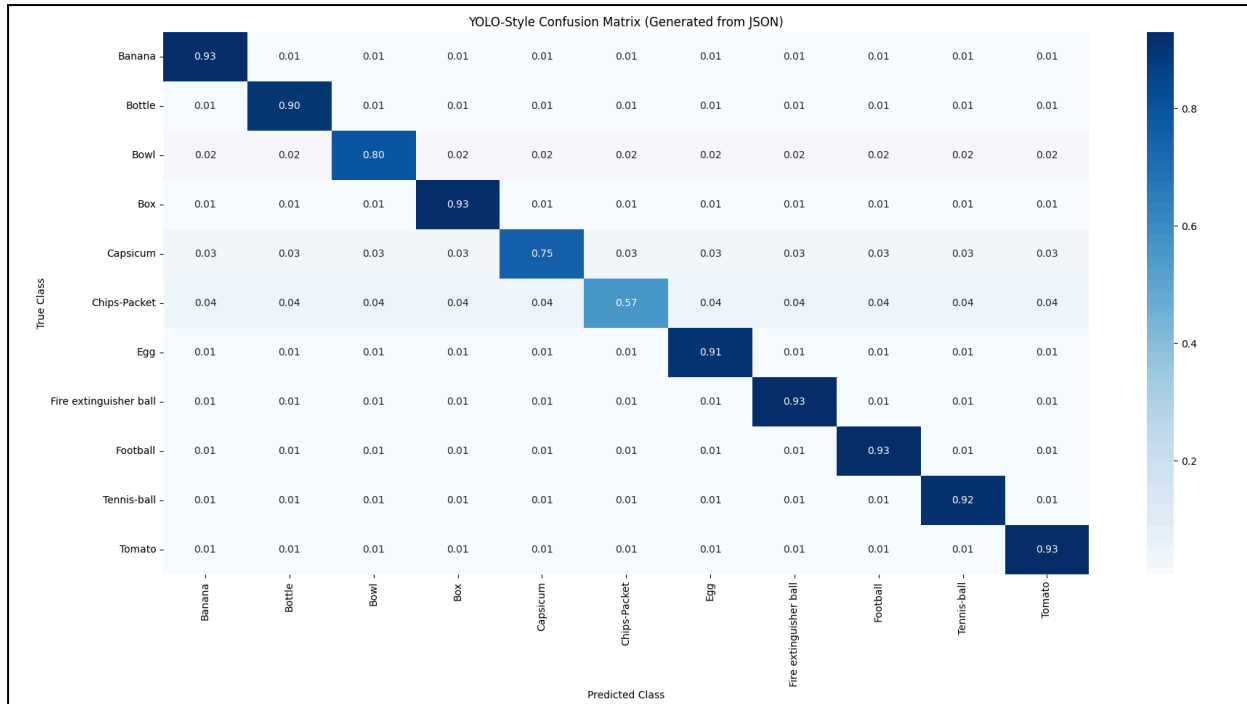


Figure 28 : Confusion Matrix of RF-DETR Model

The YOLO-style Confusion matrix obtained by RF-DETR prediction has a higher number of strong diagonal than non-diagonal values (freely scalable) with values ranging between 0.9-0.95 (majority of object classes) including banana, bottle, box, egg, fire extinguisher ball, football, tennis-ball and tomato. This tendency proves that the subjects are identified with the appropriate category, as hardly there are examples of confusion with another category after their recognition. Chips-Packet has a less diagonal value of about 0.57 with more diffuse off-diagonal values, an effect of the fact that deformable packaging containing complicated textures against cluttered backgrounds are more difficult to detect, whilst bowl and capsicum have slightly more dampened diagonal values by virtue of similar visual appearance to the surrounding objects. All in all, the confusion matrix confirms that RF-DETR works with most classes with reasonable certainty and might need some extra training data or specific augmentation of the most fundable cases in the manipulation set.

4.5.5 RTMDet-m for Object Detection

The RTMDet-m is used because it is a single-stage and anchor-free detector which is useful in real-time implementation; hence, its application in the interaction of the soft robotic manipulator and gripper is desirable. In contrast to two-stage algorithms, RTMDet-m puts the score of the classes and bounding boxes as direct prediction on top of dense feature maps and thus lossless to inference time, without compromising the accuracy of the scores, but it is useful in manipulating tasks. The machine is trained on the same 11 classes of data so that it can perceive objects that are relevant to grasping fast and accurately.

Training Loss Evaluation

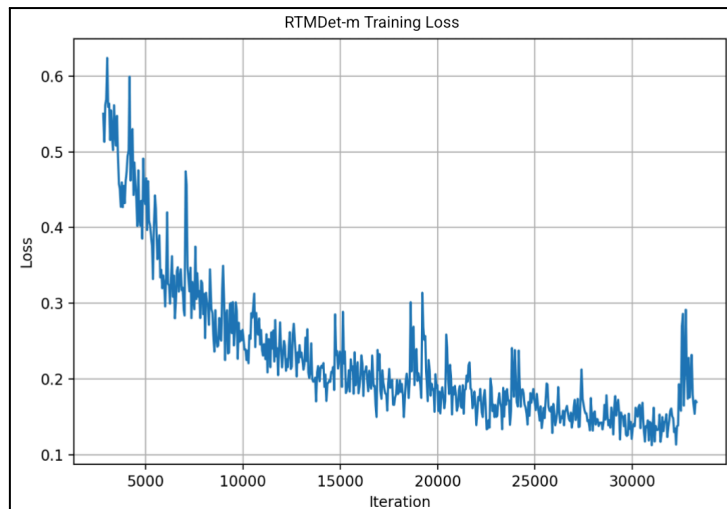


Figure 29 : Training and Validation Loss of RTMDet-m Model

The training loss curve of RTMDet-m plot vs iterations indicates a decline with smooth and monotonic change with initially high values and finally to approximately 0.1 without any sudden spikes or oscillations. This is a sign of learning consistency and is an indication that optimization hyperparameters and learning rate schedule are all fine-tuned. The fact that there are no sudden changes in the loss also suggests that the model does not face drastic gradient instabilities in the training process, which is significant when it comes to the consistent production of a good solution.

Confusion Matrix Analysis

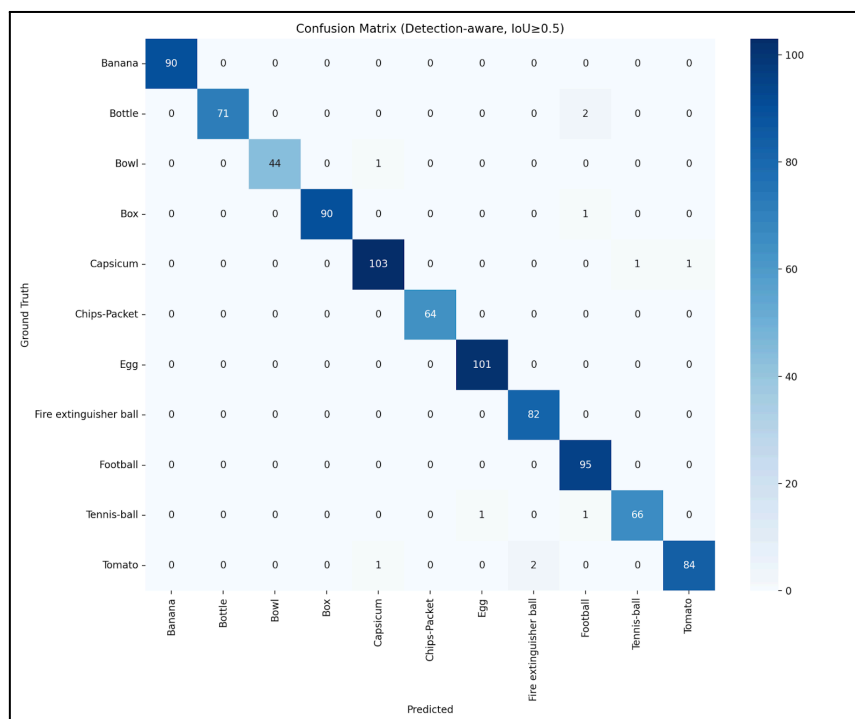


Figure 30 : Confusion Matrix of RTMDet-m Model

The detection-aware confusion matrix generated at IoU of 0.5 and above indicates that the diagonal element is strong of all the 11 classes indicating that the majority of the detected objects are correctly identified. As an example, 90 bananas are correctly identified, 71 bottles, 44 bowls, 90 boxes, 103 capsicums, 64 packets of chips, 82 fire extinguisher balls, 101 eggs, 95 footballs, 66 tennis-balls, and 84 tomatoes on the diagonal, with few false identifications per row. The off-diagonal terms, (e.g. a few eggs or tennis-balls being conflated with the adjacent ones), are sparse and mostly small, and this implies that a mistake in classification is relatively exceptional, and that it is typically found in realistic edge cases, such as some partial obliterations or other forms of shape. It is this trend that proves that RTMDet-m does not suffer loss of class separation over the collection of all labels exploited by the manipulation system.

Precision-Recall Behavior and mAP

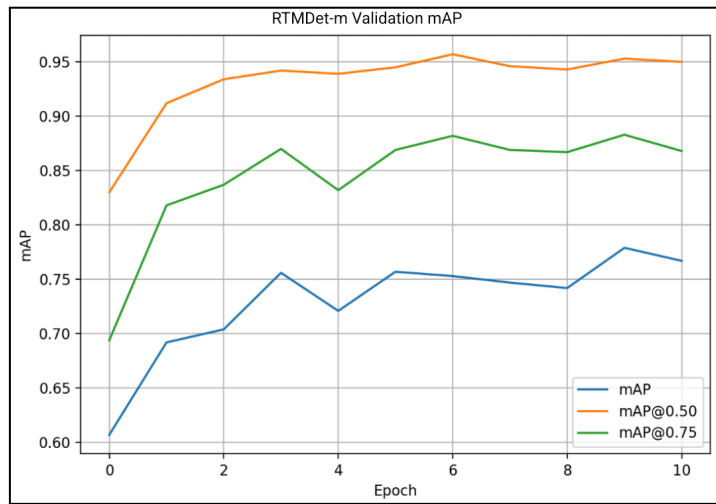


Figure 31 : Validation mAP of RTMDet-m Model

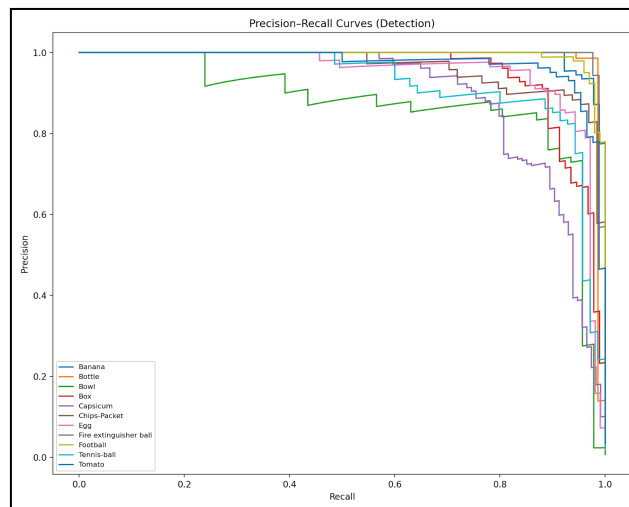


Figure 32 : Precision-Recall Curve of RTMDet-m Model

The per-class precision-recall curves depict that RTMDet-m maintains high precision with a large distribution of recall values of the majority of objects and this degradation in precision is observed at very large recall values wherein the model starts to propose marginal detections. The model on the validation dataset has a total precision of 0.752, recall of 0.800 and F1-score of 0.775, which means the model makes a trade-off between false positives and missing objects. The average value of 0.897 indicates that on average, the computed detections are close to the ground truth in their areas, which is fundamental to having a realistic representation of detection to understandable robot motions in the coordinate frame. Assuming the COCO style metrics the mean Average Precision mAP at [0.50:0.95] is around 0.77 with a more lenient overlap threshold of 0.50 to nearly 0.95 and a stricter zone of 0.75 to nearly 0.87 which indicates that the detector is now reliable at both less strict and stricter overlap weightings.

4.5.6 Quantitative Comparison of Object Detection Models

The main quantitative metrics are used to compare the four trained detectors below to identify their relative strengths:

Table 15 : Object Detection Models Comparison

Model	Precision	Recall	mAP@0.50	mAP@0.50:0.95	Key Observations
Faster R-CNN	0.9630	0.9630	0.4367	0.3495	Very high classification accuracy, but poor mAP values indicate weak localization under IoU-based evaluation, limiting its usefulness for precise grasp planning.
RF-DETR	0.9237	0.9300	0.9651	0.8470	Strong transformer-based detector with high AP at both 0.50 and 0.50:0.95, but slightly lower precision than YOLOv11 and more confusion on deformable classes like chips-packet.
RTMDet-m	0.7520	0.8000	0.9500	0.7700	Real-time friendly single-stage model with high mean IoU, but noticeably lower precision and recall than RF-DETR and YOLOv11 on this dataset.
YOLOv11-m	0.9469	0.9427	0.9645	0.8602	Highest overall balance of precision and recall, with mAP@0.50:0.95 slightly higher than RF-DETR and an exceptionally clean confusion matrix across all 11 classes.

YOLOv11-m is a faster single-stage detector that outperforms RTMDet-m in terms of mAP but is more precise and has higher recall than RTMDet-m and has more strict IoU performance and reduced to Faster R-CNN. Such factors as accuracy, localization, and

efficiency of the models establish YOLOv11-m as the most appropriate detection backbone of the four models in the case of the autonomous software robotic manipulator and gripper.

4.6 System Architecture

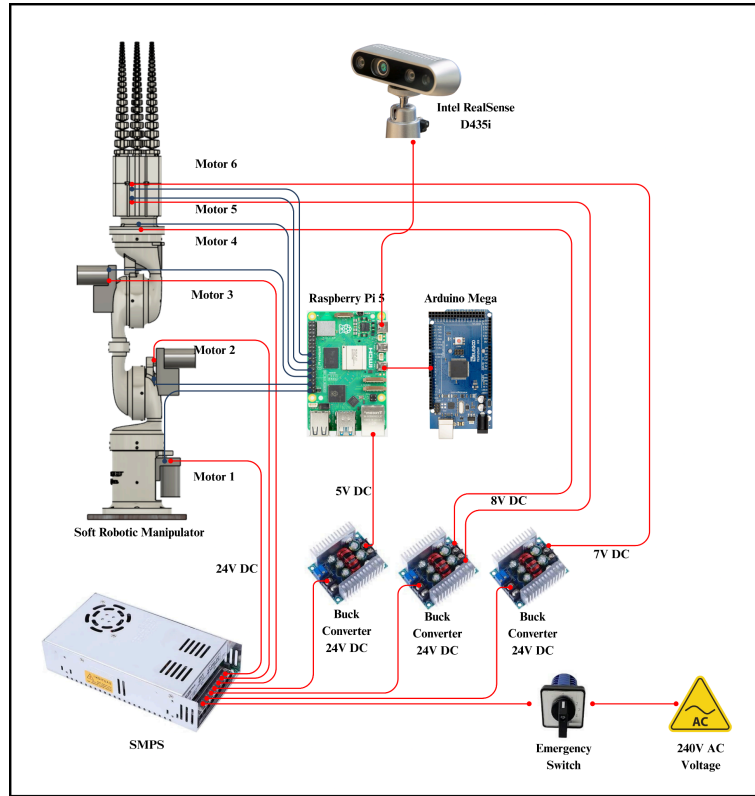


Figure 33 : System Architecture

The soft robotic manipulator and gripper system architecture has been structured into a layered system where one 24V power backbone and a Raspberry Pi control and distributed actuator modules have been augmented with an on board web-camera to provide visual feedback.

Power Distribution

The bottom tier is the mains outlet that drives the 24 V SMPS that forms one DC bus to all the downstream hardware. Branches off this bus that are heavy-current feed like the base, shoulder and elbow motor drivers with lighter branches off this bus feeding the DC-DC buck converters located close to the controller. A single buck converter supplies a controlled 5 V supply to the Raspberry Pi and the USB web camera and other buck converters provide an 8 V supply to the drivers of the wrist and gripper motor . There is an emergency-stop and fusing on the 24 V side to bring all the actuators to a stop in case a fault occurs.

Control, Computation and Vision

The Raspberry Pi is the central processing unit at the control layer, incorporating vision processing as well as motion control. The buck converter feeds 5 V into the Pi, which provides control lines to the actuators using the GPIO interface and provides access to the webcam by USB or the camera serial interface. This camera connection feeds video frames directly into the memory of the Pi without the need of any further hardware. Specific software which runs on the Pi will include: an inverse-kinematics module which transforms desired end-effector poses into the base, shoulder, elbow and wrist joint targets, a trajectory module which generates smooth joint-space commands, and a vision module which interprets the webcam images to identify objects and update the target poses on the soft gripper.

Joint-Level Actuation

The manipulator joints are applied as separated actuator nodes which are connected to the 24 V or 8 V rails. Each node (base, shoulders and elbow) is equipped with 24 V DC gear motor and motor driver is placed slightly behind the concerned joint and is wired back to the Raspberry Pi where the PWM and direction signals of the Pi are converted by the driver electronics into high-current outputs to the motors. The wrist node has the same structure, except that it uses the 8 V rail instead of the 12 V rail, to reduce the overall mass in wiring over the elbow and enhance the responsiveness of the distal bond.

Soft Gripping and Control of the Gripper

The soft robotic gripper works on the principle of the electro-rotary actuation system on the basis of servo motors. The gripper also has two actuators (servo) but each of them has a different function in the actuation process.

The opening and closing motion of the soft fingers is regulated by one servo motor and the second servo motor is the one that regulates the bending and reposition of the fingers in a lateral manner. The two servo motors are externally connected with the 8 V supply rail and they are directly connected with the Raspberry Pi by standard control signals. The set up facilitates independent but synchronized control of grasping and deformation.

The gripper is made of 6 soft, tentacle-like fingers that have three actuation strings. Bending motion is operated on with two strings per finger and the opening and closing is operated by the third string. Bending strings of all fingers are coupled and connected mechanically to a single servo motor, allowing the gripper to be synchronized in deformation. The second servo motor relates to the opening strings of all fingers that can be grasped and released at the same time.

The Raspberry Pi produces control commands according to the nature of the tasks. Object position and visual orientation are offered by an external vision module and are needed to decide on the right positioning and actuation pattern of the gripper. Linear tension in the strings which occurs as a result of the rotational movement of the servo motors brings the soft

fingers into bending and shaping around the object. In this electro-rotary actuation mechanism, the gripper can respond to objects of different shapes and surface characteristics and also provide controlled and repeatable manipulation.

Combined Energy Flow and Information Flow

Energy moves from the mains to the SMPS and on the 24 V distribution trunk through an emergency switch. Then from SMPS the power is distributed to the buck converters and motor drivers to the actuators and information are in and out to the periphery respectively. Images to the Pi are conveyed by the webcam, the electronics at the joints report to the Pi, and all the data received at the Pi is processed to provide coordinated control junctions to the base, shoulder, elbow, wrist and gripper modules; this was done in a way such that there is a coherent system architecture easily incorporating power delivery, actuation, and vision-based control.

4.7 Conclusion

All the performance information in this chapter was acquired through ROS 2/RViz simulation of 4-DOF manipulator responses. The autonomous control and manual methods were experimented on this model with an assortment of randomly selected target positions. Simulation results as indicated by the plots and averages reveal that autonomous control is much more accurate in position (more than 95 percent) and much faster (around 4 seconds) in execution in comparison to manual control (less than 80 percent accuracy and more than 35 seconds). Under consideration of the design parameters of accuracy, execution time, human intervention, and complexities and cost, autonomous control was chosen as an approach that was more effective in the case of the simulated environment. The project then proceeds to execute a real prototype based on the autonomous control strategy following these simulated results in hardware.

Chapter 5: Completion of Final Design and Validation

5.1 Introduction

Introduction of the final design saw the beginning of transformation of a simulated soft robotic manipulator to a completely realised prototype that could be assembled and tested in the laboratory. Through the analysis of the kinematic and the workspace as well as the torque calculations in the preceding sections, it has been confirmed that the 4-DOF arm geometry, soft tentacle gripper design and choice of actuators allowed the geometry to move to the desired positions and act on objects up to approximately 400 g. Having these design decisions and component ratings finalized, the second step was to produce the mechanical components through 3D printing, assemble the gearing joints using the chosen motors and servos, combine the modules in the full arm-gripper system and connect this hardware to the control and perception pipeline to experimentally validate the system in autonomous and manual mode.

5.2 Completion of Final Design

5.2.1 3D Print



Figure 34 : 3D Printing

The FDM 3D printing of the mechanical components of the soft robotic manipulator was carried out using the exact models tested in Fusion 360. The arm links, joint housings, base and soft gripper interface final versions were exported out of Fusion 360 and made printable models maintained with the dimensions and clearances verified in the design and workspace simulation period.

The printing was performed on Banbu 3D printers located in the department and SUNLU 1.75 mm white PLA+ as the rigid structural components and SUNLU 1.75 mm white TPU as the compliant soft gripper fingers were chosen, such that the physical components would reproduce the stiffness and flexibility conditions considered in the previous design calculations. PLA+ and TPU enabled the identical CAD space and printing operations of stiff components and soft components to be combined, which guarantee a uniform interface of connections, joints, and the tentacle-like gripper.



Figure 35 : a) Base, b) Shoulder, c) Elbow, d) Wrist

Each part of the 4-DoF manipulator was 3D printed, where link 1 is the base, link 2 the shoulder, link 3 the elbow, link 4 the wrist, and the tentacle fingers of the soft gripper. The designs needed to be reformulated a couple of times at this stage because the planned dimensions were quite often inaccurate in hosting the real motors, gearboxes, since what was designed did not necessarily fit to the real hardware after test-fit. Accommodations like mounting holes, shaft slots, internal cavities to hold gear trains, clearances to accommodate wiring were progressively changed in Fusion 360 and re-printed so that the motors could build without so much side movement and still rotated freely and were simple to assemble. Since the elbow link was the longest structural component, it was divided into two printed parts that could be reassembled mechanically after being printed that minimised print failures and enabled it to be installed into the build volume of the Banbu printers. Each of these hard structure parts, including the base, shoulder, elbow, and the wrist, had been 3D printed using PLA+ to ensure that the parts were stiff enough and dimensionally stable to support the arm and the heavy load.

In the case of the soft gripper, six discrete tentacles were milled in SUNLU white TPU according to the geometry of bio-inspired spiral assumed in the CAD model, and each finger had flexibility and compliance capabilities in order to wrap with objects of various shapes and sizes. The TPU material provided sufficient softness to the tentacles, which are critical in sharing contact forces without causing harm to delicate items during contact in grasping. When printed, the six tentacles were fixed symmetrically on the rigid gripper hub in such a way that, after all the tentacles were activated, they could encircle a target object and offer a secure, enveloping grip with the arm payload capacity of about 400 g.

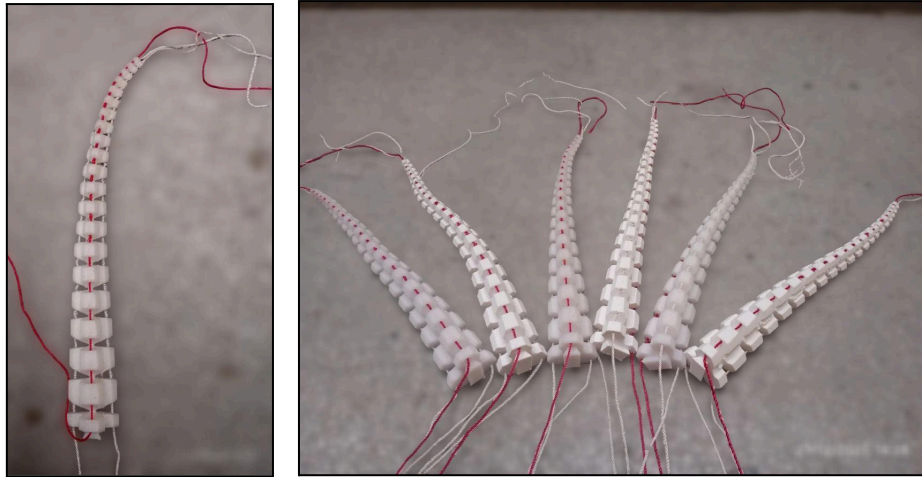


Figure 36 : Bio-Inspired Tentacles

5.2.2 Gears

The manipulator of soft robots had gears to transmit the force of the motors to the joints at appropriate mechanical advantage in such a way that relatively small actuators can safely move the heavier base and the connection segments. With gear reduction added to the joint, the output torque is raised, the holding ability increases and the motor is running at lower effective load, decreasing current, heat, and the possibility of stalling during lifting and static support. The gears ratio of the joint was chosen according to the necessary torque margins, as well as, the numbers of teeth available on the gear. The gear ratio is defined as

Gear Ratio:

$$i = \frac{d_1}{d_2}$$

Pitch circle diameter:

$$d_1 = mN_1$$

$$d_2 = mN_2$$

Where,

Module= $m=1.25$

N_1 =Teeth on driven gear

N_2 =Teeth on driving gear

Gear Ratio for Joint 1 :

$$N_1 = 10$$

$$N_2 = 15$$

$$d_1 = 1.25 \times 15 = 18.75$$

$$d_2 = 1.25 \times 10 = 12.5$$

$$\text{Gear Ratio, } i = \frac{18.75}{12.5} = 1.5$$

Gear Ratio for Joint 2 :

$$N_1=10$$

$$N_2=20$$

$$d_1 = 1.25 \times 20 = 25$$

$$d_2 = 1.25 \times 20 = 12.5$$

$$\text{Gear Ratio, } i = \frac{20}{12.5} = 2$$

to generate more torque amplification at the output by having a larger driven gear with respect to the driving gear. In joint 1(base) the ratio is 1.5, achieved by having a 15 tooth driven gear and a 10 tooth driving gear at the joint. In Joint 2 (shoulder) the ratio is 2, achieved by having a 20-tooth driven gear and a 10-tooth driving gear at the joint to give more torque at the point of greatest lifting demand. Following these ratios and tooth counts, the gears themselves were cut out of iron in the mechanical workshop so that they were strong and sufficiently resistant to wear, and the gears sides were then mounted into the 3D-printed joint housings to complete the transmission assemblies.



Figure 37 : 10 Teeth Gear

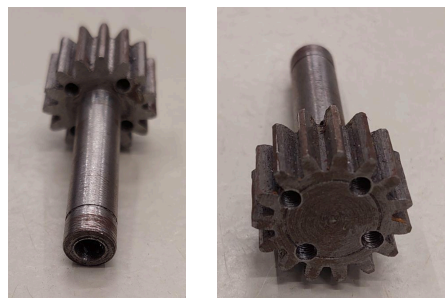


Figure 38 : 15 Teeth Gear



Figure 39 : 20 Teeth Gear

5.2.3 Mechanical Assembly of the Robotic Manipulator and Soft Gripper

The manipulator has been mounted on a special custom-constructed wooden platform which provides the structural foundation upon which the whole robotic system is constructed. One side of the platform was raised to give a good mounting platform to the robotic manipulator. This raised area helps in the support of arm structure with the power supply and control electronics being located on the lower part of the platform.

The manipulator base was bolted onto the high part of the platform. At this joint, a bearing was applied to guarantee a smooth movement between the base and the following link. The base had a high torque DC servo motor to move the shoulder link. This motor provides the main movement of the arm and gives the upper links the opportunity to move with respect to the base.

The second link is called the shoulder link and it was fitted at the top of the base. This joint consists of a bearing and a DC servo motor that gives vertical actuation to the next link. In order to increase the torque carrying capacity and decrease the mechanical load on the shoulder joint, a gear mechanism was used. This enhances the performance and the stability of lifting.

The third link is known as the elbow link. The elbow link was the longest structural part and hence it was printed in two segments. Two carbon-fiber reinforcement rods were inserted into internal channels planned in the link, prior to attaching these sections. These rods make the arm tensile and rigid. The two segments were then connected with bolts. The finished elbow connector was attached to the shoulder joint. In the elbow joint, a bearing and a high-torque DC servo motor were connected in order to move the wrist link.

The fourth connection was referred to as the wrist link which was fitted on the end of the elbow link. This connection provides the end effector with a way to position the gripper to get a grasping. A DC servo motor was attached to this pivot so as to control the movement of the wrist.

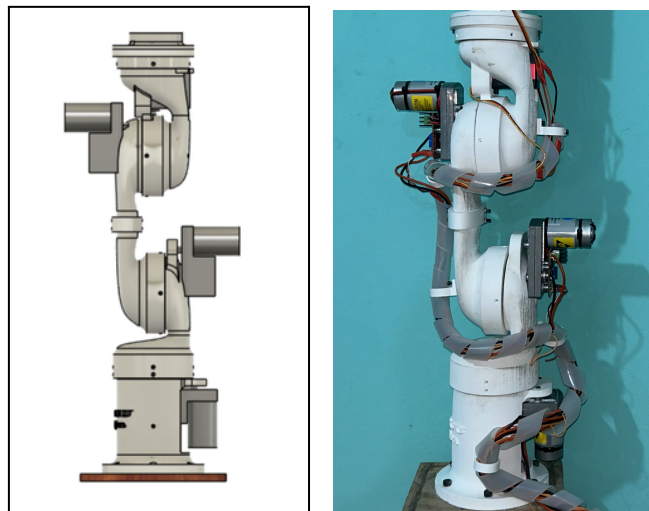


Figure 40 : Assembling the 4-DoF Manipulator, a) CAD Model, b) Real Model

The end effector is a soft robotic gripper which is attached to the wrist link. The gripper relies on the system of electro-rotary actuation and has six tentacle-like flexible fingers. Three actuation strings are inserted in each finger. The bending of the finger is done by the control of two strings, and the opening and closing is done by the control of the third string. The bending strings of each and every finger are fitted to the same servo motor whereas the opening strings are fitted to the other servo motor. The arrangement allows irregular and delicate items to be grasped with synchronous and adaptive flexibility. The entire soft gripper unit was then attached firmly to the wrist link.

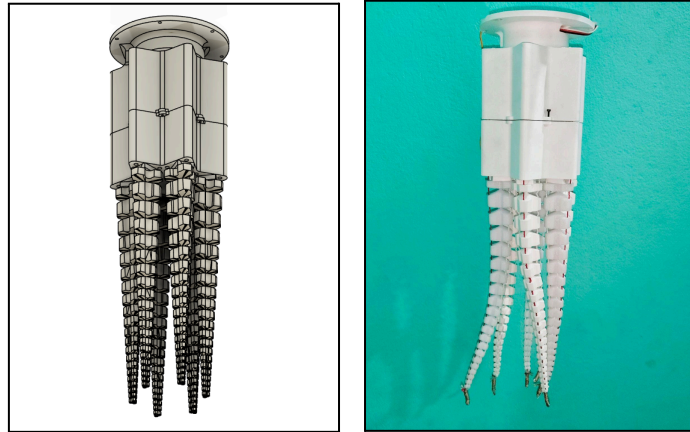


Figure 41 : Assembling the Soft Robotic Gripper, a) CAD Model, b) Real Model

Most joints in the manipulator were supplied with different rated DC servo motors to ensure the accurate and reliable movement. The high-torque servo motors powering the base, shoulder and elbow joints were 380 kg.cm, and the motors powering the wrist joint were 80 kg.cm. The soft gripper actuation system was powered by 35 kg.cm servo motors.

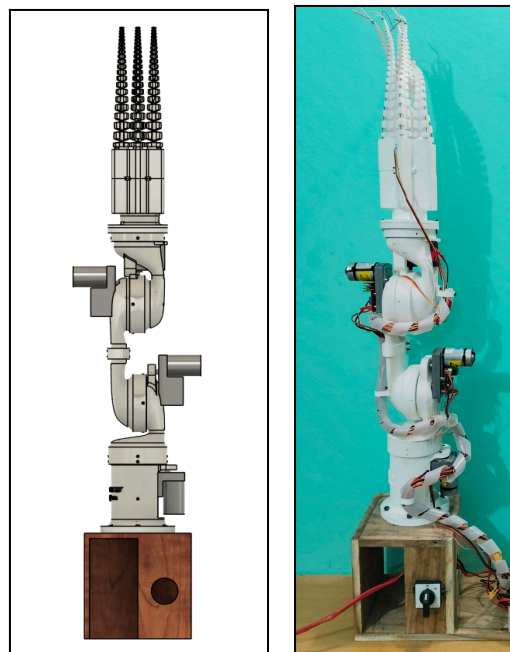


Figure 42 : Fully Assembled Manipulator with Gripper, a) CAD Model, b) Real Model

Powering the Manipulator

The manipulator power was such that it could be operated safely and under steady state. To be on the safe side, the AC main supply is linked to an emergency cutoff switch on the platform. The supply is connected to a switched-mode power supply (SMPS) that is 24 V, 30 A, and mounted on the wooden platform connected to the switch.

The SMPS 24 V output is hardwired to the DC servo motors of the base, shoulder and elbow joints. In components that demand lower voltage levels, buck converters were used. A buck converter is used to switch the 24 V to 8 V which drives the two servo motors in the gripper. The wrist motor is fed by another buck converter and the voltage is stepped down by a third buck converter to 5 V to power the Raspberry Pi 5 which is the primary controller of the system. Raspberry Pi 5 gets connected to all the servo motors and it generates control signals to coordinate the movement of the manipulators. There is a separate camera system used in detecting and identification of objects in the manipulation process.

Once the mechanical stack had been finished, power and control electronics were added. The 24 V SMPS, Buck converters to the 3-8.4 V servos, and the Raspberry Pi controller were attached close to the base area. The cables were made to pass through flexible cable protectors along the connections so that they do not snag or become damaged upon rotation. The joint motor and servo outputs were individually connected to their respective drivers and each was tested to ensure that the direction, speed control and end-stop limits were appropriate and in these tests the arm was taken through representative poses and was compared to the simulated environment and kinematic behaviour. It was when these checks were stable that the soft TPU gripper tentacles were added to the gripper hub and the entire arm-gripper system was now prepared to undergo a higher level of training in both autonomous and manual environments with the perception and control software.

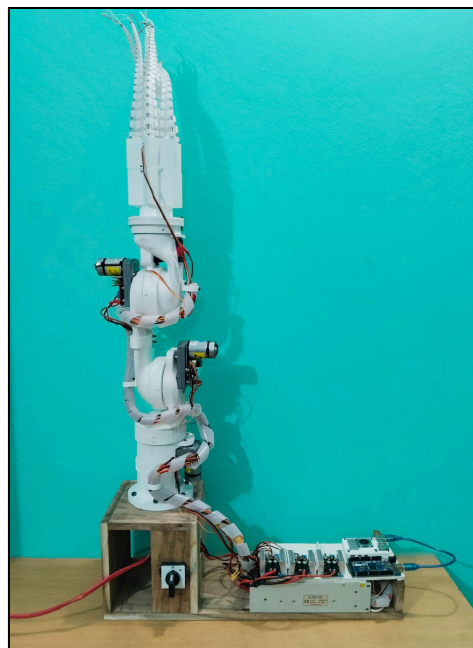


Figure 43 : Complete Setup of 4-DoF Manipulator with Gripper

5.2.4 Object Detection using YOLOv11

To detect objects, the resulting system is implemented with a YOLO based model as the main vision backbone based on a comparison made among multiple detectors using the project data. The selected YOLO variant provides a decent balance between precision, recall, as well as inference speed, and will be able to be deployed on the embedded computing platform utilized by the manipulator.

Under real-time running, the camera stream is inputted in the YOLO detector which manages to detect and localize the target objects in the arm workspace and generate bounding boxes and class labels on each detection. These detection results are translated into the approximate object positions on the robot coordinate frame and fed to the module of inverse kinematics so that the manipulator can plan and execute the motions towards the items detected on their autonomous trials.

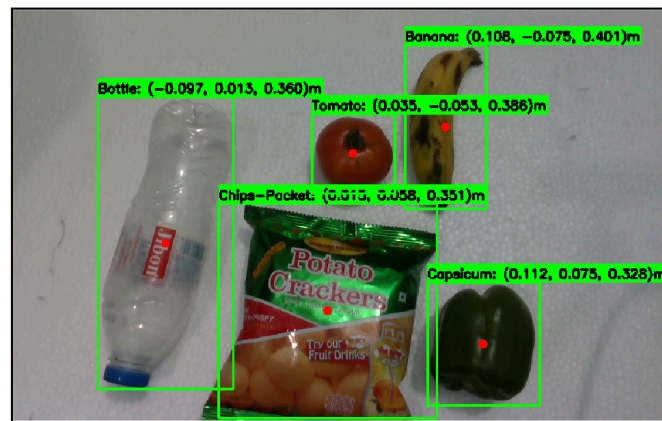


Figure 44 : Object Detection (Sample 1)

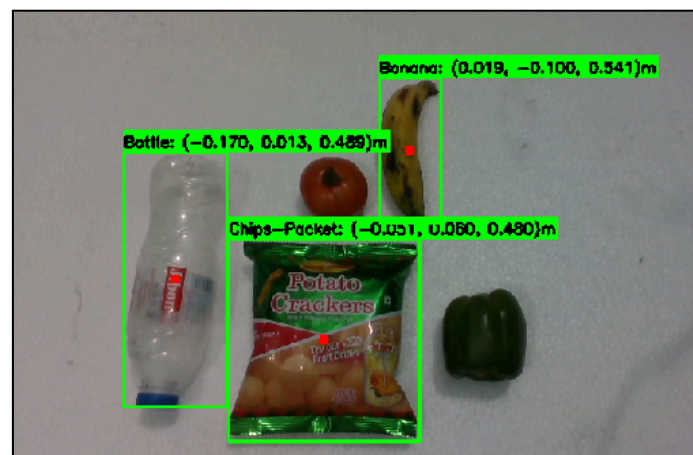


Figure 45 : Object Detection (Sample 2)

5.3 Evaluating the Final Design

5.3.1 Real-Life Testing

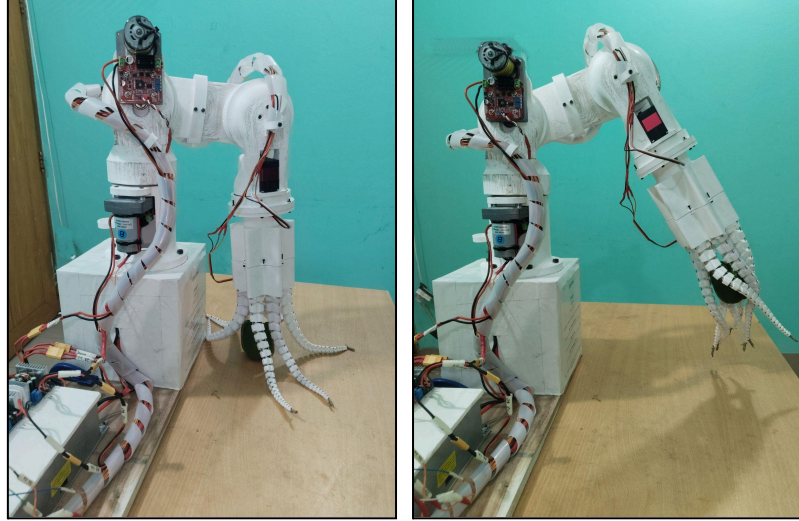


Figure 46 : Gripping Capsicum

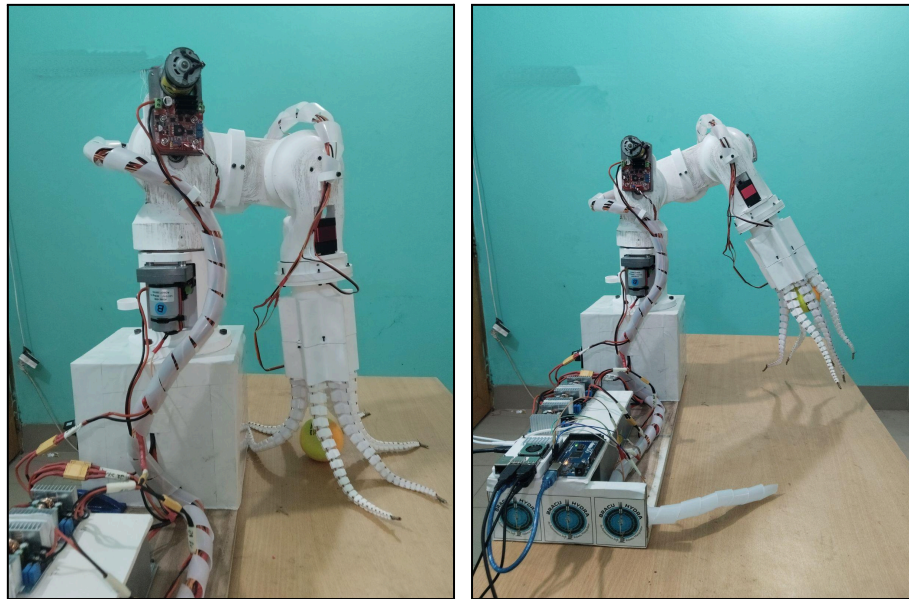


Figure 47 : Gripping Tennis-Ball

A. Autonomous Control Mode

An autonomous control of the 4-DOF robotic manipulator is executed and operated through a distributed ROS 2 control architecture on ROS 2 Jazzy. The high-level perception, planning and decision making modules are realized on Raspberry Pi 5 and low level motor control and actuator interfacing is achieved using the Arduino microcontroller. It contains a RealSense depth camera by Intel that provides 3D perception.

1) Object Localization and Perception

A deep learning model based on the YOLOv11 algorithm is used to obtain object perception because it performs a real-time inference and has minimal latency on embedded devices. Four machine learning models were trained and assessed, with consistency to the fact that the YOLOv11 had the best trade-off between speed and accuracy. The last model was trained on 11 categories of objects and succeeded in having an object detection rate of 94%.

The YOLOv11 network processes RGB images obtained by the RealSense camera and identifies processed objects in 2D bounding boxes. With a synchronized depth stream provided by the RealSense camera, the target object corresponding 3D Cartesian coordinates (x, y and z) are calculated in the camera frame. These coordinates are then translated to the robot base frame with the ROS 2 TF2 system of transformation.

2) Motion Planning and Control

The robotic arm is simulated based on a self-written URDF which is an accurate representation of the kinematic body, joint range, and the link parameters of the 4-DOF manipulator. This file is incorporated in RViz and MoveIt 2 as a visualization and motion planning tool.

The preferred end-effector pose is calculated depending on the perceived 3D location of an object that has been detected. MoveIt 2 planning pipeline is used to solve Inverse Kinematics (IK) to calculate the respective joint configurations. The planning algorithms of MoveIt 2 are then used to generate collision-free motion trajectories.

The trajectories are planned and first simulated in RViz and then implemented on the physical robot. ROS 2 Control is used to execute the program, with the joint commands being relayed by the Raspberry Pi 5 to its Arduino, which is acting as the real-time motor controller.

3) Real Life Implementation and Performance

The autonomous pipeline developed in simulation is duplicated in the actual robotic platform in order to maintain similarities between the virtual and actual execution of the task. Though perception and motion planning were accurate, the total success rate of grasping in autonomous mode was 33%. This is mainly due to the limitations of the systems like perception noise, a depth uncertainty, less end-effector compliance, grasp pose estimation error, and hardware limiting the results and are elaborated in the limitations section.

B. Manual Control Mode

Besides autonomous functionality, the manipulator also offers a manual teleoperation interface where the manipulator can be operated directly using human control. The Raspberry

Pi 5 is connected to a joystick controller that is interfaced by the standard joystick base ROS 2 joy package.

The inputs of Joystick are mapped onto either Joint-space or end-effector velocity commands in order to allow the operator to manually control the movement of the manipulator. The same ROS 2 Control framework makes these commands available to the Arduino to ensure that the low-level control pipeline is the same.

The manual mode is much better than autonomous operation due to the constant input of the human being, visual correction, and adaptive control. The test outcomes demonstrate that the success rate of object grasping when applied to manual control is 66%, which demonstrates the competence of the human-in-the-loop operation in performing precise manipulation tasks.

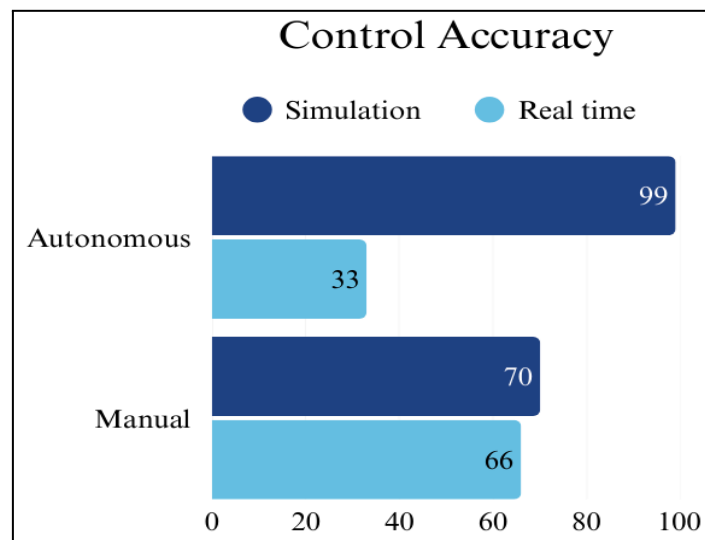


Figure 48 : Control Accuracy of Autonomous Control Mode vs Manual Control Mode

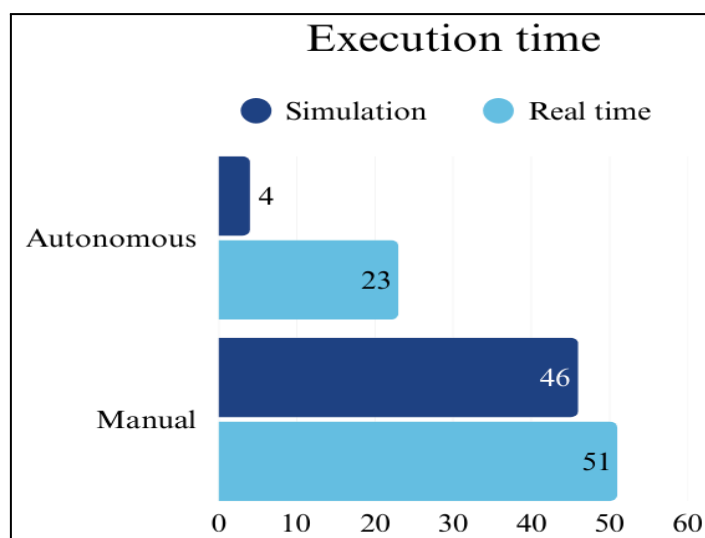


Figure 49 : Execution Time of Autonomous Control Mode vs Manual Control Mode

5.3.2 Constraints and Limitations

Motor Torque Limitation:

The servo motors employed by the manipulator are 380 kg cm ASM motors which were not good enough to handle the needed payload and dynamic loads. The motors appeared to have a torque saturation under operational conditions, and this caused a decrease in positioning accuracy and unstable movement. The use of industrial-grade actuators with sufficient torque and accuracy was not implemented because of the cost constraint, its limited availability locally, and importation barriers. The manipulator was highly influenced by the usage of low-cost, locally available, actuators, which influenced the entire precision and repeatability of the manipulator.

Accuracy of Gears:

The custom gears were produced on local production, which led to poor dimensional accuracy and backlash. Thus, the real gear ratios were different to the modeled values that were applied to the URDF and RViz simulation. This difference in the simulated system and the physical system caused kinematic inconsistencies in the system, which impaired autonomous control and performance of grasp.

System Complexity and Scope:

To enable a broad diversity of subsystems, CAD-based mechanical design, ROS 2-based simulation, 3D printing and fabrication, mechanical-electronic integration, machine learning-based perception, inverse kinematics, MoveIt 2 motion planning and ROS 2 Control were incorporated into the project. Due to the complexity of the system, and the limited time available to perform the development, it was difficult to obtain the accurate optimization of all the subsystems. This large scale limited fine-tuning and calibration, especially when it comes to autonomous performance in performing a manipulation.

5.4 Safety and Hazard Analysis

The adaptive manipulator and soft robotic gripper designed in the course of the project integrate both 3D-printed PLA/TPU structure with cable-actuation and electric motors that provide a safety profile that cannot be directly compared to either typical rigid manipulators or online-only systems. Though the soft material is used to contain impact forces, the design contains moving joints, tensioned cables, and loads provided by printed links, so failures may result in dropped objects, sudden motions, or damages of the prototype and others around it. Besides this, the use of 3D printing implies that a lot of components are manufactured as thin and fragmented structures, which can be destroyed easily by poor print or work during assemblage.

Due to these reasons, the project views safety and hazard analysis as an unceasing process that commences out of fabrication and goes on through experimental operation. The risks that are associated with fabrication boil down to the way the components are printed, assembled

and cabled, such as the chance of breaking fragile tentacle sections during the process of threading tendons, or overstraining the long shoulder connector that provides a significant amount of support to the arm. Operational hazards relate to the behaviour of the completed system upon being powered, such as the possibility of cable failure, unexpected movement due to software or driver errors, pinch points between moving components and electrical or thermal effects in the motors and power electronics. The separation of fabrication and operational hazards allows the analysis to better isolate the areas where careful printing, inspection and assembly is required and the areas where strategies of control, emergency stops and safe working practices should be exercised during use.

5.4.1 Fabrication Hazards (3D-Printed Manipulator and Gripper Parts)

Table 16 : Fabrication Hazards

Hazard ID	Phase	Description	Why it matters
FH1	3D Printing	Long print times and sensitivity to print settings mean that small slicing or parameter mistakes waste material and time, requiring full reprints of critical parts such as links and tentacle segments.	Increases project delay and cost.
FH2	Tentacle link fragility	Each tentacle is made from many small, articulated PLA/TPU segments; individual links are mechanically weak, so inserting and tensioning cables can easily crack or snap segments if force is not applied carefully	Breakage during assembly leads to re-printing, misalignment of motion, or hidden cracks that may fail during operation.
FH3	Shoulder link (between J2 and J3) weakness	The long shoulder section carries a large share of the arm's total weight; as a 3D-printed PLA link, it is more prone to bending and cracking under concentrated load or accidental impacts	Failure here can cause loss of alignment of the entire manipulator and sudden drop of the gripper and payload.

5.4.2 Operational Hazards

Table 17 : Operational Hazards

Hazard ID	Phase	Description	Why it matters
OH1	3D-printed part failure	Tensioned cables that open and close the tentacles may snap, loosen, or detach during operation. Highly loaded links between tentacle segments may crack during operation.	Might lead to immediate loss of gripping capability on one or more tentacles, incomplete opening/closing, and unplanned downtime for repair .

OH2	Excessive gripping force	Fixed closing motion of the cable-driven tentacles can apply more force than needed on fragile objects.	Risk of crushing, scratching, or permanently deforming delicate items under test, since no force or torque sensing is used
OH3	Pinch and entanglement	Gaps between tentacle segments and joints, plus exposed cables, can trap fingers, clothing, or loose wires.	Can cause minor pinching injuries, pull objects into the mechanism, or jam the system during motion
OH4	Overloading	Attempting to lift objects heavier than the intended payload limit causes the arm and gripper to operate beyond their designed torque capacity.	Can overheat shoulder and elbow motors, increase current draw, and overstress the long 3D-printed links, raising the risk of motor failure or structural cracking over repeated attempts
OH5	Unexpected or runaway motion	Software bugs, communication loss, or driver faults may cause the arm or gripper to move in an unintended way.	Could move the arm or tentacles into the operator or setup, or continue applying force when the user expects it to stop
OH6	Electrical and thermal issues	Motors and power electronics can overheat under sustained load; wiring faults or shorts may occur at connectors.	May lead to hot surfaces on 3D-printed housings, reduced component lifetime, or localised burning/smoke in a worst case
OH7	Control latency / delay	Processing or communication delay in the microcontroller or vision pipeline causes noticeable lag between commands (or camera updates) and arm/gripper motion.	Can make manual teleoperation feel unresponsive, reduce accuracy of autonomous grasping, and increase risk of overshoot or minor collisions with surrounding objects, especially in tighter workspaces

5.4.3 Hazard Score:

- Likelihood (L): Possible = 1, Likely = 2, Very Likely = 3
- Impact (I): Low = 1, Moderate = 3, High = 5
- Score: $R=L \times I$

Table 18 : Hazard Score

ID	Hazard	L (1–3)	I (1–3)	Score R = L×I
FH1	3D Print errors → Reprints	3	1	3
FH2	Tentacle link cracks during cabling	2	3	6
FH3	Shoulder link crack under high load	1	1	1

OH1	3D-printed link or tentacle failure in operation	2	3	6
OH2	Excessive gripping force damaging fragile objects	3	5	15
OH3	Pinch / entanglement of fingers or clothing	1	3	3
OH4	Overloading	2	1	2
OH5	Unexpected or runaway motion of arm or gripper	1	5	5
OH6	Electrical / thermal issues (overheating, minor short)	2	5	10
OH7	Control Latency	3	2	6

5.4.4 Heat Map:

Impact→ Likelihood↓	Low	Moderate	High
Very Likely	3D Print errors causing to reprint. (FH1)	Control Latency (OH7)	Excessive gripping force damaging fragile objects (OH2)
Likely	Overloading (OH4)	3D-printed link or tentacle failure in operation (OH1). Tentacle link cracks during cabling (FH2)	Electrical / thermal issues (overheating, minor short) (OH6)
Possible	Shoulder link crack under high load (FH3)	Pinch / entanglement of fingers or clothing (OH3)	Unexpected or runaway motion of arm or gripper (OH5)

5.5 Risk Mitigation Plan

Table 19 : Risk Mitigation Plan

Hazard ID	Hazard	Mitigation Measures
FH1	3D Print errors causing reprints	Small test pieces were printed before long prints; A short setup checklist was followed (orientation, infill, supports, temperatures) to reduce misprints and rework
FH2	Tentacle link cracks during cabling	Tentacle segments were printed with increased wall thickness and filleted cable holes, and cables were inserted manually with low initial tension, tightened in small steps while checking that no segment showed whitening or cracking
FH3	Shoulder link	The long shoulder link between J2 and J3 was reinforced by embedding two 5

	crack under high load	mm carbon-fiber rods inside the 3D-printed structure, increasing bending stiffness and improving the link's ability to withstand the arm's weight and payload
OH1	3D-printed link or tentacle failure in operation	The operating payload was limited to approximately 1 kg, and a brief visual inspection of the arm and tentacles was carried out before experiments; operation was stopped immediately whenever asymmetric motion or unusual noise was observed
OH2	Excessive gripping force damaging fragile objects	The gripper control code was configured with fixed limits on closing angle, and a slower "soft close" profile was tuned using robust dummy objects before handling fragile items, reducing the chance of over-squeezing
OH3	Pinch / entanglement of fingers or clothing	A safe working area around the arm and gripper was marked and communicated to users, and operators were instructed not to place hands inside this zone while the system was powered; sharp PLA edges near moving joints were removed or rounded
OH4	Overloading	The maximum recommended payload (about 1 kg) was documented in the operating procedure, and test cases above this limit were avoided; for heavier trial objects the arm was kept closer to the base to reduce joint torque and stress on the shoulder link .
OH5	Unexpected or runaway motion of arm or gripper	A physical safety key was installed between the mains supply and the SMPS so power could be disconnected immediately, and joint and cable-travel limits together with simple watchdog checks were implemented in software to stop motion on abnormal behaviour
OH6	Electrical / thermal issues (overheating, minor short)	Joint motors were mounted externally for natural air cooling, and the gripper motor housing was provided with ventilation openings; during extended tests motor and supply temperatures were monitored, and duty cycles were reduced if abnormal heating was observed
OH7	Control Latency	Image resolution and processing were kept minimal, and end-to-end latency was measured so that autonomous and manual tasks were planned with motion speeds and reaction times compatible with the measured delay margin

5.6 Conclusion

This chapter explained how the simulated design was transformed into a real prototype in the form of 3D-printed PLA links, TPU tentacle fingers, gears, and locally obtained actuators. The prototype was a combination of an autonomous pipeline (a detection model based on YOLOv11, inverse kinematics, and motion execution system) and a manual control function that the prototype could use in a joystick interface. The practical test demonstrated that the system is capable of sensing and pick-ups objects, such as capsicum and a tennis ball, but the practical test also demonstrated some limitations such as motor torque, lower positioning

precision, and restriction in computing the ability to execute the autonomous functions fully reliably. The manual mode on the other hand enabled the human operator to cope with these imperfections in the hardware, which reached more consistent grips and more adaptable response to unmodeled conditions. In general, the final system illustrates autonomous control as having prospective potential, but as of now being limited by practical hardware and implementation constraints, with manual control remaining a powerful, useful way to achieve the same, and it offers an equalized platform on which autonomous control can develop further.

Chapter 6: Impact Analysis and Project Sustainability

6.1 Introduction

This chapter looks at the possible benefits and the wider effects of the soft robotic manipulator and gripper that was implemented in this project. This system consists of a multi degree of freedom robotic arm that has a soft gripper designed out of six tentacle-like forming structures, which allow the natural and adaptive manipulation of unusual and delicate items. The manipulator is designed to be flexible such that it can be used in autonomous and manual mode of operation hence applicable to a vast industrial usage.

Its multi-degree-of-freedom configuration and the possibility of making non-linear motions can make the manipulator more useful and precise in the process of interacting with the objects in the cluttered or dynamically changing environment. The soft tentacle gripper also increases the functionality since it is able to contain different shaped and textured objects thus minimizing the chances of damaging a product during control. Such design features render the system more applicable to logistics, warehousing, and automation industries, where handling of each item carefully and efficiently is mandatory. The discussion of the main advantages of the given technology and the examination of its predicted social, economic, health, safety, and cultural effects in a real application is presented in the following sections.

6.2 Potential Benefits

The soft robotic manipulator and gripper offers a number of benefits in industrial tasks involving handling, particularly those of irregular and delicate items. The design offers flexibility, accuracy and soft operation, which is a useful tool in contemporary logistics and automation.

Table 20 : Potential Benefits

Benefit Area	Technical Description
Gentle Handling	The soft tentacle gripper enables safe and controlled manipulation of fragile and irregular items, minimizing product damage.
Multi-Degree-of-Freedom	The arm's multiple degrees of freedom allow for flexible, precise movement and better access in cluttered or complex environments.
Adaptability	The gripper's tentacle structure accommodates a wide variety of shapes, sizes, and textures, enhancing versatility across applications.
Operational Efficiency	Automated and manual operation modes streamline repetitive or time-consuming tasks, improving speed and reliability in industrial settings.
Safety Improvement	Reduces risk to human operators by automating handling of hazardous or delicate goods.

Cost-Effective Design	Use of modular, 3D-printed components supports affordability, simplified maintenance, and quick customization or repair.
Workforce Relief	Automation of intensive handling tasks decreases physical strain and routine workload for manual laborers.

6.3 Impact Analysis

Implementation of this soft robotic manipulator and gripper (like soft robot used in warehousing, logistics, and automation) can influence a number of areas in the industry and the society. The following are some of the key ways in which this technology can bring beneficial effects:

6.3.1 Social Impact

Table 21 : Social Impact

Impact Area	Description
Delivery Speed	The manipulator enables faster movement and sorting of items in warehouses, resulting in quicker turnaround for order deliveries.
Error Reduction	Automated picking and sorting functions reduce the likelihood of mistakes in inventory management and shipping, increasing reliability.
Employment Shift	Routine manual handling tasks are replaced by automation, prompting a shift in job roles toward oversight, maintenance, and technical support.
Accessible Technology	The modular design and straightforward control interfaces allow businesses of various scales—large and small—to implement the technology without specialized expertise.

6.3.2 Economic Impact

Table 22 : Economic Impact

Impact Area	Description
Lower Damage Loss	Using soft tentacles to grip and move goods reduces product breakage in transport, minimizing costly replacements and refunds.
Resource Efficiency	Automation helps businesses balance workforce size more effectively, cutting unnecessary staffing during periods of fluctuating demand.
Equipment Longevity	Gentle handling lessens wear on both products and mechanical systems, extending the usable life of conveyor belts, storage bins, and robotic devices.
Rapid Scalability	Modular system components can be added or changed quickly, letting companies ramp up capacity during busy seasons or expand for new operations with minimal downtime.

6.3.3 Health and Safety Impact

Table 23 : Health and Safety Impact

Impact Area	Description
Reduced Physical Risks	Automating lifting and repetitive movements lessens the physical strain and chance of musculoskeletal injuries among workers.
Fewer Workplace Accidents	Automated handling means fewer incidents involving goods being dropped, slipped, or mishandled, which can cause accidents or damage.
Control of Hazardous Items	The system can be configured to safely transport hazardous, contaminated, or sharp objects, reducing human exposure to harmful substances.
Clean Operation	Soft tentacle mechanisms operate smoothly and do not shed particles, supporting hygiene and preventing contamination in sensitive environments like food storage.

6.3.4 Cultural Impact

Table 24 : Cultural Impact

Impact Area	Description
Technology Familiarity	Frequent exposure to robotics and automation helps workers and managers become accustomed to modern technologies, easing future adoption.
Industry Reputation	Implementation of advanced soft robotics demonstrates a commitment to innovation and quality, strengthening the company's standing with partners and customers.
Local Skills Growth	The need to maintain and operate robotic systems promotes training and upskilling in automation and robotics fields within local communities.
Adaptation in New Sectors	The gentle yet effective operation of soft robots allows the benefits of automation to reach sectors—like agriculture or small goods handling—that previously relied heavily on manual labor.

6.4 Sustainable Development Goals

After the ongoing global initiatives, and our own ambition to create something that will help our society, we attempted to match our project goals to some of the Sustainable development goals (SDGs). The SDGs can be defined as 17 international objectives that have been established by the United Nations as a means of addressing the burning demands of the environment, social and economic realities with the aim of making the world more inclusive, sustainable and affluent by the close of the year 2030. The targets are also quite specific with measurable indicators used to guide the advancements on different challenges such as the industry, innovation, decent employment, and responsible production. To unlock our alignment clearly and to refer to it, to the specific SDGs, we have tabulated the most relevant of the SDGs to our project as listed below, according to the standard UN codes and descriptions of the SDGs [82].

Table 25 : SDG

SDG Name	General UN Description	Alignment with Our Work
SDG 8: Decent Work and Economic Growth 	Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all.	Our project will contribute to safer and more productive work environments by automating repetitive/unsafe productive work in industries, minimizing product damage, and facilitating job growth in robotics installation and maintenance.
SDG 9: Industry, Innovation and Infrastructure 	Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation.	Our manipulator is designed to be accessible to small/medium industries, based on modular, inexpensive design (such as 3D-printed grippers), and it improves precision in industry, and this directly drives innovation and sustainable industry development.
SDG 12: Responsible Consumption and Production 	Ensure sustainable consumption and production patterns.	Our use of 3D printing reduces waste, encourages modular repair/upgrading, and includes recyclable materials, promoting material/resource efficiency.

6.5 Sustainability Analysis

In this project, we attempted to design the modular soft robotic manipulator in such a manner that is resource-conscious and minimizes wastage. All the components of the manipulator were 3D printed. The arm was constructed with the help of PLA+ that is strong and convenient to print. The gripper was manufactured using the TPU, which is soft and pliant enough to ensure that it can hold various shapes and delicate items without decomposing them. The employment of 3D printing as opposed to conventional manufacturing assists us in material saving. In 3D printing, we just print as much filament as is required by the part and there is minimal leftover or waste. This is preferable to old methods of producing things, which tend to generate a good deal of unnecessary scraps that are discarded.

The other feature in our design that is significant is the fact that the manipulator is modular. That is to say, we constructed it in blocks or rather modules that are disassemblable or replaceable at a time. In case something goes wrong, or we desire to upgrade it to a new design, then we simply replace the part that requires it. We will not even have to dismantle the whole machine and start anew. This makes the wastage minimal and makes the manipulator last long due to repairs and updates. In constructing the manipulator we attempted to use materials wisely. We calculated all prints so as not to include unnecessary parts. Another point we paid attention to was to ensure that every item was as much as we required not a wasted addition or a waste of material.

All this will make our project a more resource-saving one, not only in that it consumes just the volume of PLA+ and TPU necessary, but also in its ability to be easily fixed and upgraded, without discarding used components as good ones. Design, accurate 3D printing and modular building are all combined to make our manipulator more sustainable throughout the entire life of the working period.

6.6 SWOT Analysis

The given SWOT analysis is going to locate the most significant strengths, weaknesses, opportunities, and threats related to the soft robotic manipulator and gripper. This systematic evaluation gives a good perspective of the status of the project as well as how it can easily be extended in the future.

	Beneficial	Harmful
Internal	Strength • Modular design allows easy repair and upgrades • Gentle handling for fragile/irregular objects • Cost-effective production makes the system accessible to small- and medium-sized enterprises. • Increases workplace safety by automating repetitive and hazardous industrial tasks. • Maintenance and part replacement are simplified due to modular construction. • Simple control, adaptable for different tasks	Weakness • Performance may vary with very heavy or odd-shaped items • Due to budget constraint, the motor used lacks precision. • Layer adhesion in 3D-printed components can be a structural weak point, decreasing mechanical robustness under high stress. • Materials like PLA+ and TPU can degrade over time • System can be sensitive to calibration errors, especially in kinematic chains with multiple degrees of freedom. • Not tested for long-term industrial workloads
External	Opportunities • Material upgrades (e.g., nylon, composites) could significantly improve strength, durability, and operational range. • Integration of force/torque sensors or tactile feedback could enhance precision and enable more advanced manipulation. • New modules or end-effectors could expand its uses • Further improvements possible with better materials or motors • Implementation with renewable energy (e.g., solar panels) can further reduce environmental impact	Threats • Supply or price changes for 3D printing materials • Rapid tech changes could make design outdated quickly • Wear and tear from repeated motion may lead to joint loosening or material fatigue without regular maintenance. • Any inherent print defects (voids, under-extrusion) may compromise structural integrity, requiring strict quality control. • Risk of electrical interference or hardware damage due to compact wiring and actuator co-location within the design.

The presented SWOT analysis reveals that the manipulator can be characterized by the delicate manipulation, its modularity and high ease of production, though such aspects as the materials durability and the performance under the heavy loads should be refined. With the changing technology, designing and changing the materials will serve to preserve the usefulness and value of the project.

6.7 Challenges in Sustainability

Although the modular soft robotic manipulator was created with the consideration of efficient material use and easily and readily repairing it, long-term sustainability still has significant challenges to the product. The last problem is the stability of the gripper joints. The joints of the soft tentacle gripper are not sufficiently robust and with time, they can degenerate as a result of bending and flexing. The design is such that each tentacle can be replaced individually in case of wear or damage - the design is helpful in the maintenance context; however, there is still a possibility of increased material usage and disruption of functioning due to frequent replacement.

The other problem is the general life of the PLA+ and TPU materials to be used various components of the manipulator. Though convenient and simple to print, they might not be as durable or resistant to mechanical forces as others and in a warehouse environment with demand or high frequency of use. Also, since the swift use of components in this project was primarily on practical building and assembly, there was not much consideration of end-of-life or potential re-use of anything other than a simple bring in replacement. This implies that it is possible to change certain components, but there is no lean replacement of worn-out components and reuse process. Moreover, the servo motors used in the manipulator had been chosen within very tight budget requirements and therefore the accuracy and repeatability of the controlled motion was restricted. These cheap servo positions bring about small errors in the placement of the tentacles especially when dealing with repetitive or delicate manipulation. They may be suitable in the prototype validation and demonstration models, but their low level of precision may be sensitive when it comes to performance in the industrial or high demand models. A future version using higher torque, closed loop, or digital servos would be much better in control accuracy and would increase system reliability.

These challenges will be significant to overcome in case the manipulator should be used in the long-term and intensively, or modified to meet tight sustainability requirements. Improvements that can be made further would be finding more durable, tougher (but still printable) materials, strengthening the brittle joints of the gripper, or working out a more comprehensible plan of dealing with worn-out parts.

6.8 Conclusion

This chapter examined how the soft robotic manipulator and gripper can be useful in social, economic, health, safety, and cultural gains particularly in areas that deal with delicate or uneven objects. The system is in agreement with various Sustainable Development Goals such as the encouragement of safer working environments, industry innovation, and the facilitation of smoother and less wasteful processing of goods. The sustainability and SWOT analyses revealed some key strengths, including modular design, the use of low-cost 3D-printed elements, and flexibility and challenges, including long-term sustainability, operation in local environments, and the utilization of improved actuators and more robust electronics. These observations show that the project is technically and contextually viable, however, additional engineering, investment, and thorough deployment planning are required to achieve the goal of sustainable use in the long run.

Chapter 7: Engineering Project Management

7.1 Introduction

The project on the soft robot manipulator is structured with the help of simple project management in order to make sure that the project may pass through an initial idea to a working physical system. To make the work clear and manageable, the project was split into three major phases, which are the proposal and planning (P), design and simulation (D), and construction and implementation (C), and each of them corresponds to a set of tasks, documents, and deadlines.

Gantt charts have been done of all three phases to indicate when each activity began and ended, the level of activity overlap, and who is accountable to each activity so that anyone can know the entire plan just by seeing it. These charts also assist the group to organize meetings, compensate for exams or other things and ensure that the key outputs including the proposal, simulation results and the final prototype are not lagged behind time. This organized yet simplistic method allows the team to organize the working process and track the progress and adjust it when necessary without losing sight of the overall goals of the soft robotic manipulator and gripper project.

7.2 Plan and Manage Engineering Project

The scope, objectives, and general requirements of the soft robotic manipulator are well outlined in advance before the detailed project management begins and they include the likely range of motion, approximate payload, actuation method, and which areas it will primarily be used in. We can then subdivide this overall goal into smaller subtasks, deliverables and milestones of each of the three phases (P, D, C) under the supervision of the ATC and identify potential risks, including material failure or delays in obtaining elements. In order to ensure that the work is on track with the project goals, we frequently cross-examine our performance with the Gantt charts and shift task assignments in case of exams or other problems influence the availability of a person. Time management, sharing the load, and coordinating both the P, the D, and the C are all considered to be ongoing so that each stage is able to enable another stage in an obvious and planned manner.

7.2.1 Project Plan for P-Phase

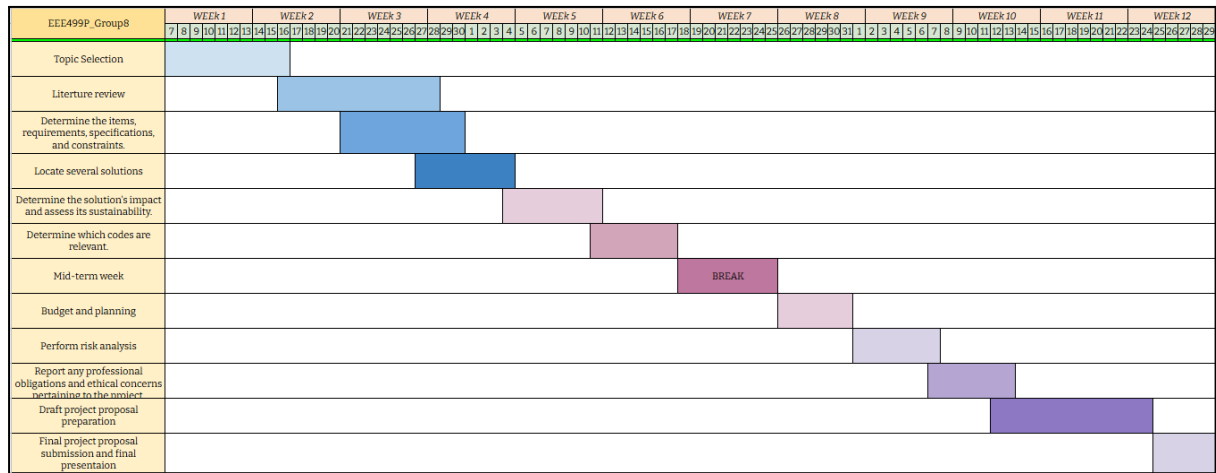


Figure 50 : Gantt Chart for P Phase

The P stage was devoted to the choice of an appropriate project subject, the background, and all documents that needed to be prepared in order to officially begin the work. Initially, we were all involved in problem identification when a soft robotic manipulator and gripper could come in handy and brainstormed various ideas with our ATC to ensure which ones were viable within our time, financial capabilities, and our laboratory facilities. Once the topic was finalised, we conducted a systematic literature review on soft robotics, soft actuators and available manipulators to get an idea about existing designs and also know the gap that our project would fill.

Based on the data presented in the literature review, we then used the data to establish the objectives and some basic specifications of our manipulator including the desired motion, the load range that was expected, materials that are to be used and the overall actuation method. Simultaneously, we developed some of our first ideas of the solution and elevated block diagrams that reflected the interrelation between the mechanical implementation, actuation power, and control unit. At this point, we also began initial budget, recording the potential elements and determining the prices, in order that we can know whether our ideas were within our means.

Having formed the concept, we developed a concept note and a presentation to the ATC, in which we clarified the problem, goals, the way we planned to do it, and the results. The responses of this meeting helped us correct some of the design assumptions and the way the entire plan was going to be done. These alterations led us to the development of the comprehensive project proposal that included background research, problem statement, goals, proposed methodology, risk analysis, and ethical and sustainability evaluation and made a submission and formal presentation of these at the conclusion of the P phase.

7.2.2 Project Plan for D-Phase

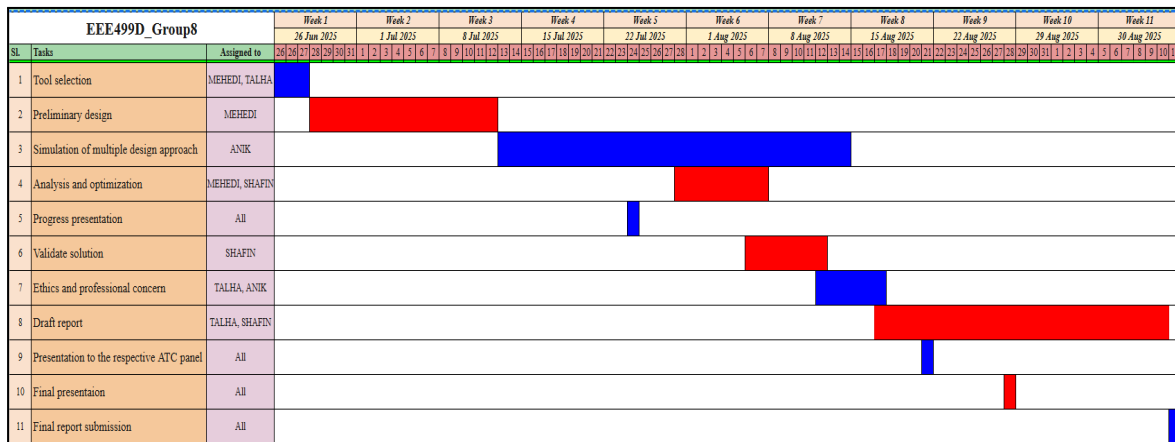


Figure 51 : Gantt Chart for D Phase

The later phase was the D phase where we left the planning phase to the detailed design and simulation of the soft robotic manipulator. To start with, we evaluated a few software tools that were available to us regarding the ease with which each one allowed us to modelize the manipulator, provide motion commands to it and watch the arm move, and selected a simulation environment that would form the basis of all the subsequent tests in the form of the desired and common joint layout of the manipulator, with the desired and common link dimensions.

Once the baseline model was finished, we focused on two different control methods regarding the same mechanical design and these are our two design approaches. First is manual control and second is autonomous control. We simulated the case in which we provided the joint commands to move the arm and close the gripper directly in the manual approach and applied a control routine which commands the use of the joint motion to reach the object and close the gripper around it in the autonomous approach.

In both strategies, time and accuracy of the arm to reach and grab the object, were our primary performance parameters. We were able to measure the time that the arm required in order to move to the object and pick it up and the proximity of the final end-efficiency position to the intended target in each simulation and compare the results with the efficiency and accuracy with which the manual and autonomous strategies retrieved under similar conditions.

During the D phase, we created progress presentations which included demonstrations of the simulation setup, trajectories, timing results and accuracy plots to the ATC and got suggestions on how to do a better job of control logic and test cases. We finally concluded this phase by recording the modelling steps, control methods, simulation outcomes and salient observations in a draft report and handing it over to the ATC panel to complete the design and simulation process and to set up smooth groundwork regarding the fabrication work in the following phase.

7.2.3 Project Plan for C-Phase

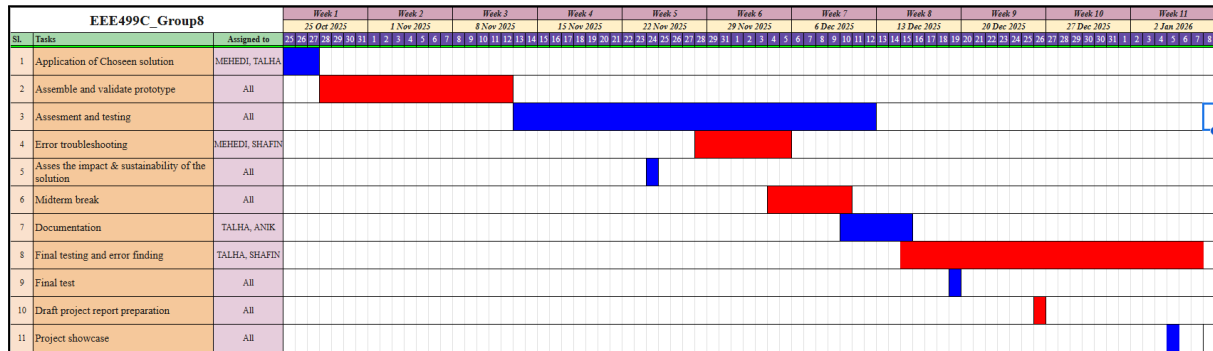


Figure 52 : Gantt Chart for C Phase

The C phase was devoted to transforming the simulated soft robotic manipulator into a realistic system that can be constructed and experimented in our laboratory using the resources. We went through the design phase first and realised where we needed to add or remove modifications so that the design could be realised using affordable and locally available components. This step entailed consideration of each section of the design, verification of supplier options and revision of drawings and specifications such that the output became a real-life component rather than an idealised one.

During the development of hardware, it was common to discover that there were hardware components that were too costly or unavailable in our country although they were suitable in theory. As an illustration, a Jetson Nano would have worked well as the primary processing unit, however it was expensive and inaccessible, in which case we chose a Raspberry Pi, which is more affordable, and can meet our control and processor requirements. Just enough of the same was compromised with motors and drive units: in order to get the necessary torque using motors which we could actually get, we varied link lengths, gear ratios and mounting arrangements in a way that kept the end design within safe operating limits but allowed it to be built.

Once these optimised decisions were finalised we engaged in further fabrication with the production of CAD models and drawings, 3D-printing or machining the components as needed and assembling the soft manipulator with the selected actuators and control equipment. In the process of assembling and initial testing we observed the behaviour of the real system during operation in relation to the predicted behaviour in the simulation and make fine mechanical and control adjustments, such as changing joint clearances, tuning speeds, or switching actuation sequences, to achieve greater reliability and more repeatability. These experiments and the new design choice and the reasoning behind the choice of every hardware were well documented so that they may be analysed in the future and made part of the final report and presentation.

7.3 Evaluating Project Progress

Workload in P Phase (≈15–20%)

During the P phase, we did not do any technical construction and coding, but narrowed down on selecting topics, completing a background, defining requirements and putting together a concept note and proposal. The work load here was the least, but the stage was necessary as it helped get a clear picture on the problem and realistic goals as well as developed the course of action in which all subsequent actions would take, and can thus be justifiably regarded as being approximately 15-20% of the total effort.

Workload in D Phase (≈30%)

The work at the D level was more technical because we had to pick and learn an appropriate simulation tool, construct the basic model and formulate our control mechanism in software programs, and, hopefully, achieved both manual and autonomous control schemes, simulated several times, and measured performance by the duration of time to reach and capture an object and the precision of the final position, which meant that the work of increasing the effort is visible, which is why we are considering this stage to be about 30 percent of the total workload.

Workload in C Phase (≈50%)

During the C phase, the work was the most critical due to the necessity of modifying the design to fit real-life constraints, selecting the components which were really available within the budget, and performing fabrication, assembling, and testing. This phase became the most time-consuming as mechanical design adjustment, the changes of actuator and motor options, and conducting similar experiments and troubleshooting were involved and, as a result, are attributed to approximately half the total project work.

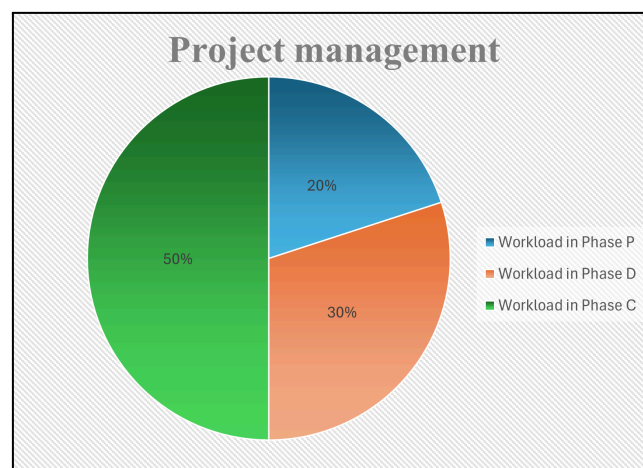


Figure 53 : Project Completion Pie Chart for Each Phase

7.4 Conclusion

The combination of the three project phases helped us to translate a mere thought, after simulation, to a full embodiment of a physical form of a soft robotic manipulator. The final prototype did not work as well as we had initially anticipated but it was able to demonstrate the key functions of reaching and grasping with both hand-controlled and autonomic control, which testifies the fact that our basic construction and method of control work, in reality.

In the meantime, the results and experiments revealed a series of aspects that can be improved, such as refining the mechanical arrangement, modifying the control program, and selecting better materials to promote accuracy, fastness, and stability. These reasons provide clear direction on the line of the future work and with further refinements and more sophisticated sources, the soft robotic manipulator can become a more efficient and powerful system.

Chapter 8: Economical Analysis

8.1 Introduction

The development of soft robotics is rapidly turning into an essential component of the modern economy that alters the attitude of the industries towards the automation and material management. Unlike their rigid counterparts, soft robotic systems, including compliant grippers and adaptive manipulators, can operate very gently as well, are flexible and safe, and can perform tasks where other robots might not perform so well. The new technological advancement is giving business new opportunities to become more productive, minimize losses incurred by damages of products and shortages of labor.

The world market is constantly increasing, and the field of soft robotics is expanding at an unprecedented rate, and the perspectives of significant growth can be seen in such spheres as manufacturing, logistics, healthcare, food processing, and agriculture. In other countries like Bangladesh, recent advances in soft robots are contributing to the industries to seek low cost access to automation, and to overcome a shortfall in technical capability. The factors that include the invention of low cost, modular soft robotics and commercialization of the same not only are shaping new market dimensions, but also making more advanced technologies available to small and medium enterprises.

The cost implications of using soft robotics are wider than covering costs. These technologies help promote the growth of the industry in the long term, innovation and more sustainable business processes through the assistance of flexible and adjustable automation in a more globalized and competitive economy.

8.2 Market Analysis

8.2.1 Global Market Growth of Soft Robotics

The market is witnessing a boom in the number of robotic arms needed and the number of robotic arms is predicted to increase to 76.2 billion dollars by 2029 with a favorable CAGR of 15.6 percent [62]. Such a steep increase is a response to higher automation in the manufacturing, logistics, healthcare, and service sectors. The soft robotics market, including items such as soft grippers, inflatable robots, exoskeletons, wearables, and other products, will be experiencing strong growth as well and it is expected to increase to \$1.1 billion in the year 2022 and grow steadily after that. The soft grippers are winning the market and are motivated by the increasing use of soft grippers in processes involving the gentle material handling and versatile automation projects.

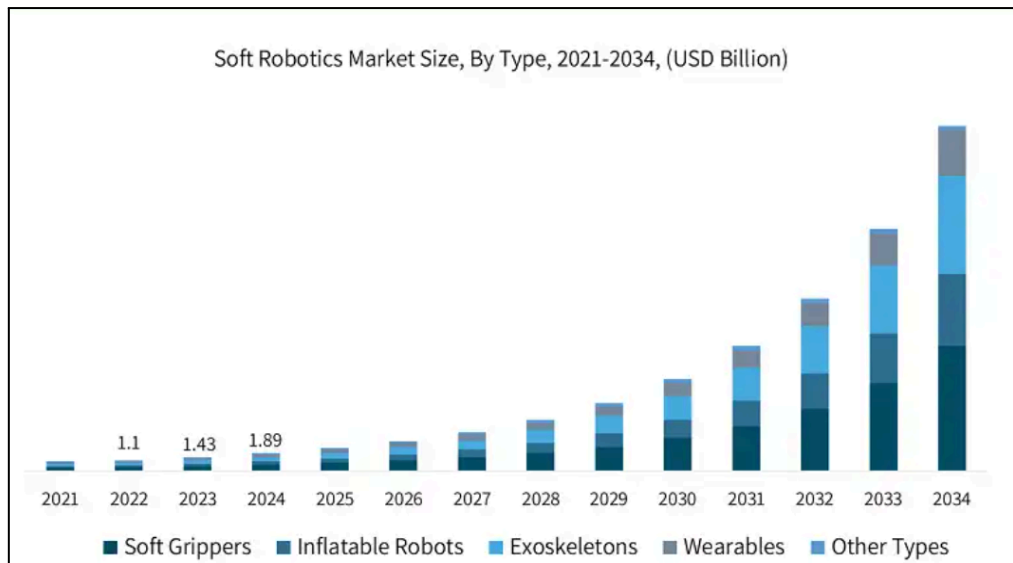


Figure 54 : Soft Robotics Market Analysis [70]

The industries are on the brink of rapid expansion as robotics technology develops, the industry is becoming more widespread and more applications can be found using this technology. The traditional manipulators and soft robotics synergy will bring a groundbreaking change in automation of next generations of both heavy and fragile jobs in industrial and user-oriented applications respectively.

8.2.2 Major Application Sectors

Soft Robotics Market CAGR based on the Application Sector by 2025 to 2034

Table 26 : Application of Soft Robotics [17], [40], [70]

Application Sector	Forecasted Market Value by 2034 (USD)	Projected CAGR (2025–2034)	Key Use Cases
Medical & Healthcare		35.2%	Prosthetics, exoskeletons, rehabilitation aids
Food & Beverage	USD 11.78 billion		Gentle packaging, sanitary handling, labor gap solutions
Logistics		33.8%	Sorting, packing, warehouse automation
Automotive	USD 3.6 billion		Delicate part assembly, quality inspection
Agriculture		31.3%	Crop handling, harvesting, pest management

The soft robotics industry in the world has a fast-growing market with forecasted growth of USD 2.6 billion in 2024 to more than USD 51 billion in 2034 rising at a compound annual growth rate (CAGR) of nearly 35. This onslaught is fuelled by the development of flexible, adaptive robots that are effectively and safely able to deal with human beings and fragile items. Major industries that have been benefiting in terms of this growth are healthcare, agriculture, logistic, and food processing providing soft robots with dexterity, safety, and automation of complicated tasks.

8.2.3 Domestic Market Overview

Bangladesh has traditionally enjoyed its labor force which is high in numbers and inexpensive, and this has made the region one of the best places in the world to produce something that has got labor-intensive aspects. Although this dynamic constrains the prevalence of automation, there is increased evidence that specific investments in robotics, particularly soft robots arms, can produce long-term payoffs where human workers are put under pressure.

To begin with, robots are a good fit in dangerous, high-risk environments - those in which workers are prioritized, and manual solutions endanger lives. As an illustration, cleaning reactors, dealing with toxic chemicals, or dealing with biohazards are spheres, where no wage savings can explain putting workers in danger. Second, robotics are properly adapted to extremely repetitive, tedious tasks that are notorious due to creating psychological exhaustion, injury, and quality deterioration with time. Robots can provide a steady production in big warehouses, sorting plants, and pack lines and cut down errors, which even conscientious employees could not tolerate.

Nevertheless, in workbooks, which require complex resolution, improvisation, and situational considerations, the labour force in Bangladesh is preferable, since it is the less rigid and less expensive option. The truth behind this is subtle: robotics investment should not be promoted as a one-shoe-fits-all solution but in strategic sectors where safety, reliability, and high scale are requirements in terms of international competitive edge, increasing labor costs, or regulatory requirements. Innovative and progressive companies in Bangladesh, in particular the export-oriented or the quality-oriented production companies, have started to put an emphasis on focused automation to future-proof their organization, seal the skills gap, and address the needs of the international customers.

As global standards as well as global competition challenges develop, the selective investment in robotics by Bangladesh will also be a source of economic growth and sustainability. With government incentives, public-private research and education programs can become a key to reduce the barriers to expertise and uptake of robotic devices, making sure that they complement, but not substitute workers, and place Bangladesh at the forefront to continually succeed in the evolved industrial setting.

8.2.4 Domestic Market Growth

Although the low cost of labor has been a major competitive advantage to Bangladesh, the past several years have witnessed a gradual rise in investments in the sector with respect to automation and robotics. The 6Wresearch says that the market of Bangladesh robotics, industrial and service robotics in particular, was estimated to be worth USD 44.6 million in 2025, and substantial growth was projected to be in the manufacturing, logistics, and warehousing. Remarkably, the industrial robotics market segment, which includes robotic arms, will generate USD 2.33 million in revenue in 2025 due to the increasing automation in the textile, assembly, and precision-based tasks.

The trend in investment is that the sophisticated manufacturing oriented and export oriented organizations like DBL Group and Square Pharmaceuticals have already invested in automation, which has increased the production capacity by 25 percent and reduced the labour expenses by 15 percent of the involved factories. Although start-up capital may be high in the case of robotics, the industry is backed by an increasing need to optimize processes, improve quality, and adhere to global standards.

Moreover, it is reported that there is a great market opportunity: by 2041, Bangladesh can possibly automate up to 53 percent of the total jobs (ILO), and automation can potentially raise the national GDP by 19 percent. According to McKinsey there could be a potential of 30 percent productivity improvement in the major areas that have higher adoption of technology by the year 2030.

Table 27 : Investment in Robotics in Bangladesh

Metric	Value (Bangladesh, 2025)
Robotics market revenue (total) [58]	USD 44.6 Million
Industrial robotic arms revenue [59]	USD 2.33 Million
Potential percent jobs to automate 2041 [23]	53%
Productivity gain (by 2030, McKinsey) [23]	30% Increase
Reported labor cost savings (DBL Group) [23]	15%
Production capacity gain (DBL Group) [23]	25%

8.3 Development Cost

Table 28 : Development Cost

Category	Parts	Unit Price (BDT)	Quantity	Subtotal (BDT)	Total Cost (BDT)
3D Print	Sunlu TPU 95A	3200	1	3200	10700
	Sunlu PLA+ (White)	1500	5	7500	
Motors	35 kg.cm 270° Digital Servo	2350	2	4700	27600
	380kg Servo	6000	3	18000	
	80kg Servo	4900	1	4900	
Microcontroller	Raspberry Pi 5	12000	1	12000	16900
	Active Cooler for Pi	700	1	700	
	Sandisk Extreme Pro 128GB SD Card	2500	1	2500	
	Arduino Mega	1700	1	1700	
Camera	Intel RealSense D435i	40000	1	40000	40000
Joystick	Logitech Gamepad f310	2000	1	2000	2000
Power Supply	48V-30A SMPS	2400	1	2400	4350
	Emergency Switch	450	1	450	
	Buck Converters 24V to 8V	500	3	1500	
Wires	12 AWG Silicone Wire	100	4	400	2325
	14 AWG Silicone Wire	100	6	600	
	18 AWG Silicone Wire	50	20	1000	
	26 AWG Silicone Wire	15	15	225	
	Shrink Tube	10	10	100	
Bearings	608-ZZ Bearing (NSK)	100	3	300	6330
	61814 Bearing (SKF)	1500	4	6000	
	7 mm Bearing Clip	2	15	30	
Bolts & Hardware	Allen Key Head Bolts & Nuts (M2, M2.5, M3, M4, M6)	4	100	400	1350
	Insert Support (M3, M4, M5)	2	25	50	
	Brass Inserter M2, M3, M4	10	60	600	
	Allen Key Set	300	1	300	
GRAND TOTAL					111555

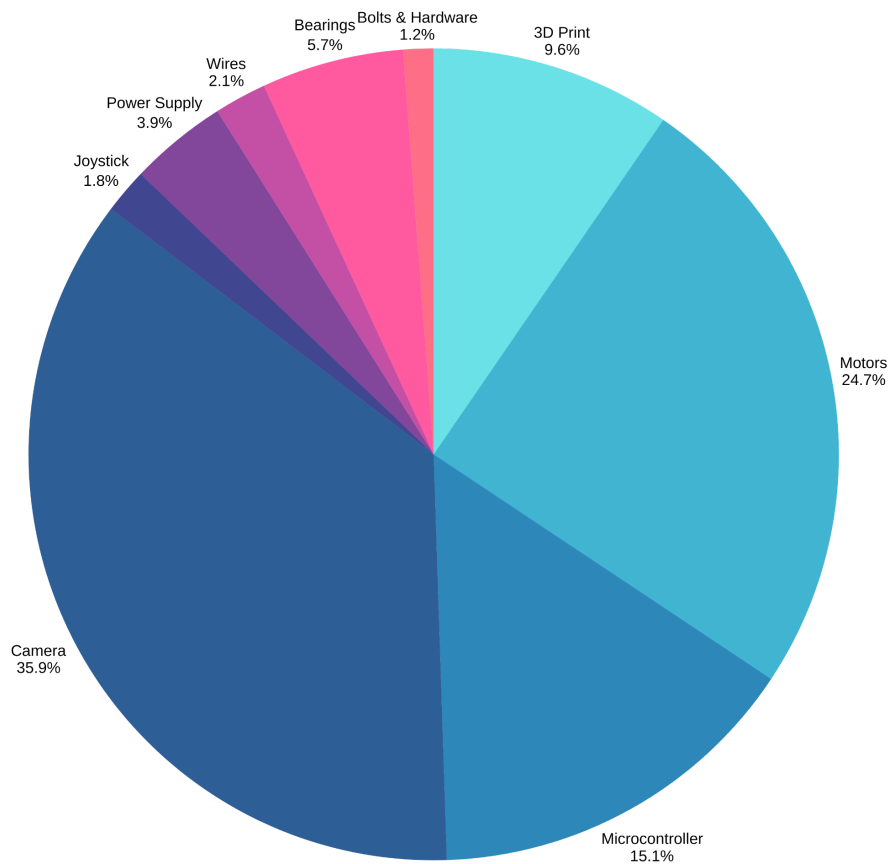


Figure 55 : Cost Breakdown Pie Chart

8.4 Feasibility

The following critical dimensions by which the project may be evaluated are technical feasibility, financial sustainability, and market relevance which determine the overall feasibility of such a project of soft robotic manipulator and adaptive arm system. These aspects are highlighted in a tabular form as shown in the table below.

Table 29 : Feasibility Overview

Dimension	Key Indicators	Feasibility Summary
Technical	3D-printed design using TPU, cable-driven actuation, low-cost electronics	Feasible within a university lab environment using standard prototyping tools and open-source systems.
Financial	Development cost: ₹111555 funded through personal	Financially manageable for academic use; however, long-term scaling requires additional investment.
Market	Soft robotics CAGR>30% in healthcare/logistics; trend toward safer, flexible systems [33]	Strong market alignment, though commercialization is limited by infrastructure and awareness gaps.

The manipulator uses cheap and practical bits such as 3D-printed chassis, microcontroller-based servos, and simple sensors therefore it can be used in experimental applications like object manipulation, compliance gripping, and workspace automation. It has a modular design giving it the capability to be scaled and reconfigured to fit a particular research or educational requirement.

Having a budgeted amount of ₳111555, the project was done with locally available components. No parts or motors were exported so we don't need to rely on the international market for the production of the manipulator and gripper. From cost breakdown it can be seen that, the majority of the production cost goes to 3D filaments, motors and camera. If the design is considered, having the 3D models of the designs, we can easily reproduce the parts and for that we do not need heavy manpower as the production will be done by 3D printers. As such our design reduces our production cost where it is mostly reliant on the material prices, not on the manpower. As such we can keep the selling price on the lower end so that even the small industries can purchase it. The proposed soft designed robotic manipulator and gripper system promises the increasing demands of lightweight and safe and adaptive automation tools, which are destined to dominate logistics, sorting, educational robotic tasks, and low-risk situations.

8.5 Return of Investment

8.5.1 System Cost, Price, and Deployment Context

The proposed soft robotic gripper and manipulator is an automation proposed as a modular, locally-manufacturable process on repetitive handling tasks in Bangladeshi factories. The current prototype (excluding transportation and cash-out expenses) costs a total of about 111,555 BDT in hardware, of which motors and servos consumed 24.7 percent, 3D-printed filaments about 10 percent and electronics and control hardware about 18 percent. Based on this, it is suggested that a commercial selling price should be 1,15,000 BDT which has the potential to cover assembly, integration effort, overhead and warranty and is significantly lower than other imported robotic arms aimed at such applications in garments, food as well as light assembly.

Labour Saving: One Station Operator

The current minimum wage in Bangladesh for ready-made garment (RMG) workers and most low-skill workers in the industry is 12,500 BDT per month. Assuming an average schedule of 26 working days in a month and 8-hour shifts, this would be close to [83].

$$\text{Daily wage} \approx \frac{12500}{26} = 480 \text{ BDT}$$

$$\text{Hourly wage} \approx \frac{480}{8} = 60 \text{ BDT}$$

In common export-oriented mills, there is a single repetitive handling station to one operator: feeding clothes or components onto a conveyor or packing cartons, loading boxes with finished goods or sorting in a warehouse. The flexible robot arm is particularly engineered to be capable of doing so in a way that is compliant in grasping that suppresses fatigue, adds some consistency when it comes to textiles or dealing with delicate objects. With each robot installed on one of these stations, and operating a full shift, it is effectively replacing one full-time operator, which is a saving of approximately 12,500 BDT every month:

$$\text{Monthly Labour Saving} \approx 12500tk$$

This is equal to the reported figures of labour-saving through case studies where Bangladeshi manufacturers who have undertaken automation have already traded in labour-cost savings of about 15 percent in automated portions of their manufacturing. [23].

Operating Cost: Electricity and Maintenance

Power Consumption

This system includes 6 industry motors: three 24 V, three 8 V and one 5 V microprocessor powered with a 30 A SMPS. In normal industrial uses, average currents per 24 V motor are likely to be 2 A, these same currents per 8 V motor are likely to be 2 A, and the control electronics can be expected to consume 0.5 A on average. The power levels of the respective ones are

around

$$P_{24V} = 3 \times 24 \times 2 = 144 W$$

$$P_{8V} = 3 \times 8 \times 2 = 48 W$$

$$P_{5V} = 1 \times 5 \times 0.5 = 2.5 W$$

The overall sustained power consumption is hence about

$$P_{total} = 144 + 48 + 2.5 = 195W = 0.2 kW$$

We are therefore considering that the manipulator will have an operation time of 8 hours on a daily basis and 26 days per month.

$$E_{Month} = 0.2 \times 8 \times 26 = 41.6 kWh$$

The average commercial and industrial electricity prices in Bangladesh assume 12.4 BDT/kWh in 2025. With this value it is possible to regulate the monthly electricity expenditure that may be attributed to the robot.

$$C_{power} = 41.6 \times 12.4 = 516 BDT/month$$

Maintenance: Soft Grippers and Motors

Maintenance needs to be well-considered since the device is modular, and the grippers are made of soft TPU. During continued vigorous use, the grippers should have frequent contact with the objects and surfaces and therefore be likely to wear or tear away. The cost of consumable per month will be assuming that the grippers will be refabricated twice every month and with the help of a reel of filament made out of TPU which costs 3,000 BDT.

$$C_{gripper} = 3000 \text{ BDT/month}$$

The dimensions of the rigid manipulator structure (links, bearings, fasteners) are sized to survive rated loads with primary lifetime experience of 3-4 years, which is in agreement with the predicted lifespan of light industrial mechatronic systems. The modular design also allows only the damaged motor to be changed in case of either overload, or unintended collision, not the whole arm. The system has high-torque servos which may cost up to 6,500 BDT each. Assuming a conservative estimate that one of these motors will require replacement at least once per year, the amortised per-month cost of this risk is

$$C_{motor,avg} = \frac{6500}{12} \approx 542 \text{ BDT/month}$$

The non-labour operating costs (whole of electricity plus routine maintenance) can hence be mentioned as.

$$\begin{aligned} C_{operation} &= C_{power} + C_{gripper} + C_{motor,avg} \\ C_{operation} &= 516 + 3000 + 542 = 4058 \text{ BDT/month} \end{aligned}$$

This is rounded up giving it an operating and maintenance cost of approximately 4,100 BDT per month.

Net Saving Including Maintenance

The net economic benefit per month is 12,500 BDT with the monthly labour saving of 12,500 BDT and the total cost of operation of about 4,100 BDT.

$$S_{net} = 12500 - 4100 = 8400 \text{ BDT/month}$$

This is a modest estimate: it does not attribute benefits in terms of less product damage, higher quality or higher throughput, although effective automation initiatives in Bangladesh typically claim 15-25 percent improvements in these measures where robotics are applied to highly selected processes.

8.5.2 Cumulative Cashflow and Payback

Assume the initial investment with an industrial customer is selling price $I = 115000 \text{ BDT}$, and net monthly saving is $S_{net} = 8400 \text{ BDT}$ cumulative net cashflow after n months of operation will be

$$Net(n) = -115000 + 8400 \times n$$

The break-even point occurs when $Net(n) \geq 0$ which yields

$$n \approx \frac{115000}{8400} = 13.69 \text{ month} \approx 14 \text{ months}$$

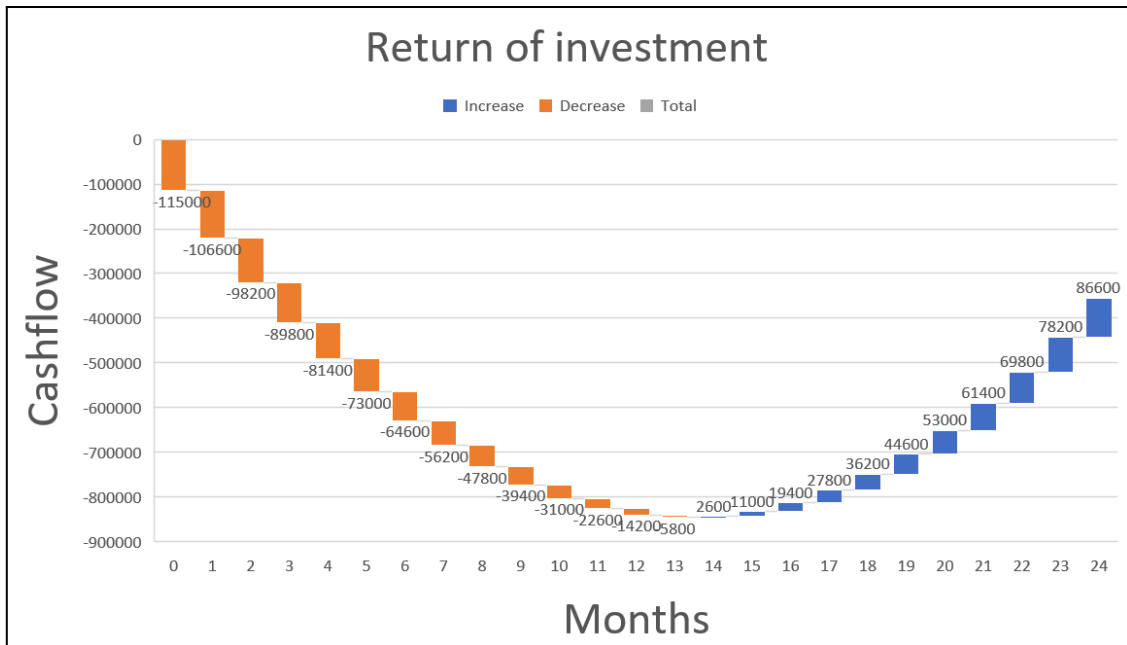


Figure 56 : ROI Chart

Therefore, with the addition of gripper replacement cost at 3,000 BDT/month and the amortised motor replacement, the payback is found to be around 14 months operating in a single shift. Thereafter, the robot will deliver approximately 8,400 BDT in net savings monthly or over 1,00,000 BDT in a year regarding the rest of its service life.

8.6 Conclusion

Both the policy and the financial analysis of the suggested soft robotic manipulator prove that the given technology was not just technically plausible in a Bangladeshi setting, but also the trends observed in the market were clear. International and national statistics show that the sphere of robotics and automation is growing continuously, and the current market of robotics is already bringing tens of millions of dollars of annual revenue, and the share of industrial robot arms is increasing as companies in the textile sector, logistics, and pharmaceuticals start pursuing focused automation. Disruptive automation is already demonstrated to be able to bring tangible gains to large export-oriented investors like DBL Group and Square Pharmaceuticals, who report gains in capacity and declines in labour cost after introducing

robots into key areas of their business. The above developments indicate that the locally developed, cheaper robotic systems have a substantial potential of engaging in and catalyzing this trend.

In this environment, the modular architecture of the proposed manipulator is the strongest with regard to economic power. The arm is constructed by using replaceable structural parts, commercially acquired motors, and 3D-printed soft tentacles, such that in case of damage or overloading the user will be able to only replace the damaged part rather than the whole system. Correspondingly, the most reliable components are the soft tentacles, which are repeatedly in contact in the course of grasping, and the motors, which might fail when subjected to constant overload, though both are easily replaced with few tools and without much professional expertise and are inexpensive in terms of downtime and replacement. This modularity lowers both the ownership cost and lifetime cost as well as making the platform affordable even to small and medium enterprises who lack in house robotics specialists.

The model of return-on-investment used in this chapter has been kept on the low side deliberately. It assumes that the manipulator will be replacing only one minimum-wage operator on a given shift, and contains specific allowances as regards electricity and the replacement of tentacles and amortised motors breakdowns, but will still provide payback of around fourteen months and a net savings of over 100,000 BDT/per year of the remainder of system life. In practice, a single robotic cell can either harm or redeploy two or more workers at neighbouring repetitive stations, and maintainability is sub-linear due to the long lifespan of the rigid structure, and only cheap modules need to be replaced in case of a failure. In this case of multi-operators, the effective ROI as well as net savings per month would be significantly greater than the estimates herein and the payback period would be under one year. Collectively, these results demonstrate that a flexible soft robotic manipulator is potentially a financially competitive, maintainable and scalable solution that can provide such plastic alternatives to Bangladeshi industry to advance towards safer, more adaptable and competitive automation on the world stage.

Chapter 9: Ethics and Professional Responsibilities

9.1 Introduction

Engineering is a profession that requires ethical conduct and professional responsibility, particularly when one is handling a project that can have a contact with individuals or things in reality. In this project, we designed and constructed a soft robotic arm with a gripper that has soft and tentacle-like components to pick up the delicate and irregularly shaped objects in a manner that aids in their safe collection. We do not just want to develop a useful device but in a way that presents it in a manner that commends positive ethics.

There are a number of issues, which we should take into account. To begin with, the security of individuals that can utilize or be near the robot is a priority. We should ensure that the robot is reliable and nonhazardous. Second, we are supposed to be transparent and sincere about the strengths and weaknesses of our work. Third, privacy should be respected, in case our system includes cameras or sensors to monitor the surroundings. Fourth, we should consider eco-friendly materials and other design advantages. Lastly, we need to also respect the efforts of other people and not plagiarize.

Professional codes are available like those offered by the National Society of Professional Engineers (NSPE) which assisted in making our decisions. They make us always remember to put safety and health first, be truthful, keep confidential information secret and responsible and fair. These are the ethical and professional responsibilities mentioned in this chapter applied to our work with soft robotics and how we implement these principles during our work.

9.2 Identifying Ethical Issues and Professional Responsibility

Table 30 : Ethical Issues and Professional Responsibilities

Ethical Responsibility	Description	Example in Project	Relevant NSPE Code/Principle
Safety & Public Welfare	Make sure design and operation do not harm users or bystanders.	Safe tentacle movement and control logic	NSPE Code Canon 1: Hold paramount the safety, health, and welfare of the public [48]
Honesty & Integrity	Be truthful about project data, results, and limitations.	Accurate reporting and documentation	NSPE Code Canon 3: Issue public statements only in an objective and truthful manner [48]
Privacy & Confidentiality	Respect privacy in image/data collection and use.	Limited use of camera images in control	NSPE Code Canon 4: Act for each employer or client as faithful agents or trustees [48]

Environmental Responsibility	Consider how materials, parts, and energy use affect the environment.	Choose recyclable materials, efficient motors	NSPE Code Canon 1, Canon 6: Hold paramount the safety, health, and welfare of the public; Conduct themselves honorably, responsibly, ethically, and lawfully [48]
Fair Attribution	Give credit to others for their work; avoid plagiarism.	Cite sources and use proper references	NSPE Code Canon 5: Give proper credit for engineering work [48]
Professional Competence	Only do tasks within your skill and knowledge; seek help for complex issues.	Follow best design practices, consult experts	NSPE Code Canon 2: Perform services only in areas of their competence [48]

9.3 Apply Ethical Issue and Professional Responsibility

Table 31 : Application of Ethical Issues

Ethical Principle	How We Apply It in Our Project	Example in Project
Safety & Public Welfare	We have tested our design and code to avoid hazards or injury.	Setting safe movement limits for tentacles and gripper.
Honesty & Integrity	We have reported our results and limits clearly in all documents.	Sharing both successful and failed test results.
Privacy & Confidentiality	We only use camera images for object detection, not for storage.	Live video only; no saving personal data or sensitive images.
Environmental Responsibility	We have selected materials with low environmental impact where possible.	Using recyclable or reusable plastics and efficient motors
Fair Attribution	We have cited sources and give credit for any outside work or ideas.	Including citations in documentation and presentations.
Professional Competence	We have followed guides and seek advice when needed.	Consulting teachers or experts for complex parts; not guessing solutions.

9.4 Ethical Considerations Across Applications

Every planned use of the soft robotic manipulator and gripper introduces its own ethical challenge. Some of the important considerations are listed in the following table:

Table 32 : Key Consideration Regarding Ethical Issues

Application	Ethical Considerations	Design Measures
Industrial Automation	Keep workers safe, support efficiency, consider ethics of automation (do not aim to replace humans).	Helper for hazardous tasks, maintains human supervision.
Precision Handling	Assure careful, safe manipulation of fragile items in industry.	Gentle arm movement for fragile parts, reduces waste, improves precision.
Logistics and Warehousing	Lower worker injury risk, promote safety, limit human presence in dangerous zones.	Manipulator takes on risky jobs, creates safer and more efficient warehouse routines.
Agriculture	Protect the environment, avoid harming plants or animals, and enable sustainable farm work.	Soft arms prevent crop/livestock injury, allow precise work for less waste and more sustainable farming.
Sustainability	Minimize environmental footprint, use sustainable and efficient materials and energy.	Used recyclable TPU, energy-efficient operation to reduce waste and overall impact.

9.5 Conclusion

This project has planned and developed a soft robotic manipulator system that will be safely handled and automated in numerous ways. This has enabled us to put a lot of emphasis on ethics and professional responsibility in the process of our development through a set of possible codes, which include the NSPE Code of Ethics of engineers.

Safety, honesty, privacy, the effect on the environment and attribution, and competence were some of the aspects that we firmly incorporated in our designs and decisions. This involves the selection of materials that will cause less environmental impact, developing mechanisms that will lower the risk to consumers and ensuring that our progress and outcome remains clear and accurate. We have ensured that we have been able to credit other work done previously and also maintain professional integrity in how our team will conduct their operations.

Discussing those ethical aspects of our manipulator, in the overall design, and the purposes of its application, in particular, we assume that our project will be able to meet requirements to responsible engineering. Having accomplished this project is not just an indication of our technical skills, but also the desire to be responsible to society, the people and the environment. By following these principles, trust in engineering will be supported, and the technology will continue to improve to the social good.

Chapter 10: Conclusions and Future Work

10.1 Project Achievements

Despite several hardware and computational limitations, the project successfully demonstrated the design, development, and partial implementation of an autonomous 4-DOF soft robotic manipulator with a compliant gripper. The complete ROS2-based control architecture was deployed on a distributed embedded system comprising a Raspberry Pi 5 and an Arduino microcontroller. The major subsystems, including perception, motion planning, and low-level actuation were all incorporated into a working robotic platform.

The autonomous control pipeline which included the object detection based on YOLOv11 and MoveIt2 trajectory planning was fully made, tested, and simulated in RViz and Gazebo platforms. Despite poor motor precision and torque-delivery characteristics, in which the actuators could not provide performance to their promised 380kgcm torque, the system managed to perform end-to-end autonomous operations at a lower level of performance. The manual control mode was also operational in full, and uses a joystick interface to directly teleoperate using the same ROS2 Control framework. The reason this mode had a higher success rate of grasp is because of human feedback and real time correction.

The project demonstrated a strong multidisciplinary integration of robotics perception, control, and embedded systems. It also laid the groundwork for future upgrades, such as incorporating higher-torque, more precise actuators and offloading vision and planning computation to a more powerful embedded processor or workstation. Overall, the team achieved a functional semi-autonomous robotic platform that validated the feasibility and potential of a soft robotic manipulator for object handling tasks.

10.2 Limitations Identified

Even despite such accomplishments, there were a number of limits that limited the overall performance and the level of autonomy of the system. The former weakness is in the motion quality of the hardware platform. The cheap servos and drive electronics required in the prototype worked well to provide coarse positioning, and coordinated movement, though failed to provide very smooth and high-bandwidth movements; the arm would show significant snatching and small amplitude vibrations during certain movements, particularly at higher speeds or at payload limits. This limits the capabilities of the manipulator in tasks where a high level of control is needed in terms of path following or where human interaction with a very delicate object is needed.

A second constraint is a limitation with regard to computation and real-time control. In spite of the fact, the Raspberry Pi controller is powerful enough to execute ROS nodes and basic machine-learning inferences alongside machine control, it lacks hard-real-time commitments,

and allocation of resources among image processing, machine-learning inferences, and motor control leads to latency and time jitter. Consequently, it was not possible to resolve the project to completely run the prepared machine-learning/image-processing pipeline in a tight closed loop with the arm, but some sequences were performed in a semi-autonomous manner with a manual trigger, instead of constantly planning movement of the arm by visioning. Lastly, the existing prototype possesses a very limited degree of sensing on the gripper: not being able to measure contact force or deformation directly means that grasp force is currently uncontrollable in response to object characteristics, which is a fault during the handling of highly sensitive or highly variable objects.

10.3 Improvement Strategies

The identified limitations can be overcome by upgrading the soft robotic manipulator in both hardware and system architecture in the future human work. On the actuation side, the existing low-cost servos should be replaced with commercial motor modules with higher resolution, or an industrial motor; in combination with drivers capable of operating with increased loads, this would enhance smoothness of motion, precision of position, and load strength. Improvements to the joint design and transmission, e.g. minimizing backlash and friction, would add more functionality to the trajectory tracking and enable the arm to work better in the areas where high precision of motion, combined with the soft nature of the interaction with delicate objects is required.

Of equally high importance is the decision of the controller. The current prototype has used the Raspberry Pi which is sufficient to provide basic ROS communication and high level sequencing, however higher rate, tightly synchronized multi-axis control, smoother paths and more dynamic performance would have to utilize a more powerful motion-control platform. The logical next step is to pair the Pi (or any other single-board computer) with a special purpose real-time motor controller or industrial grade servo controller that does low-level loops, or to adopt a complete shift to a controller that can support multi-axis motion control.

Simultaneously, the gripper sensing abilities are to be improved. Integrating basic tactile, pressure, or strain measurements into the tentacle soft TPU would allow the closed-loop estimation of contact forces and object interaction, and have the controller (on the modified hardware platform) automatically adjust grip strength depending on object size and stiffness. As feedback is available and the necessary level of computation is achieved, the system can transition to the fully autonomous soft-robotic platform that perceives the environment and combines it with planning and grasping the objects, and adjusting its grip to a more demanding logistics and light-manufacturing setting.

Chapter 11: Assessment of Complex Engineering Problems and Activities

11.1 Introduction

The chapter analyses the proposed project based on Complex Engineering Problems (EP) and Complex Engineering Activities (EA). This chapter is meant to argue that advanced engineering knowledge, non-routine problem solving, and multidisciplinary integration can be used in the design, development, and implementation of the soft robotic manipulation system. The analysis shows the level of knowledge needed, existence of mixed design requirements, level of analysis, the involvement of the stakeholders, system interdependence, and the unfamiliarity of the issues being addressed and the tasks being done. This assessment is compatible with the requirements of outcome-based education (OBE) and it offers the justification that the project meets the requirements of an ambitious engineering task.

11.2 Complex Engineering Problems

Table 33: Attributes of Complex Engineering Problems (EP)

	Attributes	Put tick (✓) as appropriate	Description
P1	Depth of knowledge required	☒	Requires advanced, multi-disciplinary technical knowledge.
P2	Range of conflicting requirements	☒	Involves several competing technical and practical constraints.
P3	Depth of analysis required	☒	Needs detailed, rigorous modeling and performance evaluation.
P4	Familiarity of issues	☐	Deals with problems not commonly seen in standard practice.
P5	Extent of applicable codes	☐	Lies partly outside existing standards or codes of practice.
P6	Extent of stakeholder involvement and needs	☒	Must satisfy multiple stakeholders with different expectations.
P7	Interdependence	☒	Composed of tightly coupled, interacting subsystems.

P1: Level of Knowledge Needed

The approach of this project needs knowledge that extends past fundamental EEE courses. It entails motion planning via ROS 2 and MoveIt, 4-DOF robotic kinematics, and detection of objects by use of YOLOv11 model on camera pictures. These take more of an emphasis on

robotics, control and perception which are sophisticated and are not commonly taught in a typical undergraduate EEE lab.

P2: Diversity of Competing Requirements

There are a number of contradictions between some design requirements within the project. Improving the payload capacity increases the weight of the arm and gripper. Complex algorithms are accurate and slow in real-time. The material of low cost 3D-prints should also be such that it can be reused. Precision is also required to work with delicate items, whereas the electronics and servo motors are constrained by cost. The balance of all these must be maintained.

P3: Depth of Analysis Required

There are several stages that the project should be analyzed. Equations of motion were derived and experimented to make sure there was proper movement. URDF models were simulated. Avoidance of unsafe moving was achieved by computing workspace limits. Success rates were realized and object damage measured with respect to various shapes. All of the analyses were used to better design and control decisions.

P4: Familiarity of Issues

Most of the problems that have been discussed in this project are unexplored to common EEE students. Delicate handling soft grippers and autopilot autonomous control over vision are not usual examples that are taught. Research papers are frequently studied as part of ROS 2 incorporation. These topics are quite new and typically dealt with in standard EEE laboratories which tend to concentrate on simple rigid robots.

P6: Level of Stakeholder Engagement and Requirement

Supervisors anticipate that the system can be used as a credible research platform. Some key requirements are safety and repeatability. Light industry or agriculture and applications that require soft handling with objects may require a gentle handling by the future users. These are the academic as well as practical needs which affect the ultimate system design.

P7: Interdependence

Every component of the system is highly interdependent. The shape of the gripper influences the view of the camera. The possibility of motion is altered by changes in camera position. The servo torques limit the achievable positioning of the manipulator. When one of the components does not perform well, it impacts the entire system. Subsystems have to therefore cooperate well with each other.

11.3 Complex Engineering Activities

Table 34 : Attributes of Complex Engineering Activities (EA)

	Attributes	Put tick (✓) as appropriate	Description
A1	Range of resource	☒	Uses diverse physical, computational, and software resources.
A2	Level of interaction	☒	Requires significant coordination and interaction among people/tasks.
A3	Innovation	☒	Involves novel or creative approaches beyond standard practice.
A4	Consequences for society and the environment	☒	Has potential impact on society and/or the environment.
A5	Familiarity	☐	Extends beyond previous hands-on experience using principles-based work.

A1: Range of Resources

There are numerous resources utilized in the project. Fusion 360 is applied in the field of mechanical design. 3D printers create hard links and soft TPU grippers. Actuation is offered by servo motors. The ROS 2 is run on a Raspberry Pi, and visual data is captured by cameras. All the steps need various tools or technology.

A2: Level of Interaction

The job is associated with constant communication with the coworkers and managers. Decisions regarding design are discussed and reviewed. Spinning camera angle and motion planner settings is done in group testing. Teamwork is important in understanding experiments as there must be common troubleshooting.

A3: Innovation

The project presents a new concept in relation to the combination of soft and biologically inspired gripper tendrils in a rigid robotic arm. Grasp points are detected automatically by the system using the vision-based object detection with the help of the YOLO system. This allows soft and independent manipulation, something that is hard to accomplish with the conventional hard grippers.

A4: Consequences on Society and Environment

Light handling will minimize degradation of farm goods leading to less food wastage. The light design saves on material consumption and energy consumption. More secure

communication between people and robots is also provided. Such are the results which lead to efficiency of industry and sustainability of the environment.

A5: Familiarity

Our group members were new in many of the tasks in this project. URDF model, MoveIt setup, and YOLO training involved learning new skills. There was also unfamiliarity with hardware and software synchronization. The project is an integrative project that brings in ideas that cut across various disciplines hence a new and tricky experience.

11.4 Conclusion

According to the determination made in this chapter, it is clear that the project meets several features of Complex Engineering Problems and Complex Engineering Activities. The job demands high technical skills over and above the normal course work, meets unfamiliar and non-routine problems, and entails close analysis and high level of interdependence between mechanical, control and perception subsystems. The tasks performed require applying various resources, constant cooperation, and new methods to perform safe and adaptive interaction. In spite of the fact that there are no formal industrial codes that should be adhered to during the project, the established engineering practices are used, as this project is based on research-oriented prototype. In general, the chapter supports the idea that the project exhibits the features typical of a complex engineering system and also fulfills the proposed academic and professional learning objectives.

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Appendices

1. Project Files

<https://drive.google.com/drive/folders/1-q-C3wqhsT8Ea8PwBkuKIKoou3JqOh8C?usp=sharing>

2. CAD Files :

<https://drive.google.com/drive/folders/1OII0V3CauPI--ghYOYwZ6gIggNLqnyxF?usp=sharing>

3. Codes :

<https://drive.google.com/drive/folders/1vWFtp8wSTQMgPl6K8nG0Hw1cemgUevIT?usp=sharing>

4. Project Logbook :

<https://drive.google.com/drive/folders/1uOfZEdcsphXNxHFetJrdoHWPJeDbxQ7d?usp=sharing>