A Project Report on

Design and Prototyping of Robotic Arm for Waste Sorting

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Abstract

Waste management and recycling system is a very important part of our society. Along with growing urbanization, it has become crucial to introduce automation in waste management as it creates a clean environment for everyone, reducing pollution and reusing recyclable materials. Manual waste sorting can cause serious health issues to the workers due to various disease-causing agents present in the garbage. To solve this, we have introduced an automatic sorting system which segregates waste into the following categories: plastic, paper, glass and metal with the help of a 4 DOF robotic arm and a vacuum gripper. Waste detection and classification is done using YOLOv7- a pretrained object detection model and the waste dataset trained in this model has been taken from RoboFlow (waste segregation) consisting of 4096 images for training, 571 images for testing and 1179 images for validation. This entire system is tested, and the model accuracy is found out to be 70%.

1. Introduction

1.1 Problem Statement:

Effective waste management and segregation are critical to the world's sustainable development. India generates 62 million tons of garbage every year. A total of 43 million tons (70%) will be collected. Of these, 12 million are processed and 31 million are sent to landfills. India relies on industrial-scale landfills and the unorganized sector to deal with its growing garbage problem. 5.8% of the litter in our area is typically composed of metal, 3.5% glass, 1.6% plastic, 12.9% paper and 1.8% fiber. 53.7% of this waste is biodegradable, so only 20.7% goes to landfills. Efficient selective sorting is often implemented to improve recycling and reduce the harmful impact on the environment.

Need of recycling:

Recycling the most often used objects in daily life, especially plastic bottles and paper cups, can help you create a cleaner environment while also saving energy and petroleum resources.

• Recycling used plastic bottles and paper cups helps to keep the environment clean and saves a lot of petroleum resources.

Glass can be recycled indefinitely without loss of purity or quality. It can take over a million years for glass to fully decay, posing a serious problem for already overcrowded landfills. Worldwide, 381 million tonnes of plastic waste is generated each year. Most types of plastic are recyclable, with about 50 major groups and hundreds of individual variations. Each tonne of recycled paper or cardboard can save up to 17 trees, 2 cubic meters of landfill space and 4,100 kW/h of electricity. Making new paper from recycled paper instead of pulp requires 70% less energy.

The existing system for classifying garbage primarily uses human sorting after bin-level sorting, which is risky, time-consuming, and ineffective because of which there is a great need of garbage categorization. Our motivation is to find an automatic method for sorting waste for efficient recycling. This will not only have positive environmental effects but also beneficial economic effects.

Deep learning research on object recognition technology has been busy in recent years as a result of the impressive findings of picture categorization using deep learning. A deep computer vision approach called object recognition is used to recognise and classify items in pictures, movies, and even live video. It is trained on a large number of annotated photos in order to perform this process on new data. The use of CNNs distinguishes deep learning object recognition from other methods. A concealed core layer, an output layer, and an input layer make up the majority of them. These neural networks may be learned in supervised, semi-supervised, or unsupervised fashion. This shows the percentage of training data that has been annotated. For both single and multiple item detection, deep neural networks produce findings that are by far the quickest and most precise. In this project, we've used YOLOv7, a real-time object detector with improved speed and accuracy over earlier iterations.

We have developed a 4 degree of freedom robotic arm which will sort waste into four categories. Firstly, a CAD model of the robotic arm is designed in Autodesk Fusion 360. Later, static structural analysis of the arm is conducted to make sure that the model is not constrained at any joint. The body of the robotic arm is made of Stainless-steel consisting of 4 links and is manufactured using laser cutting methods. YOLOv7 is implemented on Google Colab in which a waste dataset taken from RoboFlow has been trained. The pick and place operation of waste is performed by the robotic arm using a vacuum gripper. The design calculations and analysis of the robotic system is included in Section 3.1. The vacuum gripper is selected according to our requirements. The suction force and vacuum pump calculations are included in Section 3.3.1. Maximum load that the robotic arm can handle is 300g for 1cm suction cup and 500g for 3cm suction cup. Other components like servo motors, power supply and microcontroller selection is done in Section 3.3.1. After assembly of the system, the accuracy of YOLOv7 is tested.

1.2 Objective:

The objective of the project is to design and prototype a robot arm for sorting and computer vision system to classify garbage into four classes: plastic, glass, paper and metal, and sort them into respective bins.

- To minimize the impact caused by the incorrect dispose of garbage, more specifically domestic, we want to propose the use of an automated system based on computer vision techniques for the correct separation of waste in recycling categories.
- For physical separation of the trash objects, design and prototype of a robot arm is proposed which will automate the separation process.

The main objective of this project is to offer an automated recycling method that can sort/separate recyclable materials from the rubbish that is disposed of every day. Due to the serious health risks associated with working in unclean conditions, this technology can help replace manual labour. By using robotics and computer vision techniques, we hope to separate waste into categories such as plastic, paper, glass, metal, etc.

1.3 Scope:

The human population is rapidly growing. As a result, the environment becomes more and more polluted. Emitted garbage is often not biodegradable in a same way. This made classification more significant. Trash identification and classification have long been a concern. Finding a solution to this issue is encouraged because manual sorting is time-consuming and dangerous for workers in many nations. Artificial intelligence was utilised in industrialised nations like the United States and the United Kingdom to sort trash. With advances in AI, there are numerous initiatives being undertaken to categorise garbage using pre-trained architectures like VGC-16 and AlexNet.

Today, in India, mostly automatic waste segregation is performed only to classify different types of plastic and these systems are very expensive and not affordable in a lot of areas in India. We can develop an automatic system which proves to be affordable and helps in India's waste management issues.

1.4 Methodology:

We will design a system consisting of a robot arm with 4 degrees of freedom and a computer vision system. The camera module will be integrated with the computer vision system where trash will be detected and classified into different classes. The robot arm will then segregate the different types of waste respectively.

Currently the focus of our waste classification is to segregate following recyclable items:

1. Glass
2. Paper/cardboard
3. Plastic
4. Metal

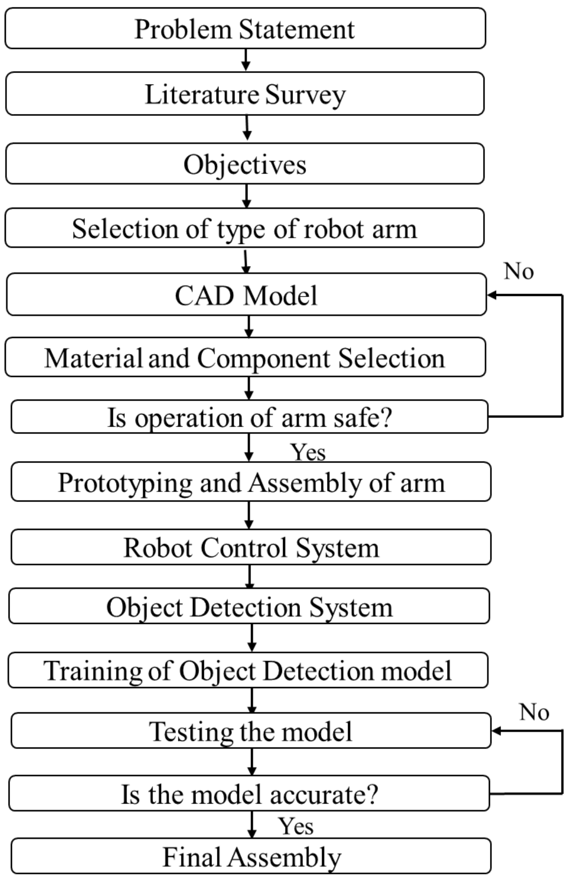


Fig.1. Flowchart depicting the sequence of operation

The robot arm frame is made from stainless steel. The parts are laser cut including the holes and slots after the design and analysis of CAD model. The components are attached using nuts and bolts.

The Arduino UNO is the microcontroller used to control the robot arm as well as the gripper mechanism. The programming of inverse kinematics and the gripper module is done on Arduino IDE.

A vacuum pump is used to create vacuum for the gripper, and this pump is controlled using a relay module. The pipes of 8mm diameter are used to assemble the gripper mechanism.

The robot arm is controlled using servo motors, selected based on the calculations. In total, five servo motors are used. These motors are used to control the 4 degrees of freedom of the arm and gripper. A 24V and 5A common power supply is used to power all the electronic components. Maximum payload of the robot arm is set as 500g.

YOLOv7 object detection model is used for the detection and classification of waste since its accuracy is higher than the earlier versions of YOLO. A dataset consisting of 4878 images is taken from RoboFlow for training the model.

2 Literature Review:

The Literature review covers several studies related to design of robot arm, object detection models, automated systems for waste sorting, etc.

Some articles based on Robotic Waste Sorting are as follows:

B. Susha et al [1] have developed a robot vehicle with wheels and a robot arm that searches for trash using IR, metal, ultrasonic, and moisture sensors. The robot arm locates, gathers, and sorts various forms of waste before depositing it into the proper bins. Metal sensors are used in the investigation, however only dry and damp rubbish are eventually distinguished. A robot arm created by S. Z. Diya et al [2] can pull trash out of a bin and put it on a conveyor belt. Utilizing three separate sensors—voltage, IR, and inductive sensor—the system can sort three different trash categories, including plastic, biological waste, and metal waste. The robot may function independently or be remotely controlled using a mobile Java application, and the system features a database that keeps track of the various materials that have been found. The inductive sensor was used to locate the metallic waste. Organic objects have non-zero voltage while plastic displays zero voltage. The IR sensor can locate any object on the detecting system. The system starts to identify when this sensor's output is high. The design of a robotic vehicle that employs computer vision to autonomously classify plastic garbage into seven categories is presented by J. Bobulski and M. Kubanek [3]. A conveyor belt collects waste from the surrounding area and passes it underneath the camera. There, items are catalogued and sorted utilising a sliding mechanism into the proper containers. We suggest a 15-layer CNN network for trash identification in this research. PET, HDPE, PVC, LDPE, PP, and PS are the seven categories into which plastics fall. The outcomes demonstrate that his 60x120 photos were successfully processed by the 15-layer network, which utilised cross-validation to achieve an average accuracy of 87%.

In [4] the authors described a system that combines an electronic robotic arm with electronic sensors mounted on a transportable chassis and connected through Wi-Fi to perform waste sorting and collection. A robotic arm that sorts waste into biodegradable and non-biodegradable waste is mounted to the vehicle along with two bins.

[5] A modular Cartesian robot with a closed linkage arm powered by two Dynamixel motors and a three-claw gripper designed and built to assist in the sorting of cardboard is presented. In addition, a test conveyor was designed and built. TrashNet was used to create the dataset, which contained approximately 400 images, and YOLO v3 was used to develop the cardboard detection image processor. The camera used for this was the Intel RealSense Depth Camera D435. The model only recognised cardboard in two of his 12 lab test images in the final programme.

[6] Analyze the design, development, and production of a robotic arm for sorting various materials. We constructed the robotic arm's body out of plastic, added five servo motors, and added optical sensors to perform simple object detection. The mechanical gripper was created using plexiglass in both its design and production. The Basic Stamp's programming sequence directed the robotic arm's movement, and the system was designed to recognise materials using the idea of reflection. SolidWorks was utilised to simulate the robotic arm's motion and model the intricate design.

In [7] the author shows off an artificial intelligence system that finds and stores places. To perform trash detection in both indoor and outdoor settings, Mask-RCNN was employed with 5 different classes (opaque PET bottles, cardboard boxes, transparent PET bottles, soda cans, opaque plastic containers), and the total Make a new 1434-item rubbish dataset. The RealSense d435i camera is used to recognise objects. Finally, the geometry is used to compute the gripping on a robotic arm using a two-finger gripper.

This paper [8] demonstrated a 6-dof robotic arm for recycling and sorting waste. To help the robot handle complex site scenarios, it employs SLAM technology and the instance segmentation method. A database was created and used to train a Mask R-CNN computer vision model for identifying leftover pipes and cables.

In [9], for a variety of sorting activities, pilot robotic cells are developed and assessed to industry requirements. An experimental test bench is built around a dual-arm CloPeMa robot and its flexible-supported, pinch-like two-finger gripper. It consists of two separate, six-degree-of-freedom industrial manipulators (Motoman MA1400). The process is done with a manipulator or conveyor belt. Industrial robots, specialised grippers, new manipulation techniques, and visual feedback are all developed.

This paper [10] describes the development of an autonomous tomato harvesting robot system. Deep-ToMaToS, a deep learning network pipeline capable of three-level maturity classification and 6D pose estimation of the target fruit, is used. Based on the ADD S metric, the experimental results showed a 6D pose estimation accuracy of 96%, and the proposed harvesting motion control algorithm achieves an average harvesting success rate of 84.5%. CV was performed using TensorFlow 2.5.0, with 16,000 pieces of data used for model training and 4,000 pieces of data used for testing.

This paper [11] tells about the development and testing of a robotic sorting system that includes a pneumatic gripper, a SCARA robot, a 5 m conveyor, and a vision system. PLC is used to synchronise the camera system. A vision system that connects with an inventive sequence algorithm made up of a 3D line scan camera and an RGB + NIR camera determines the sizes and locations of objects on the conveyor.

This paper [12] We present such a robot picker and suggest a method for classifying goods into two storage areas. One for human and one for robot pickers. The non-dominant genetic sorting algorithm II (NSGA-II) was used to create a zoning system that reduces human labour while increasing product category similarity in each zone. To test the strategy, I used a case study.

This study [13] here, they present a C&D garbage recycling robot with real-time localization and mapping capabilities (SLAM). In addition, for precise recognition and stable gripping of rubbish objects, we applied a deep learning approach and a very accurate 3D object selection mechanism. Under various spatial density settings, detection accuracy for various forms of demolition debris was examined.

This article [14] introduces a novel robot design for applications requiring quick and energy-efficient waste sorting. This parallel robot is capable of simultaneously providing 3-DoF of translation and opening and shutting a built-in gripper. The platform that can be customised at the end of the parallel construction allows the clamp to move. The two-gear train gripper on this platform is directly controlled by the four actuators that are fastened to the manipulator's base. Both the differential and inverse kinematic models have been created.

The authors in [15] outline the robot's concept for automatically categorising plastic waste into seven different groups based on camera images. For garbage recognition, this vehicle employs artificial intelligence and computer vision techniques. In industries and on uneven terrain, the automobile might be useful.

To increase the gripping flexibility of robotic manipulators, a trimodal adaptive end-effector is developed in [16]. Depending on the size and porosity of the object, it can use efficient gripping techniques. This work focuses at deploying gripping modes that are efficient for holding onto the recyclable object, even though its mechanical design permits the three gripping modes to be deployed individually or in conjunction with one another. A real-time vision system is created to measure the size and porosity of the recyclable products in order to choose the best modes.

In [17] General garbage must first be sorted in order to be used as a resource effectively. We created a technique employing neural network image processing to identify and categorise the waste on the transport line in order to sort this out. Model for detecting TensorFlow One of Zoo's models, Faster RCNN ResNet101, was used for the task of trash object recognition and classification. This model was initially trained to identify the position and class of objects in the COCO database. Over 13,000 photos of municipal garbage have been compiled in a database. The accuracy of the neural network model was 64% on average.

Some articles based on Object detection models for waste sorting are as follows:

This paper [18] suggests an i-YOLOX model for detecting domestic garbage that is based on deep learning. Numerous images of actual rubbish can be seen in the new trash image dataset. In this study, the initial point for all improvement studies is YOLOX-S. The FPS increased by 40.4%, the number of parameters fell by 23.3%, and the average accuracy of i-YOLOX increased by 1.47%, according to the experimental data. In practical applications, our upgraded model successfully detects garbage in outdoor settings. This paper [19] With an average accuracy of 64% and 92 frames per second, we propose to locate 15 items in 3 categories using the sophisticated YOLOV4 network framework. We discovered that the upgraded YOLOV4 can more precisely identify garbage types and is better suitable for embedded systems. This paper [20] gives a method for classifying and detecting garbage that is based on the cutting-edge real-time object detector YOLOv7. The f measurement for Mask-RCNN was 85%. The f readings for YOLOv5 and YOLOv7 were 95.1% and 95.9%, respectively. Four different categories of non-decomposable junk data make up the dataset.

1000 pictures of trash, including different types of waste, plastic bottles, polyethylene wrapping, and potato chips.

This work [21] presents a modified YOLOv3 to identify and categorise various objects in the photos, such as trash, plastic waste, and cars. A GUI-based system for classifying waste that can differentiate between different forms of trash, including dry, moist, and vehicular displays a customised version of YOLOv3 to help viewers recognise and classify numerous items in the images, including autos, rubbish, and plastic waste. The development of a GUI-based waste classification system that can distinguish between distinct types of trash, such as dry, moist, and vehicle waste The accuracy of the system can be increased by adding more images to the database.

The recently released YOLOv7 was employed in this study [22] to identify and classify garbage. Train the trash data set that was gathered in reality using the YOLOv7 model. The experiment's findings demonstrates the superiority of the YOLOv7 model over other object detection models. In order to undertake algorithm research, this study uses common home waste such as peels,bottles, cigarettes, glass, tiles, batteries, etc. The dataset consists of 2400 data bits with various shooting angles, scenes, and degrees of degradation, etc., with 30% used for testing and 70% for training.

In [23] Shirawattananon, C. As yet another transfer learning model, ResNet-50 is used. The model is trained using data from TrashNet and self-collected sources. After 24 epochs, the model's training loss was 0.0346 and 98.81. Classification accuracy for the recognition model was 98.53%, while that for the IoT-based sorter was 89.77%. For training and testing, 31,956 improved photographs in total—representing 70% and 30% of the total—were used. In [24] BS Costa and others To automatically classify garbage into four categories, various classification models were investigated.metal, paper, glass, and plastic. We tested the accuracy of different neural network models, including VGG-16, AlexNet, KNN, SVM, and RF, using 400–500 photos from each class to train the model. The findings demonstrate that the VGG-16 method, which can achieve up to 93% accuracy, is effective in comparison to all other methods. VGG-16 performs better in terms of prediction accuracy than other models.This study [25] utilises machine learning to automatically sort garbage. Two well-known learning algorithms, CNN and SVM, were employed for deep learning. Each method separates the three major waste categories into plastic, paper, and metal using a different classifier. The accuracy of the two classifiers is contrasted to determine which will operate most effectively on a Raspberry Pi 3. With a high score of 94.8%, SVM surpassed CNN in terms of classification accuracy. In [26] to create a CW segmentation model using a dataset of 5366 images, DeepLabv3+ is introduced. To calibrate the model performance, orthogonal experiments are used to test a number of trainings hyperparameters. With a time, performance of 0.51 s for each image, the suggested approach segmented nine different categories of materials/objects with a mean Intersection over Union of 0.56.

In [27] The proposed approach divides trash into that which can be digested and that which cannot using CNN. Also presented is the architectural design for a smart garbage can that makes use of a microcontroller and multiple sensors. It makes use of Bluetooth and IoT connectivity for data monitoring. Based on the CNN model, the proposed architecture's classification accuracy is 95.3125%, and its SUS score is 86%. In [28] The goal is to create an intelligent robot that uses image processing to discriminate between perishable and durable garbage. The robot sorts the waste into perishable and non-perishable waste after treatment and sorting. Building an intelligent garbage classification system using IoT and deep learning-based learning models is the aim of this research. An artificial intelligence (AI) platform with pre-trained object detection models handles detection and garbage processing. In [29], The pre-training of the YOLOv4 multi-label identification algorithm utilises the PASCAL VOC dataset. The multi-label garbage dataset is then used to train the model, and the results indicate that the AP values for glass, fabric, metal, plastic, and paper are, respectively, 97.46%, 98.08%, 84.25%, 89.87%, and 95.95%. In [30], establishing the first waste detection baseline that can be replicated is the aim of this paper. New benchmark datasets are also provided for the identification and categorization of rubbish. This gets up to 70% of the average precision and roughly 75% of the classification accuracy on the test dataset.

3 Design and Fabrication of the Robot

3.1 Design of Robot Arm

Whenever any mechanical component is to be manufactured the design goals should be mentioned and met.

Design Objectives

Reliability: Creating a reliable robotic arm was our top priority. Our robot arm is reliable, safe, and flexible.

Driveability: The car must be capable of navigating Indian roadways. The performance and stiffness of the vehicle must be unaffected by potholes and speed limiters.

Manufacturability: All the parts are made in a way that makes it simple to produce and assemble them.

Weight reduction: Our main objective when designing the robot arm was to make it lightweight and simple to use. Weight reduction was done and a second prototype with a weight of 3.2 kg was produced because the initial CAD model's weight of 3.67 kg proved to be heavier than anticipated. These two prototypes are displayed.

Inverse Kinematics Model:

Our robotic arm has 4 degrees of freedom but to reduce complexity of the robot we have considered the base of the robot arm as separate and so the pick and place operation is demonstrated using only 3 degrees of freedom.

Table 1: DH parameters

Link	a_{i-1}	α_{i-1}	α_i	θ_i
0 − 1	0	0	0	θ_1
1 − 2	L_1	0	0	θ_2
2 − 3	L_2	0	0	θ_3
3 − 4	L_3	0	0	0
	Link Length	Link-Twist (z_{i-1})	Joint Offset	Joint Angle (x_{i-1})

$$O_{T_4} = OT_1{}^1T_2{}^2T_3{}^3T_4$$

$$i-1_{T_i}\begin{bmatrix} c\theta & -s\theta & 0 & a \\ s\theta C\alpha & C\theta C\alpha & -S\alpha & -S\alpha d \\ S\theta S\alpha & c\theta S\alpha & c\alpha & c\alpha d \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$O_{T_1} = \begin{bmatrix} c\theta_1 & -s\theta_1 & 0 & 0 \\ s\theta_1 & C\theta_1 & 0 & 0 \\ 0 & 0 & 10 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad 1_{T_2} = \begin{bmatrix} c\theta_2 & -s\theta_2 & 0 & L_1 \\ s\theta_2 & C\theta_2 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad 2_{T_3} = \begin{bmatrix} c_3 & -s_3 & 0 & L_2 \\ s_3 & c_3 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$O_{T_4} = \begin{bmatrix} c_{123} & -s_{123} & 0 & L_3C_{123} + L_2C_{12} + L_1C_1 \\ S_{123} & C_{123} & 0 & L_3S_{123} + L_2S_{12} + L_1S_1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad 3_{T_4} = \begin{bmatrix} 1 & 0 & 0 & L_3 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$O_{T_4} = \begin{bmatrix} c_{123} & -s_{123} & 0 & L_3C_{123} + L_2C_{12} + L_1C_1 \\ S_{123} & C_{123} & 0 & L_3S_{123} + L_2S_{12} + L_1S_1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

End effector position E(x, y, Φ)

Coordinates of ‘P_2 ‘

$$x_2 = x - l_3 \cos \emptyset$$

$$y_2 = x - l_3 \sin \emptyset$$

We got $P_2 (x_2 , y_2)$

$$\emptyset = \theta_1 + \theta_2 + \theta_3$$

$$\left\{ \begin{matrix} x_2 = l_1 C\theta_2 + l_2 C\theta_{12} \\ y_2 = l_1 s\theta_1 + l_2 s\theta_{12} \end{matrix} \right\}$$ ……Squaring & adding

$x_2^2 + y_2^2 = l_1^2 + l_2^2 + 2l_1 l_2 C\theta_2$ $[c_1c_{12} + s_1s_{12} = c_{1\text{-}12} = c_2]$

Therefore, $C\theta_2 = \left(\frac{x_2^2+y_2^2-l_1^2-l_2^2}{2l_1l_2}\right)$ i.e. $\theta_2 = \cos^{-1}\left(\frac{x_2^2+y_2^2-l_1^2-l_2^2}{2l_1l_2}\right)$

θ_2

$$\theta_1 = \tan^{-1}\left(\frac{y_2}{\varkappa_2}\right) - \tan^{-1}\left(\frac{l_2 S\theta_2}{l_1 + l_2 c\theta_2}\right)$$

θ_1

$$\underbrace{\theta_3 = \emptyset - (\theta_1 + \theta_2)}_{\theta_3}$$

$\angle G - \angle B = \theta_1$

$\angle G = \tan^{-1}\frac{y_2}{x_2}$ & $\angle B = \tan^{-1}\frac{l_2 S\theta_2}{l_1+l_2 c\theta_2}$

3.1.1 CAD Modelling

The software used for CAD modelling of the robotic arm is Autodesk Fusion 360. Three iterations were done in the design of the robot arm and the optimized model was chosen for further manufacturing processes.

The first prototype was heavy as the largest link had a weight of 193g and thickness of 2mm. A 20 kgcm servo motor was not able to move the base link of the robot arm. In the second prototype the weight of the arm is reduced by making slots within the links and reducing the thickness of the links by 0.5mm. For the base link, a 35kgcm servo motor is used.

Fig.2. CAD Model

3.1.2 Analysis and Material selection

Ansys 2020 R2 is used for the robotic arm's static structural analysis in order to calculate the arm's deformations, internal forces, stresses, and stability. The entire robotic arm assembly has been subjected to analysis to see whether the dimensions taken into account for each connection and joint are safe. With elements that are 2 mm in size, the complete assembly is meshed. Our base's bottom half has been regarded as a fixed support. The results are shown below.

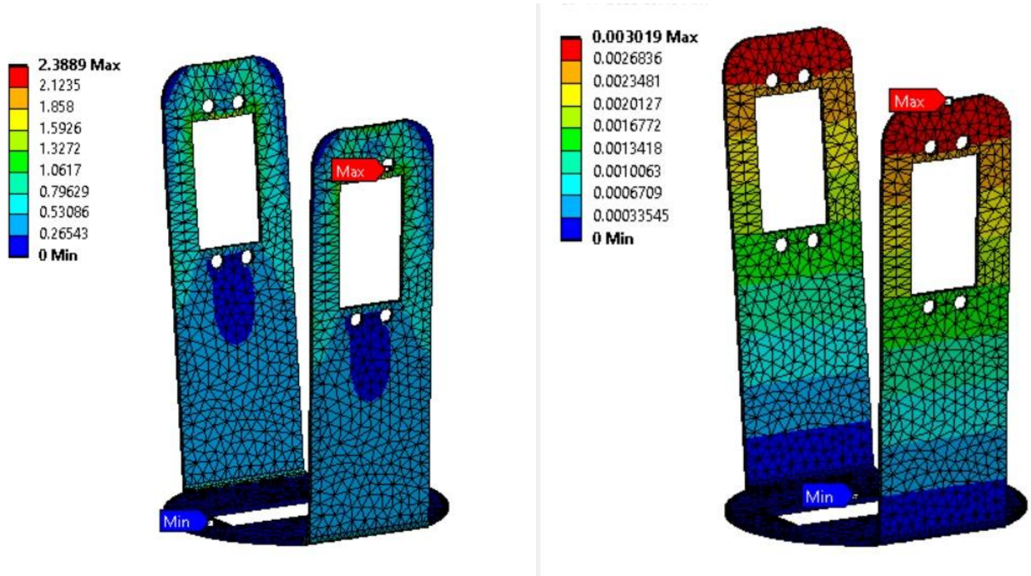
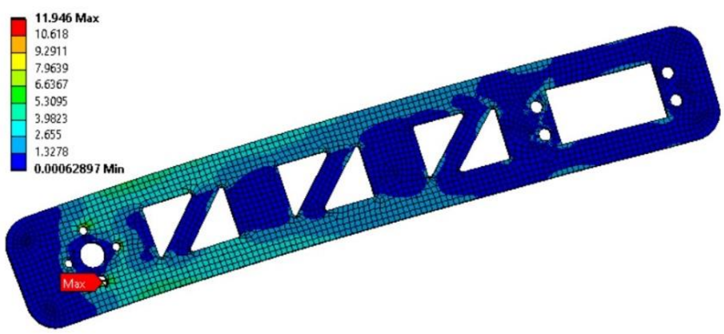
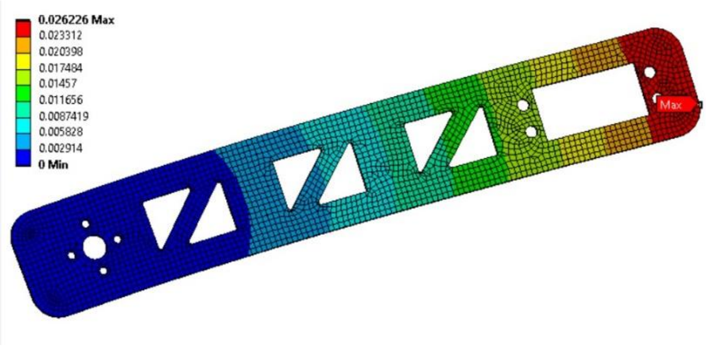


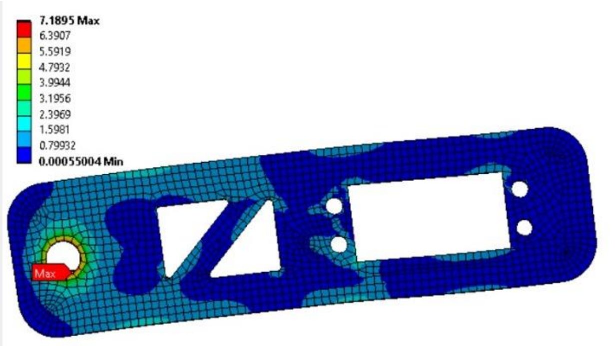
Fig.3 (a) Stress analysis on Base Link 1 (b) Deformation in Base Link 1



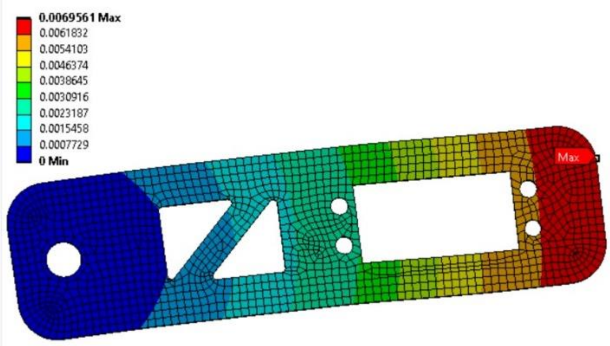
(c) Stress analysis on Link 2



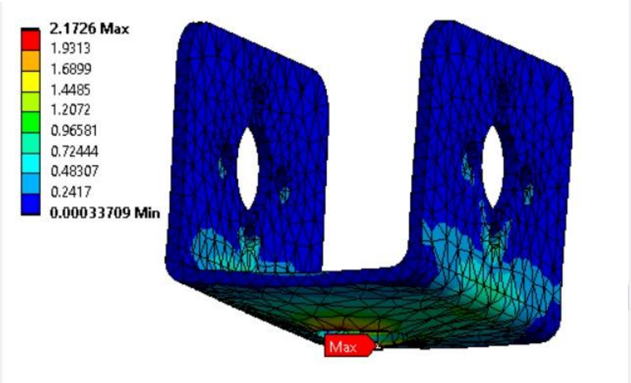
(d) Deformation in Link 2



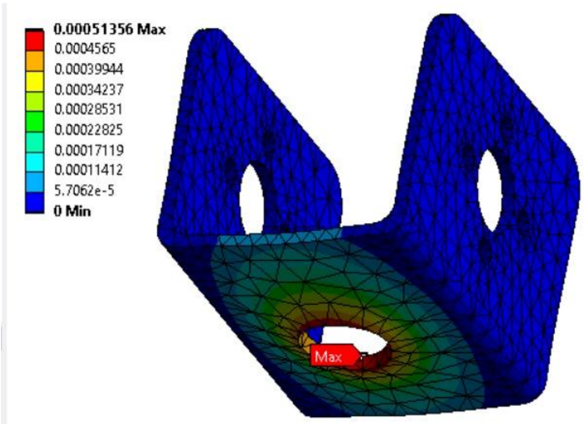
(e) Stress analysis on Link 3



(f) Deformation on Link 3



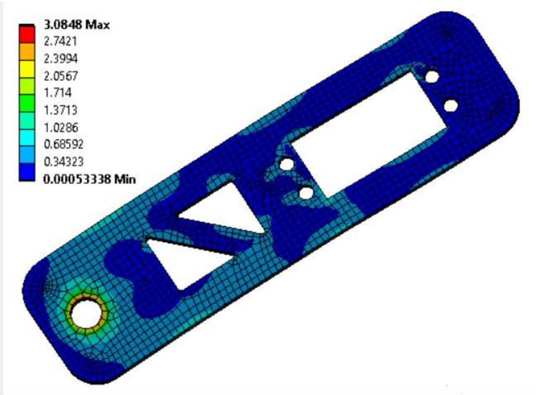
(g) Stress analysis on Gripper Link

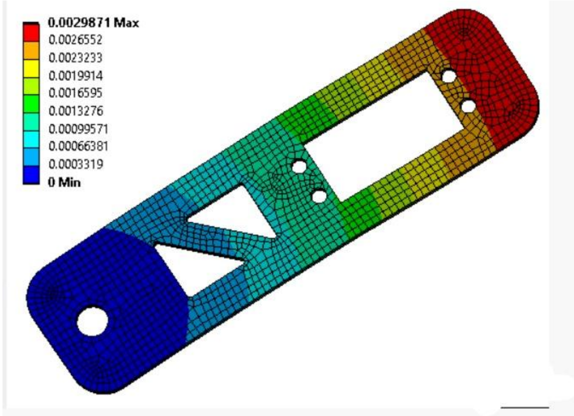


(h) Deformation in Gripper Link

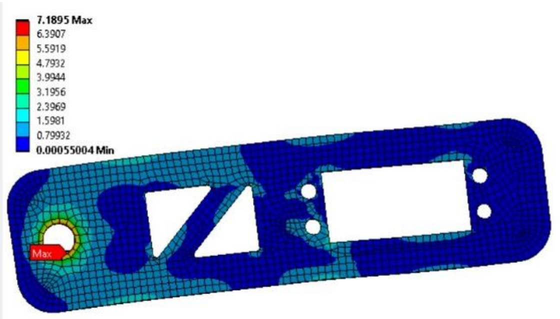
Thickness variation has been conducted of each link individually. Widths of 3.5mm, 1.5mm and 1mm are analyzed to finalize the width of each link. The results are shown below.

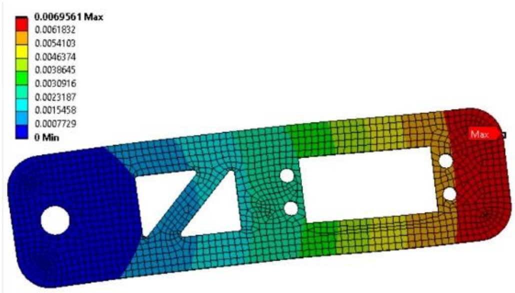
For 3.5 mm:



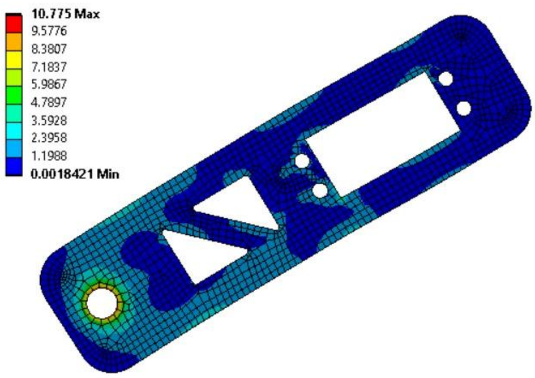


For 1.5 mm:





For 1 mm:



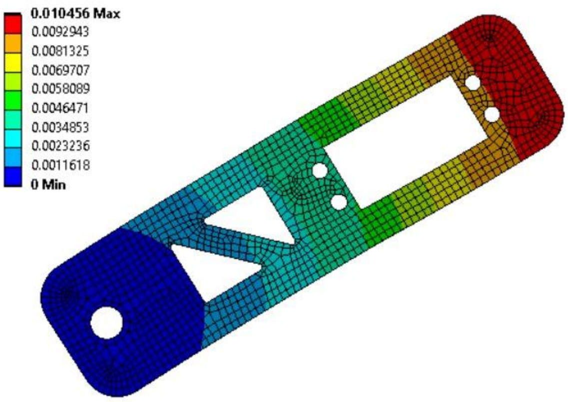


Fig. 4. Thickness variation of the links

When choosing the optimal material for the arm, take into account the following factors/parameters:

1. Power: Yield Since our material will be ductile, the material's strength will be taken into account. (Metric: MPa)

2. Price: Price Band (Average)

3. Accessibility: Is the product easily accessible in the market?

4. Machinability: This refers to how easily a material can be machined.

5. Weight: The material's weight

6. Anti-Corrosive: The material's ability to fend against corrosion.

Table 2: Comparison between different materials

Material	Strength	Cost	Machinability	Weight	Anti-corrosiveness	Availability
AISI 1018	370	Low	Easy	Average	Medium	High
SS 304	650	Medium	Easy	Average	High	High
Al 6061	310	High	Medium	Low	High	Medium

After the comparison SS304 is chosen as the material for the structure of the robot arm.

3.2 Mechanism (Robot Arm and Gripper)

The amount of work that needs to be done and the various robot motions are taken into consideration when choosing the degree of freedom for the robotic arm. Accordingly, we have chosen a 4 DOF robot that can pick up, hoist, move horizontally, set down, or show an object in x, y, or z space while altering its orientation along one axis.

Suction cup grippers, commonly referred to as vacuum grippers, can be a cheap yet very reliable gripping solution for a variety of applications. Vacuum grippers offer secure, potent grips in collaborative robot (cobot) applications when used in the appropriate integration and gripper type. When there is enough of a pressure differential between the atmosphere and the vacuum, or negative pressure, vacuum grippers may lift, hold, move, and do other things. This happens when a part's flat and large enough side allow a vacuum gripper to create a significant enough pressure difference. One benefit of vacuum grippers is their versatility in handling things of various shapes and sizes (even when those items are imperfectly positioned).

3.3 Control Circuit

3.3.1 Component selection

(a) Arduino Mega 2560 R3

Fig. 5. Arduino Mega 2560 R3 and cable

The Arduino is an open-source microcontroller board designed by Arduino. cc and based on the ATmega2560. The board has several digital and analogue input/output pins. The board features 54 digital I/O pins, and 16 analogue I/O pins, and is programmable via a type B USB cable using the Arduino IDE. It can be powered by a USB cable or an external 9-volt battery, with voltages ranging from 7 to 20 volts.

(a) Servo motors

(a) (b) (c)

Fig. 6 (a) 20 kgcm (b) 35 kgcm (c) 10kgcm servo motors

Servo motor is a rotary actuator or linear actuator that allows for precise control of angular or linear position, velocity, and acceleration. It consists of a suitable motor coupled to a sensor for position feedback. Four servo motors used have a stall torque of 20kgcm with an

Input Voltage Range of 4V-8.4V and maximum current rating of 3A. The gears inside are made of copper metal and the dimensions of the motor are (55 x 20 x 43) mm. The motor can rotate upto 180°. One servo motor used at the base link has a stall torque of 35 kgcm with an input voltage range of 4V-8.4V and maximum current rating of 3.8A. Its dimensions are same as the 20 kgcm servo motor. One servo motor of 10kgcm stall torque is used with an input voltage range of 6.3V and maximum current rating of 0.4-0.6A.

Torque calculations have been performed on each link below:

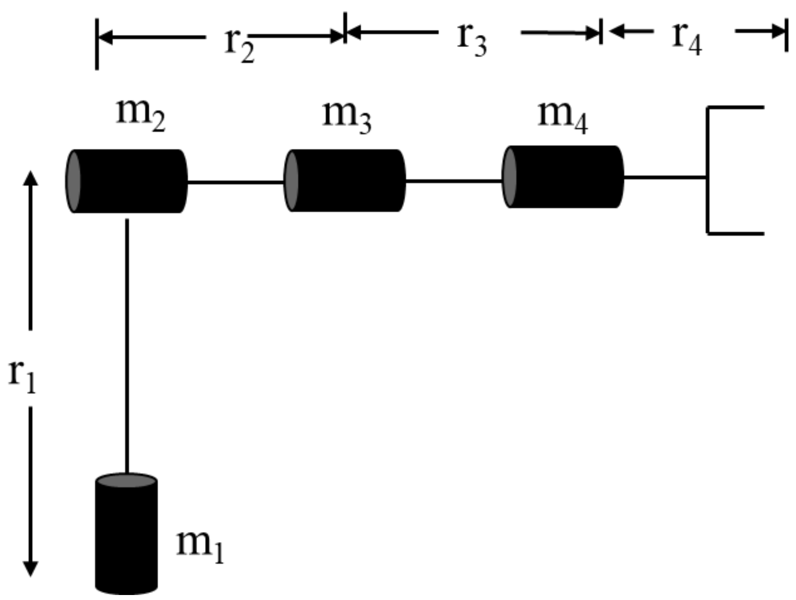


Fig.7. Orientation at which Torque is maximum

Here, m_1=208g , m_2= 192g , m_3= 114g ,m_4= 32g ,r_1= 10 cm, r_2= 20 cm, r_3= 10cm, r_4= 3 cm, m_{j4}= 20g, m_{j3}= 20g

For gripper link (Link 4):

$T_4 = [r_4 \text{ x load x g}] + [\frac{r4}{2} \text{ x } m_4 \text{ x g}]$

T_4 = [3 x 0.5 x 9.81] + [1.5 x 9.81 x 0.032]

T_4 = 15.185 N cm = 1.548 kg cm

For Link 3:

$T_3 = [(r_3+r_4) \text{ x load x g}] + [(r_3+\frac{r4}{2}) \text{ x } m_{j4} \text{ x g}] + [\frac{r3}{2} \text{ x } m_3 \text{ x g}] + [r_3 \text{ x } m_{j4} \text{ x g}]$

$T_3 = [13 \text{ x } 0.5 \text{ x } 9.81] + [11.5 \text{ x } 0.032 \text{ x } 9.81] + [5 \text{ x } 0.114 \text{ x } 9.81] + [10 \text{ x } 9.81 \text{ x } 0.02]$

$T_3 = 74.927$ N cm = 7.6404 kg cm

For Link 2:

$T_2 = [(r_2+r_3+r_4) \text{ x load x g }] + [(r_2+r_3+\frac{r4}{2}) \text{ x } m_4 \text{ x g}] +[(r_2+r_3) \text{ x } m_{j4} \text{ x g}] +[(r_2+\frac{r3}{2}) \text{ x } m_3 \text{ x g}] +[r_2 \text{ x } m_{j3} \text{ x g}] +[(\frac{r2}{2}) \text{ x } m_2 \text{ x g}]$

$T_2 = [(20+10+3) \text{ x } 0.5 \text{ x } 9.81] + [(20+10+1.5) \text{ x } 0.032 \text{ x } 9.81] + [(20+10) \text{ x } 0.02 \text{ x } 9.81] + [(20+5) \text{ x } 0.114 \text{ x } 9.81]$

$T_2 = 205.5975$ N cm = 20.965 kg cm

For Link 1:

$T_1 = [\frac{r1}{2} \text{ x } m_1 \text{ x g}] + T_2 + T_3 + T_4$

$T_1 = [5 \text{ x } 0.208 \text{ x } 9.81] + 20.965 + 7.6404 + 1.548$

$T_1 = 40.3558$ kg cm

(c) Suction Cup

(a) (b)

Fig. 8. Suction Cup (a) 3 cm diameter (b) 1 cm diameter

Two suction cups were used for testing the pick and place operation. The suction cups have diameters of 3 and 1cm respectively. 3cm suction cup is able to lift weights upto 500g but it is only able to lift objects with a flat surface whereas suction cup with 1cm diameter lifts objects upto 300g but can lift objects irrespective of their surface.

To calculate the gripping force generated with a payload of 500g, there are two cases (a) Suction pad (Horizontal) where the workpiece load exerts vertical forces (b) The theoretical suction force is the force acting perpendicular to the surface.

F_h- Theoretical Holding Force

s- factor of safety

a- Acceleration

g- Acceleration due to gravity

μ - Coefficient of friction

m – weight of payload (500g is considered as it will require maximum force)

(a) Horizontal workpiece, vertical force-

$F_h = s \times m \times (g+a)$

$F_h = 2 \times 0.5 \times (9.81 + 5)$

F_h = 14.81 N

(b) Horizontal workpiece, horizontal force-

$F_h = s \times m\,(g + \frac{a}{\mu})$

$F_h = 2 \times 0.5\,(9.81 + \frac{5}{0.5})$

F_h = 19.81 N

Based on the above calculations, it is observed that on comparison load cases (a) and (b) results, the second case has maximum force and is considered for further calculations.

(d) Vacuum Pump

Fig. 9. Vacuum Pump 12V

There are numerous applications for the R385 6-12V DC vacuum pump. When properly powered, the pump can handle heated liquids up to 80°C and can pump air up to 3m vertically and up to 2m down the tube. It has a working current range of 0.5A to 0.7A and a maximum flow rate of up to 1–3L/min.

For the suction cup the force calculated above is 19.81N. To calculate the pressure in the suction cup:

Force = (Pressure difference) x Area of the suction cup (area of 3 cm cup is considered as it will produce maximum pressure)

$19.81N = \Delta P \times Area$

$19.81 = \Delta P \times (\pi r^2) = \Delta P \times (\pi\ 0.03^2) = \Delta P \times (0.002826)$

$\Delta P = 7009.907$ Pa

Atmospheric pressure – P_{in} (Pressure inside the cup) = 7009.907 Pa

$100000 - P_{in} = 7009.907$ Pa

$P_{in} = 92990.093 Pa = 0.92990093$ bar

(e) Ultrasonic Sensor

Fig. 10. Ultrasonic Sensor

An ultrasonic sensor is a piece of technology that detects the distance between objects using ultrasonic sound waves and then transforms the sound's reflection into an electrical signal. Audible sound waves take longer to travel than ultrasonic sounds. The two main parts of an ultrasonic sensor are the transmitter and the receiver. Here, the height of the object that needs to be sorted is determined using an ultrasonic sensor. It has a 5V working voltage and can detect things that are 2 cm to 400 cm away.

(f) 12V Relay Module

Fig. 11. 12V Relay Module

A 12V relay is an automatic switch that is generally used in automatic control circuits to control a high current using a low current signal. The input voltage of the relay signal ranges from 0 to 12V. Relays are electromechanical devices that act as switches. The relay coil is activated by DC, enabling contact switches to be opened or closed. A single channel 12V relay module typically has a coil and two contacts, such as ordinarily open (NO) and normally closed (NC) (NC).

(g) Pipe and wires

A pipe of 8mm diameter and 1000mm length is used to connect the vacuum pump to the suction cup. Wires are used to make all the connections in the circuit and the entire circuit is soldered on a PCB board.

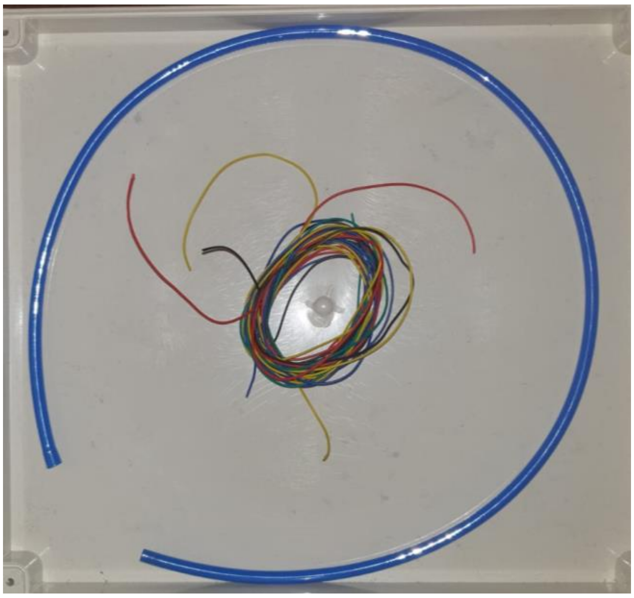


Fig.12. Pipe and wires

(h) Power supply

A single power supply with a maximum voltage rating of 24V and maximum current rating of 5A is used to power all the servo motors as well as the gripper mechanism. For our application we have set the voltage rating to 12V since most of the components operate at or under 12V. A multimeter is used to measure the amount of current and voltage that each component draws while operating. The values are mentioned below:

Table 3: Voltage and current drawn for each component

Component	Voltage drawn	Current drawn
10 kgcm servo motor	6.3V	0.4-0.6A
20 kgcm servo motor	7.1-7.4V	0.4A
35 kgcm servo motor	7.1-7.4V	0.4A
Vacuum pump	12-15V	0.15-0.16A

The total current drawn from all the components is 1.56A and the maximum voltage drawn is 12V and therefore a power supply of 24V and 5A is selected for the project.

Fig. 13. Power supply

(i) Webcam

Lenovo 300 FHD Webcam is used to detect and classify the waste objects. It has an Easy Plug-and-Play Setup.

Fig.14. Lenovo 300 FHD Webcam

(j) 8V and 12V voltage regulator

The basic purpose of a voltage regulator is to keep the voltage constant. A constant voltage output is produced as a result of the regulator's resistance fluctuating in response to the input voltage and the load. All of the servo motors receive an input voltage of 8V, which is obtained by using the 8V voltage regulator. The vacuum pump receives input from the 12V voltage regulator.

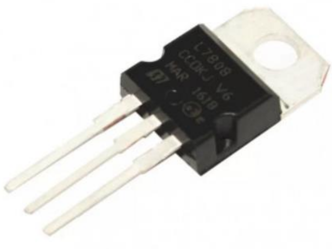


Fig.15. 8V Voltage regulator

3.3.2 Block and Circuit Diagram (PCB)

Block diagram:

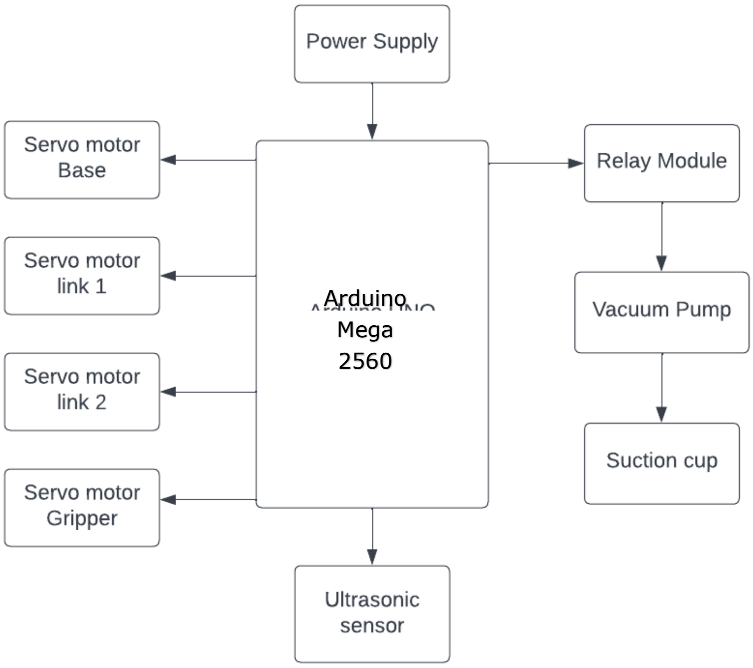


Fig.16. Block diagram for circuit design

Circuit diagram: Circuit diagram of the gripper mechanism is shown below:

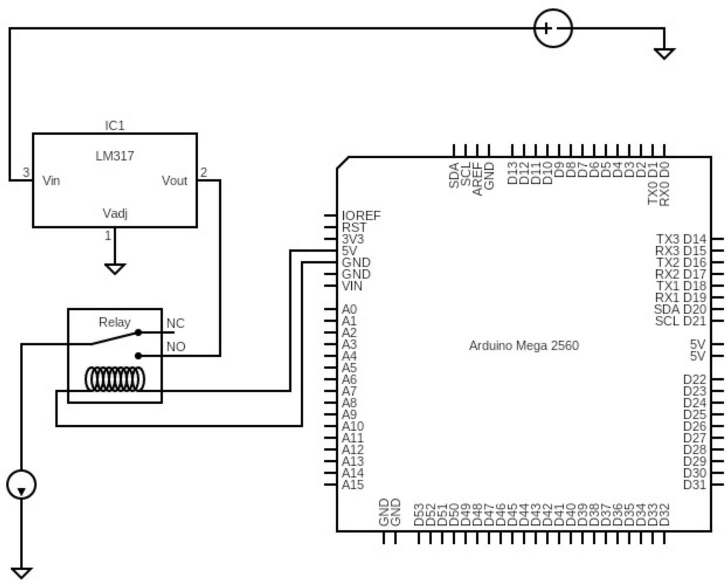


Fig.17. Circuit diagram of the vacuum pump control

The integrated circuit diagram of the entire setup which includes the servo motor control circuit and the vacuum pump control circuit is shown below:

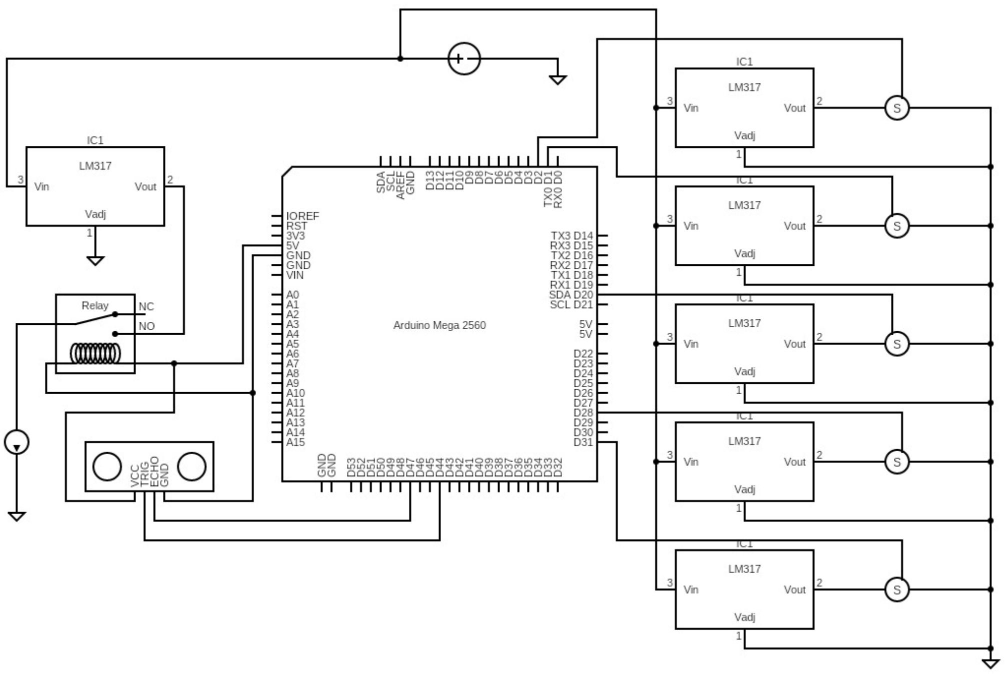


Fig.18. Circuit diagram for the entire setup

3.3.3 Code

(i) Code for Inverse Kinematics

```
float inversekinematics(float x, float y, float phi){
  // y = heightofobject();
  float a,b;
  float x2 , y2;
  float t1, t2, t3;
  x2 = x - l3*cos(phi);
  y2 = y - l3*cos(phi);
  phi = th1 + th2 + th3;
  a = (x2*x2 + y2*y2 -(l1*l1 + l2*l2)) / (2*l1*l2);
```

```
  th2 = acos(a);
  b = ( l2*sin(th2) ) / (l1 + l2*cos(th2)) ;
  th1 = atan(y/x) - atan(b);
  th3 = phi - (th1 + th2);
  t1 = radtodeg(th1);
  t2 = radtodeg(th2);
  t3 = radtodeg(th3);
  return(t1,t2,t3);
}
```

(ii) Code for Ultrasonic sensor

```
float heightofobject(){
  // Clears the trigPin condition
  digitalWrite(trigpin, LOW);
  delayMicroseconds(2);
  // Sets the trigPin HIGH (ACTIVE) for 10 microseconds
  digitalWrite(trigpin, HIGH);
  delayMicroseconds(10);
  digitalWrite(trigpin, LOW);
  // Reads the echoPin, returns the sound wave travel time in microseconds
  duration = pulseIn(echopin, HIGH);
  // Calculating the distance
  distance = duration * 0.034 / 2; // Speed of sound wave divided by 2 (go and back)
  x = distance_base - distance;
  return x;
}
```

(iii) Code for Gripper Mechanism

```
void drop(){
  digitalWrite(relaypin,LOW);
}
```

```
void vacuum(){
  digitalWrite(relaypin,HIGH);
}
```

(iv) Final code

```
#include <Servo.h>

//input from user
String input;

// Servo objects
Servo baseservo;
Servo link1servo;
Servo link2servo;
Servo endservo;

// Servo pins
int basepin = 11;
int link1pin = 10;
int link2pin = 9;
int endpin = 6;

//Relay Pin
int relaypin = 8;
int dropdelay = 3000;

//ultrasonic pins
int echopin = 2;
int trigpin = 3;
```

```
long duration;
float distance_base = 100;
float distance;

// Servo angles
float th1, th2, th3;
float baseangle;

float pi = 3.14159265358979323846;

// End effector position
float phi = pi/2;
float x = 0;

// link lengths
float l1 = 10;
float l2 = 20;
float l3 = 10;



// for fixed base servo angles
float plastic_bin, glass_bin, paper_bin, metal_bin;

//function declaration


float inversekinematics(float x, float heightofobject,float phi);
void vacuum();
void drop();
float movearm(float th1, float th2, float th3);
```

```
float heightofobject(float x);
float radtodeg(float radian);
float movebase(float baseangle);



//function definition

float movebase(float a){
  baseservo.write(a);
}

float radtodeg(float radian){
  float degree;
  degree = ( (radian * 180) / (pi) );
  return degree;
}

float inversekinematics(float x, float y, float phi){
  // y = heightofobject();
  float a,b;
  float x2 , y2;
  float t1, t2, t3;
  x2 = x - l3*cos(phi);
  y2 = y - l3*cos(phi);
  phi = th1 + th2 + th3;
  a = (x2*x2 + y2*y2 -(l1*l1 + l2*l2)) / (2*l1*l2);
  th2 = acos(a);
  b = ( l2*sin(th2) ) / (l1 + l2*cos(th2)) ;
  th1 = atan(y/x) - atan(b);
```

```
  th3 = phi - (th1 + th2);
  t1 = radtodeg(th1);
  t2 = radtodeg(th2);
  t3 = radtodeg(th3);
  return(t1,t2,t3);
}

float heightofobject(){
  // Clears the trigPin condition
  digitalWrite(trigpin, LOW);
  delayMicroseconds(2);
  // Sets the trigPin HIGH (ACTIVE) for 10 microseconds
  digitalWrite(trigpin, HIGH);
  delayMicroseconds(10);
  digitalWrite(trigpin, LOW);
  // Reads the echoPin, returns the sound wave travel time in microseconds
  duration = pulseIn(echopin, HIGH);
  // Calculating the distance
  distance = duration * 0.034 / 2; // Speed of sound wave divided by 2 (go and back)
  x = distance_base - distance;
  return x;
}


float movearm(float th1, float th2, float th3){
  link1servo.write(th1);
  link2servo.write(th2);
  endservo.write(th3);
}
```

```
void drop(){
  digitalWrite(relaypin,LOW);
}
void vacuum(){
  digitalWrite(relaypin,HIGH);
}
void setup(){
  baseservo.attach(basepin);
  link1servo.attach(link1pin);
  link2servo.attach(link2pin);
  endservo.attach(endpin);
  pinMode(trigpin,OUTPUT);
  pinMode(echopin,INPUT);
  pinMode(relaypin,OUTPUT);
  Serial.begin(9600);
}

void loop(){
  digitalWrite(relaypin,LOW);
  // movearm();  // with initial values

  // say what you got:
  Serial.println("Enter: 0-plastic , 1-paper , 2-glass , 3-metal ");
  while(Serial.available()==0){
  }
  r = Serial.readString();
  Serial.println("Sorting waste !!!!!!!!");

  if(input=="0"){
```

```
  Serial.println("PLASTIC");
  a = heightofobject();
  inversekinematics(x,a,phi);

  movearm(t1, t2, t3); //home position
  movebase(30); //plastic_bin
  movearm(th1, th2, th3); //drop position
  drop();
  delay(3000);
  movearm(0,0,0); //home position
  movebase(0); //home position
}

else if(input=="1"){
  Serial.println("PAPER");
  a = heightofobject();
  inversekinematics(x,a,phi);

  movearm(t1, t2, t3); //home position
  movebase(40); //PAPER_bin
  movearm(th1, th2, th3); //drop position
  drop();
  delay(3000);
  movearm(0,0,0); //home position
  movebase(0); //home position

}
else if(input=="2"){
  Serial.println("GLASS");
```

```
    a = heightofobject();
    inversekinematics(x,a,phi);

    movearm(t1, t2, t3); //home position
    movebase(50); //GLASS_bin
    movearm(th1, th2, th3); //drop position
    drop();
    delay(3000);
    movearm(0,0,0); //home position
    movebase(0); //home position
  }
  else if(input=="3"){
    Serial.println("METAL");
    a = heightofobject();
    inversekinematics(x,a,phi);

    movearm(t1, t2, t3); //home position
    movebase(50); //METAL_bin
    movearm(th1, th2, th3); //drop position
    drop();
    delay(3000);
    movearm(0,0,0); //home position
    movebase(0); //home position
  }
  else{
    Serial.println("Enter valid input");
  }
}
```

3.4 Object Detection system

Find every item in the real objects, like B. Object identification is the process of accurately and quickly identifying objects in images and videos, such as people, objects, cars, and flowers. To identify each occurrence of an item category, object identification systems employ derived features and learning strategies. It is a computer vision technology that determines how objects seem, frequently utilising deep learning or machine learning. Approaches to deep learning were investigated in this study.
The location of an object in a picture can be predicted quickly and accurately using deep learning-based object detection. Deep learning is used by object detectors to automatically pick up the visual cues required for detection tasks.

Three computer vision tasks can be used to categorise object detection tasks:

Predict the kind or class of items in a picture using image classification. In this exercise, class labels are given to photographs. Locate one or more objects in the image and draw a big box around them. This is known as object localization. Object detection: Using a bounding box and the type or class of the detected object, this technique determines if an object is present in a picture. There are two ways to classify images based on their classes, using transfer learning or pretrained models. The main difference between the two is that transfer learning is based on machine learning. In this case, the pre-trained model is trained to solve a problem similar to the problem it was trained to solve, so you can use the model according to your customization requirements. A pre-trained model is a numerical network that was originally trained on a large data set using deep learning techniques. For this project, we will use a pre-trained model as it runs faster. The model used is YOLOv7, which provides real-time object detection. It's much faster, more accurate, and has a better neural network architecture.

3.4.1 Algorithm for object detection

The flowchart shown below depicts the algorithm followed in the process of object detection using YOLOv7 model.

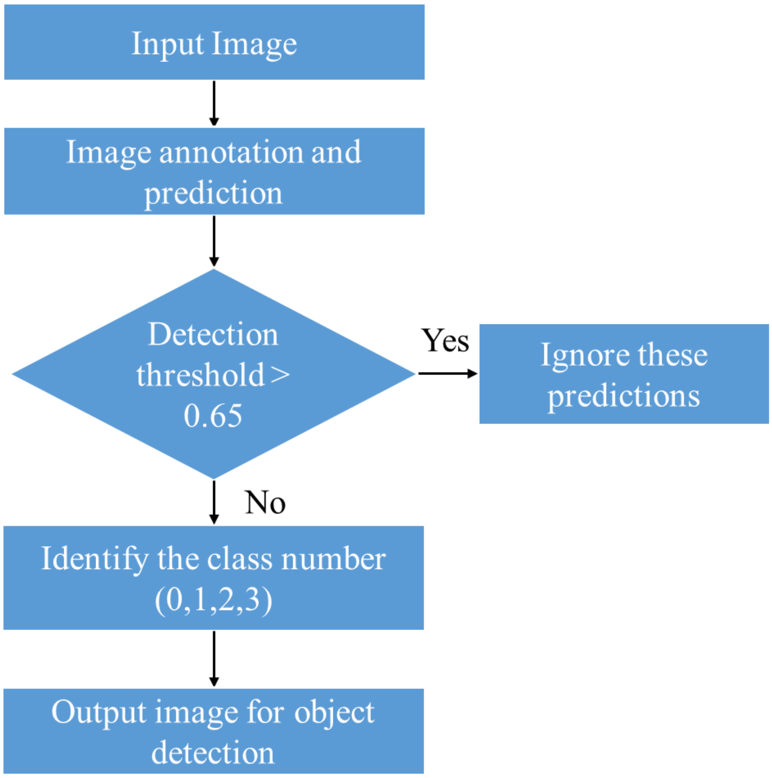


Fig.19. Algorithm for object detection

3.4.2 Tuning Model

The experimental process of determining the ideal hyperparameter values to maximise model performance is known as tuning. A group of variables known as hyperparameters are those whose values the model is unable to infer from the training set of data. The learning process is governed by these values. Number of neurons, activation function, optimizer, learning rate, stack size, and epoch are the hyperparameters that need to be tuned. In the following stage, the number of layers must match. This is not present in other conventional algorithms. Accuracy may be affected by various layers. The object detection model was first executed using 25 epochs but since its accuracy was not up to the mark, the model was tuned by increasing the number of epochs to 50. The model's accuracy increased eventually. The batch size was taken as 16. Model tuning provides optimized values for hyperparameters, which maximize your model's predictive accuracy.

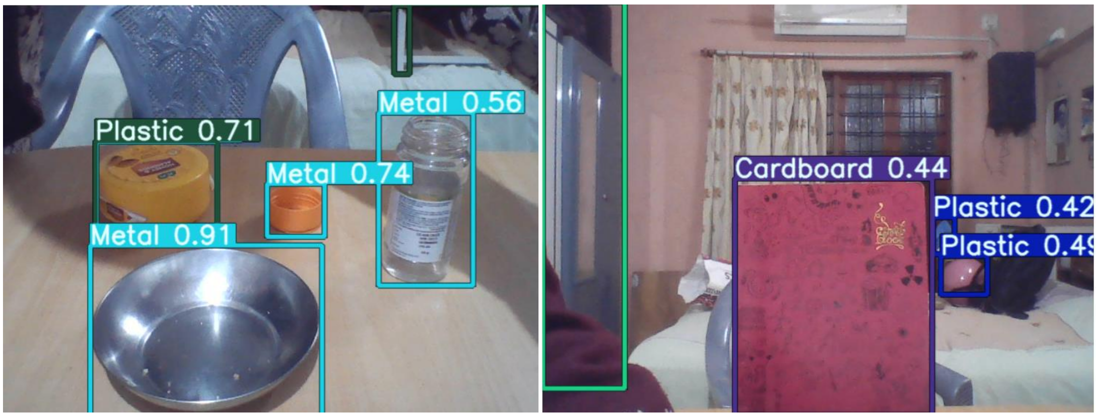


Fig. 20. Real-time object detection using YOLOv7

3.5 Manufacturing and Prototype

Laser cutting is used in the robot arm's manufacturing process. It uses a powerful laser that is guided by computer numerical control (CNC) and optics to steer the material or beam. Usually, a motion control system is used in the process to adhere to a CNC or G-code of the design that needs to be cut onto the material. To leave a high-quality surface completed edge, the focused laser beam burns, melts, vaporises, or is blasted away by a jet of gas. The robot's skeleton was laser-cut using the following inputs.

Robot base: The robot base is made of Mild steel and has a thickness of 4mm. Its dimensions are 192 x 204 mm. It serves as a support to the entire structure of the robot arm.

Fig.21 (a) CAD Model of the base

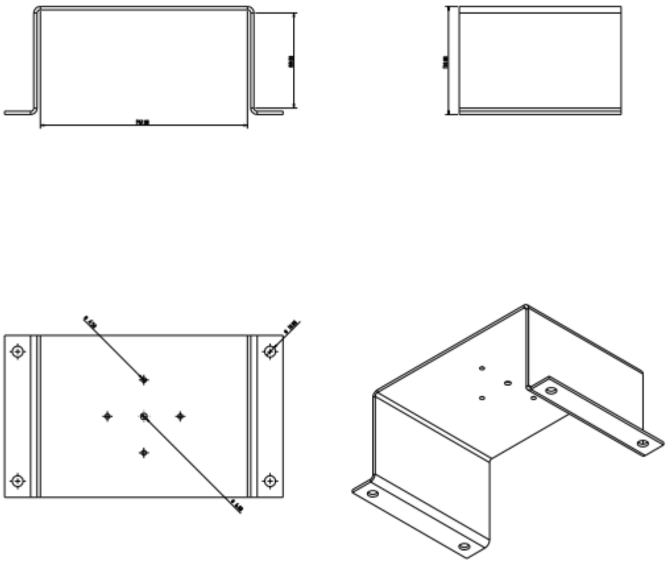


Fig. 21(b) Production drawing of the base

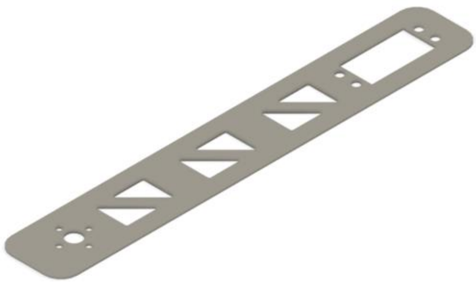


Fig. 22 (a) CAD Model of Link 2

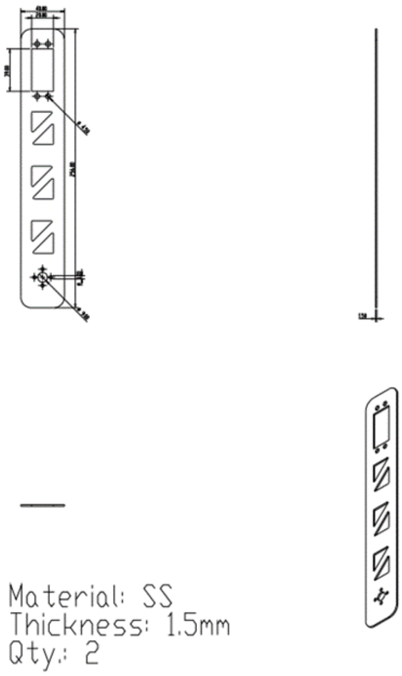


Fig. 22 (b) Production drawing of Link 2

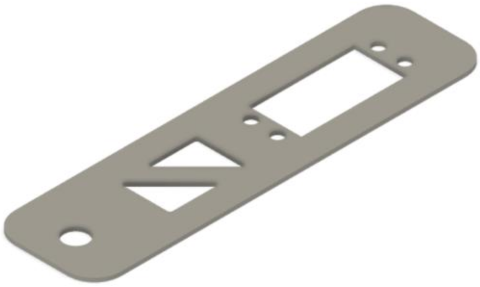


Fig.23 (a) CAD Model of Link 3

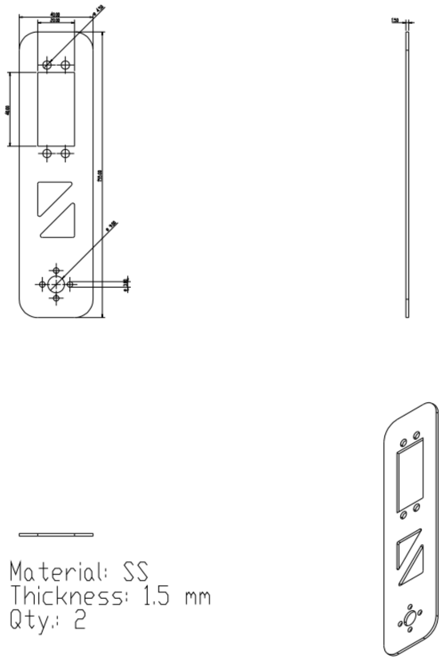


Fig.23 (b) Production drawing of Link 3

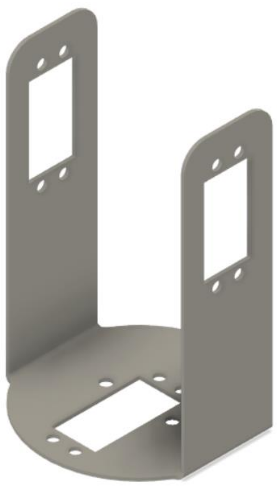
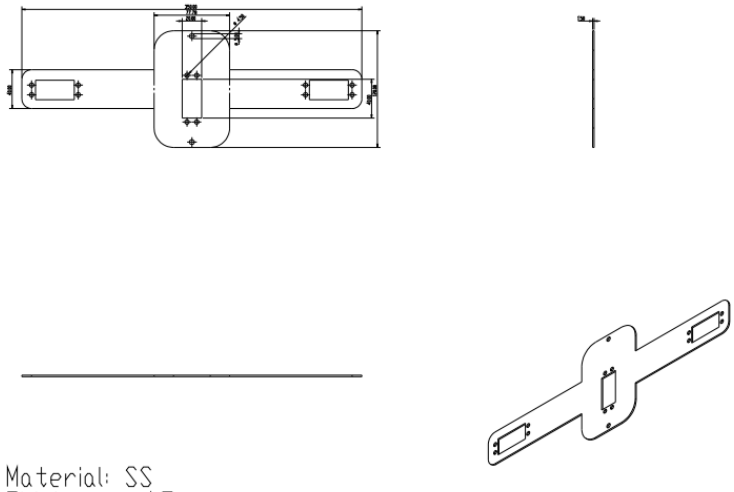


Fig.24 (a) CAD Model of Link 1

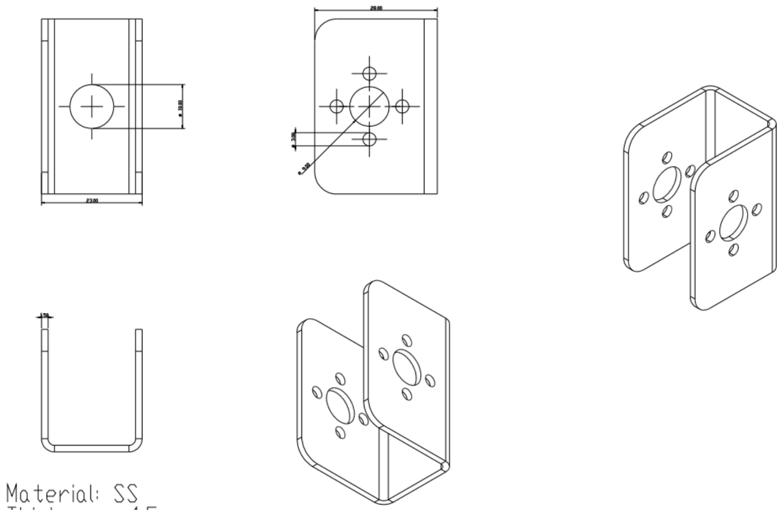


Material: SS
Thickness: 1.5 mm
Qty.: 1

Note: Bending lines are marked as centre lines

Fig.24 (b) Production drawing of Link 1

Fig.25 (a) Gripper Link



Material: SS
Thickness: 1.5 mm
Qty.: 1

Fig.25 (b) Production drawing of Gripper link

Bending is a process by which metal can be deformed by plastic deformation material and change its shape. The material is subjected to stress beyond its elastic limit but less than its ultimate tensile strength. Bending operation is performed on base link and clamp link. The manufactured components are shown below.

(a) Base of the robot arm

(b) Gripper Link

(c) Links 2 and 3

(d) Base Link 1

Fig.26. Components obtained after Laser Cut operation

The robot arm is assembled with the following considerations in mind:

• Reliability

• Sturdiness

• Fit and Finish

• Quality of Materials

The robot arm's base is fixed. We used a roller bearing with an ID of 55mm and an OD of 80mm to reduce friction between Link 1 and the base. The plate inside the bearing is connected to our base, while the movable outside half is fixed to Link 1. Servo motors are used to connect the linkages to one another.

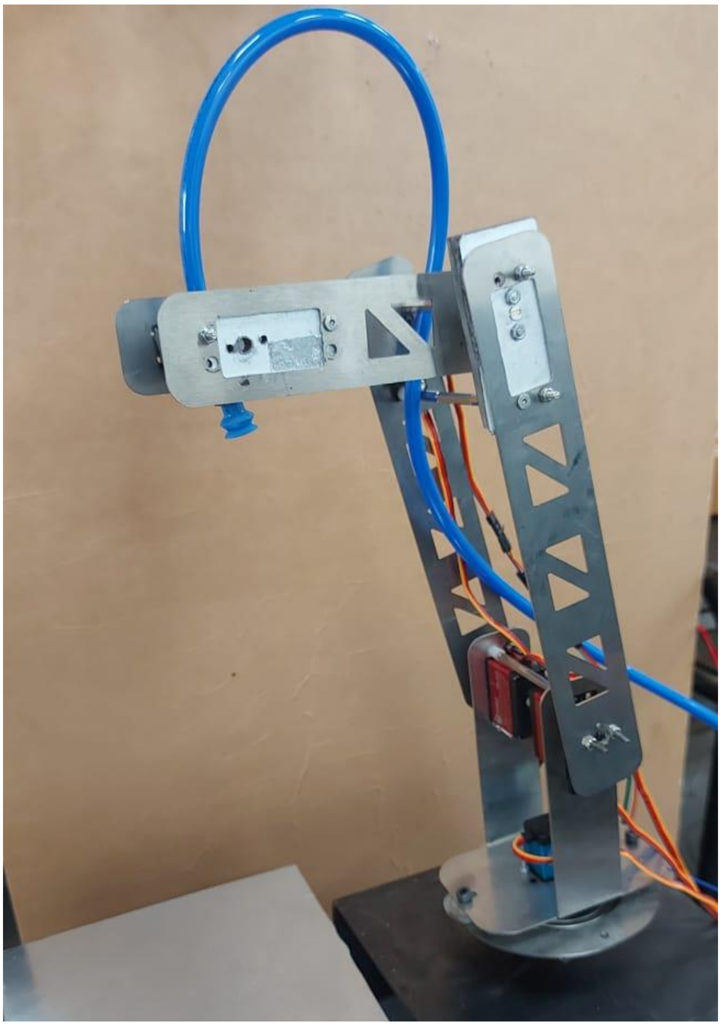


Fig.27. Assembled Robot arm

4 Bill of Materials

Reno.	Components Name	Cost
01	Arduino Mega 2560 and cable	1080
02	Servo motors (35 kgcm x1, 20 kgcm x 3,10 kgcm x 1)	6400
03	Vacuum Pump (12V)	250
04	Relay module (12V)	80
05	Robot body parts (Laser cut)	2000
06	Suction Cup (dia. 1cm), (dia. 3cm)	1200
07	Pipes for pump (8mm)	50
08	Ultrasonic sensor	80
09	Camera module	700
10	Zero Board PCB	20
11	Female to Female Jumper Wire	100
12	Male to Male Jumper Wire	100
13	Power supply (12V)	600
14	Breadboard	50
15	Servo atttachments + nut bolts	500
16	Voltage regulator	80

5 Future Scope

In this project, objects need to be placed at a pre-defined position and the operator has to place an object one at a time at the exact same location (at a particular co-ordinate) so that the robot arm can pick the object properly. In future, a conveyor belt can be designed in which the objects will move through the robot arm and get sorted without any manual operation. Class numbers have been defined for each class: 0-plastic, 1-paper, 2-glass, and 3-metal. After an object is classified in any class the operator must manually input the class number in the inverse kinematics code so that the robot arm can place the object in the correct bin. Instead of this manual operation, we can integrate the camera and robot arm together so that the class number will automatically serve as an input to the robot arm. In this way, the robot arm will be able to classify the objects without any manual operation. The accuracy of the vacuum gripper can be increased by increasing its suction diameter and the pressure that the vacuum pump generates. The accuracy and efficiency of the object detection model can be increased by increasing the number of epochs in the code and by using a larger waste detection dataset.

6 Conclusion

Designing and Prototyping of a 4 degree of freedom Robot arm is conducted for sorting waste into 4 categories: plastic, paper, metal and glass. The sorting of waste is conducted using YOLOv7, a computer vision technique. Design and static structural analysis of the robot arm is performed on Ansys 2022 R1 which confirms that the design is safe to operate. Servo motors are selected based on the torque calculations and the vacuum pump is selected based on its flow rate. Maximum payload that the robot arm can pick is found to be 300g for the 1cm suction cup and 500g for the 3cm suction cup. A trash dataset was imported from RoboFlow containing 4878 images and YOLOv7 model was trained for this dataset with 50 epochs using Google Colab. Out of 10 images, 7 number of images were correctly classified. The accuracy of the model is 70 %.

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