OPTIMIZING ROBOT GRASPING USING SOFT ORIGAMI ZIGZAG GRIPPER WITH ARTIFICIAL INTELLIGENCE

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ABSTRACT

The covid-19 pandemic leads to an increased need for automation in food industries. Current soft robots require cast moulding, high assembly effort, large actuators, and upfront actuation awareness due to the absence of artificial intelligence. Soft origami structures exhibit high levels of compliance. We developed a 3D print-in-place under-actuated soft origami zigzag gripper using TPU with artificial intelligence object pose estimation to grasp objects with high repeatability of success under different conditions. A self-designed 3D robot arm is used for object grasping. Grasping performance tests were conducted using different gripper designs, robot arm speed, and gripping force on objects with different masses and morphology. The soft origami zigzag gripper has better-grasping performance than the hard gripper as analyzed by paired t-test. The logistic model of the soft origami zigzag gripper's grasping performance achieved an accuracy of 0.940 and AUC=0.911. Jetson Nano running AI CNN Resnet18, enhanced grasping performance with vision object classification achieved an accuracy of 0.923 and F1 score of 0.956. The AI CNN MobileNetV2 is used for object classification and experimental results showed it had lower accuracy as compared to the AI CNN Resnet18. The object classification using artificial intelligence optimized the robot grasping to improve automation in food processing and food handling to avoid contamination. All these can be used in the automation process in the food industry to overcome health and safety challenges.

Keywords: origami, soft origami gripper, robot grasping, object classification, artificial intelligence.

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1. INTRODUCTION

The Covid-19 pandemic has affected the entire supply chain of the food industry from growers, and manufacturers to retailers. They have to fulfil requirements to implement social distancing measures and have faced workforce shortages as employees fall sick or self-isolate. There is also a greater demand for food safety. All these challenges have increased the need for higher automation across the food industry. Automation robotics coupled with an artificial intelligence-based system, food production, and delivery processes can be efficiently handled and also enhance operational competence by reducing human error. As for food handling, automation with soft robots helps to minimize human contact to avoid contamination.

Soft-bodied robots offer safer and more compliant interactions between the environment, machines and humans, as compared to traditional rigid robots (Rus and Tolley, 2015; Laschi *et al*., 2016) [22] [17]. Besides safe interactions, soft robots have high adaptability and robustness due to their flexible nature. As for manipulation, the compliant nature allows soft grippers to conform to objects with both ease and high grasping performance (Shintake *et al*., 2018; Hughes *et al*., 2016) [25] [11]. Traditional rigid robotic grippers are designed to precisely perform manipulation tasks, and they often require precise measurements of the target object's location and geometry before grasping (Cutkosky, 1989) [5]. Thus, they have limitations in grasping different objects and handling uncertainty. To address these limitations, there has been significant progress in the development of soft grippers in recent years (Kim *et al*, 2013) [16]. Numerous gripper technologies have been developed, from the most dexterous multi-finger robotic hands (Gosselin *et al*., 2008) [10], two-finger grippers (Belzile and Birglen, 2013) [2], conformable soft hands (Deimel and Brock, 2016; She *et al*., 2015) [6] [24], adhesion-based soft grippers (Song *et al*., 2017) [26] and universal jamming grippers (Brown *et al*., 2010; Kapadia and Yim, 2012) [3] [14] to industrial vacuum suction grippers (Kessens and Desai, 2011) [15]. Manipulation of multi-degrees of freedom robotic fingers needs precise control of configuration and contact forces (Catalano *et al*., 2014; Firouzeh and Paik, 2017; Falco *et al*., 2018; Falco *et al*., 2020) [4] [9] [7] [8]. Conventional soft vacuum suction elastomer grippers have issues with accurate shape reconfiguration and control (Rus and Tolley, 2018) [22]. To achieve a desirable level of gripper shape reconfiguration and control, origami-inspired designs such as the vacuum-driven origami magic-ball soft gripper have been explored as a potential solution (Li et al, 2019) [19].

Origami structures are often considered to be a network of rigid or semi-rigid panels interconnected by compliant hinges (Tachi, 2009; Belcastro and Hull, 2002) [27] [1]. Panels provide stiffness, structure, and self-constraint, while hinges introduce folding degrees of freedom, thus leading to a mechanism-like behaviour. Since paper-based origami grippers require tedious manual work to fold, are relatively fragile and prone to fatigue due to repeated folding and unfolding (Jeong and Lee, 2018) [12], manufacturing methods such as 3D printing (Kan *et al*., 2019; Lee *et al*., 2020) [13] [18] have been introduced to replace paper origami. 3D printing technologies can realize objects that include various types of joints and moving parts. The print-in-place and the multi-material deposition capabilities have been used to produce a stable junction

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between flexible (Thermoplastic polyurethane, TPU) and rigid (Poly-Lactic Acid, PLA) materials to manufacture elastic hinges without any assembly operation.

The gripper, as the end-effector of a robotic arm, is responsible for the contact between the robot itself and all the humans or objects present in the workspace. Therefore, it is important to provide grippers with intelligent behavior. The use of sensors and the development of machine learning algorithms allow the gripper to achieve this objective (Romeo *et al*., 2021) [21]. The gripper has to "understand" when to open and close its fingers in the process of grasping and releasing a given object. Vision and/or proximity sensors can be integrated into the gripping systems to provide information about the object's position for the gripper to grasp it when the best conditions apply (Mizoguchi *et al*., 2010) [20]. Besides that, grippers could also be provided with optomechanical tactile sensors to improve force adjustment (Saen *et al*., 2014) [23]. Integration of artificial intelligence in the gripping system helps the grippers to achieve better-grasping performance.

Our engineering objectives are to develop a 3D print-in-place easy assembly underactuated soft origami-inspired gripper with artificial intelligence capability to grasp various kinds of objects with high repeatability under different conditions. We would like to determine the factors that affect the grasping performance of a gripper and develop artificial intelligence in soft origami robots for object classification.

2. METHODOLOGY

In this section, we first introduced the 3D print-in-place soft origami zigzag gripper in Section 2.1. In Section 2.2, the self-designed 3D robot arm used for robot grasping is presented. The procedure of the grasping performance evaluation is discussed in Section 2.3. Finally, in Section 2.4, we used artificial intelligence for object classification. After recognizing objects, the 3D robot arm performed the pick-and-place operations.

2.1 Soft Origami Zigzag Gripper

We designed a unique gripper that is a combination of origami and soft Thermoplastic polyurethane (TPU) which makes it a more compliant gripper. Usual origami requires folding and hand coordination in generating the creases for mountains and valleys folded on paper and is now replaced with soft TPU 3D Printing. This method will pre-set all the mountain valleys similar to origami paper which allows organic hinges without the rigid hinge normally associated with rigid grippers. TPU filament with 95A Shore hardness is used for this soft origami zigzag gripper as shown in Table 1. Care is taken that folding hinges are printed thinner than other non-folding hinges. This preserves the shape and yet allows deformation as though it has a natural hinge.

Table-1. Mechanical characteristics of TPU (left) and printing settings Soft Origami Zigzag folding (right).

Mechanical Properties	Print Settings
100% Modulus: 9.4 ± 0.3Mpa	3D Printer Nozzle Temperature: 190C- 230C
Tensile Strength: 29 ± 2.8 Mpa	Printing Speed: 20mm/s- 40mm/s
Bed Temperature: 25C-60C	Elongation at Break: 330.1 ± 14.9%
Cooling Fan: 100% On	Shore Hardness: 95A

The soft origami zigzag flexible hinges in this design are subjected to tensile and bending loads. This project employed finite element analysis (FEA) in ANSYS software to analyze the displacement of the mechanism to determine optimal displacement at the optimal level of the design variable, as shown in Figures 1 and 2. The finite element analysis uses mechanical properties from TPU in the table above as the material. The soft origami zigzag gripper was designed using Autodesk Fusion360 software, and then converted to a STEP file and inserted in the Static Structural of ANSYS simulator.

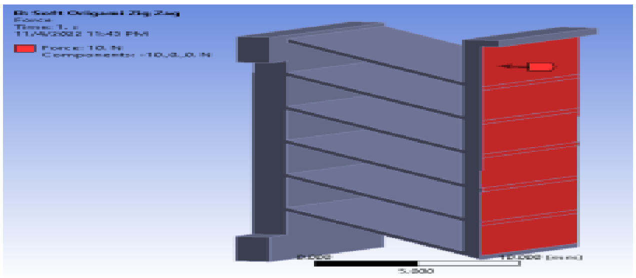

Figure-1. Finite element analysis using static structural method with forces applied to the soft origami zigzag gripper.

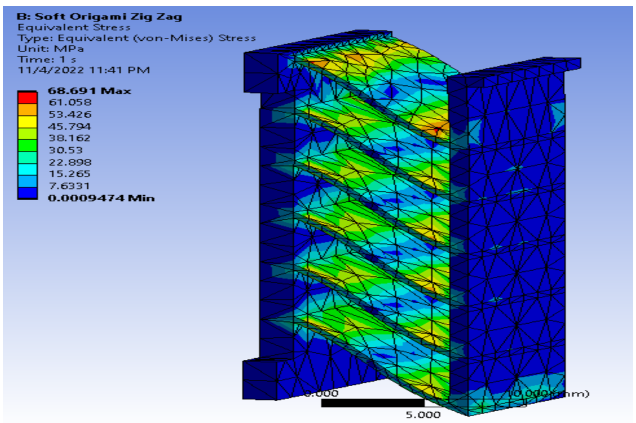

Figure-2. Finite element analysis shows strain forces starting around the zigzag area with greater strain at the hinge area showing flexible characteristics.

This soft origami zigzag gripper design is implemented on Autodesk Fusion360 and printed on a 3D Printer with TPU profile settings. We used an origami Zigzag folding formation with a 60-degree slant. The slanted ribs allow natural hinge movement as opposed to perpendicular ribs. Perpendicular ribs tend to buckle randomly and cause unwanted movement. The origami zigzag design in Autodesk Fusion360 is designed with all ribs hinged at a 60-degree slant. This has a unique mechanic while pressing at the gripper, the 60-degree parallel ribs will push the gripper up and cause lift on the object. This creates an actuation that allows better grip mechanics. Each side of the gripper has 3 Origami Zigzag folding designs which allow uneven objects like eggs or oval shapes to be enveloped as shown in Figure-3. This also allows better grip holding. A DC servo motor is used to actuate the gripper.

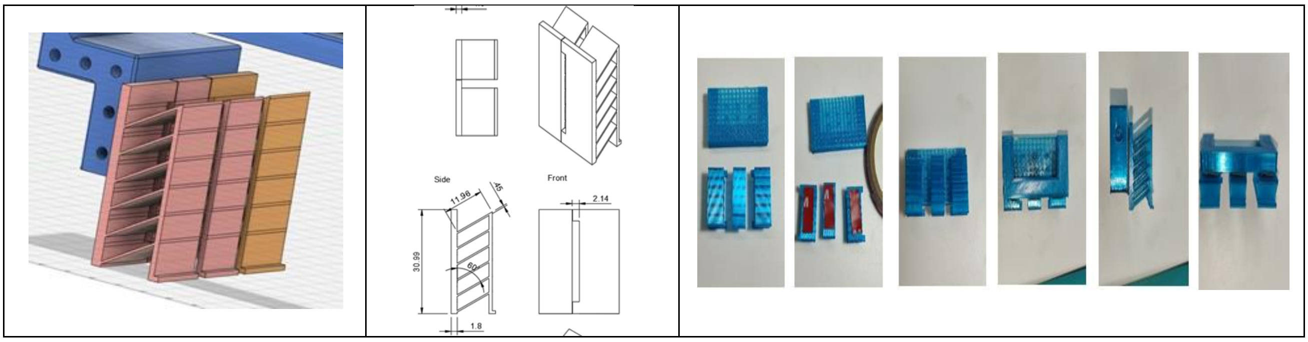

Figure-3. Design gripper with Origami Zigzag formation (Left) and Printed Origami Zigzag Gripper parts (Right).

The following Figure-4 showed the completed printed design and assembly of the Soft Origami Zigzag Gripper made from TPU. All these remove the need to fold and crease like the usual paper origami, with origami shapes pre-set during 3D printing.

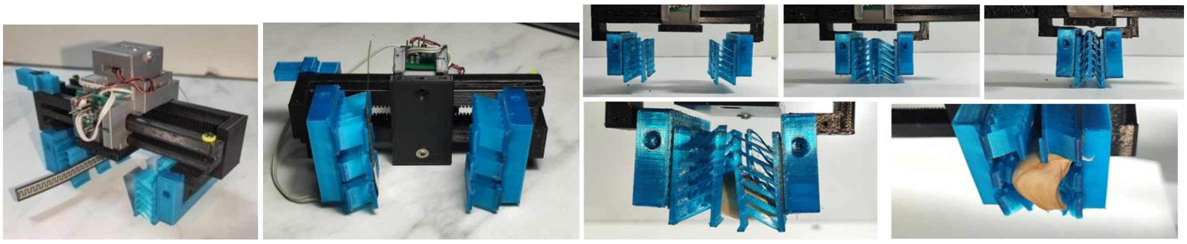

Figure-4. The Soft Origami Zigzag Gripper completed assembly with a DC servo motor as the actuator and the Soft Origami Zigzag Gripper with an object in a grasping position.

2.2 3D printed Robot Arm - Design and Assembly

A 3D Printed robot arm is designed in Autodesk Fusion360 and printed using the 3D printer Creality Ender 3 V2. This robot arm is built to cater to speed and higher precision and the ability to have multi-function grippers. This design used RC servo motors with higher torque and acceleration to help with the gripper design and evaluation and more test evaluation. The robot arm was designed and simulated based on a pelletizer parallelogram robot which has better load capacity on the gripper and is sturdier built due to counterbalance gravity torque from the parallel arm links, as shown in Figure-5. The robot arm was printed using PLA+ and PLA Brembo Filament.

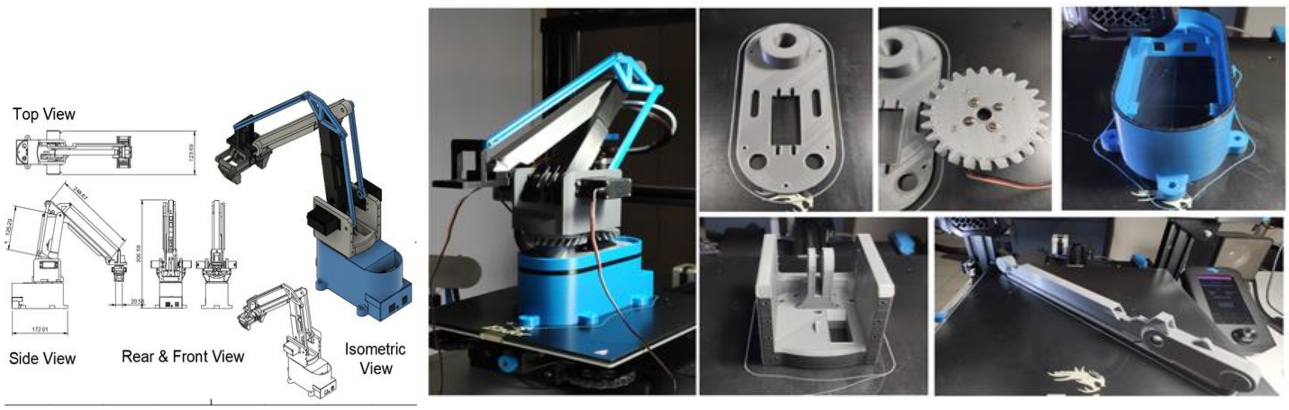

Figure-5. Self-designed 3D Printed Robot Arm.

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The equipment, materials, and software used are listed in Tables 2 and 3:

Table-2. The 3D printed robot arm's software and equipment.

Software	Equipment
Autodesk Fusion 360 (CAD STL design) Ultimaker Cura (3D Print Slicer) OctoPrint (3D Print Server) Arduino IDE	Creality Ender 3V2 3D Printer filament 1.75mm PLA, PLA+ and TPU 95A Arduino Uno, screws, and bolts.

Table-3. The 3D-printed robot arm has these specifications.

3D Printed Robot Arm Specifications	
Size	172 x 304 x 350 mm (max extension)
Weight	800g
Degrees of Freedom Joint	5+
Motor	Gearbox + Servo motor
Repeatability	$\pm$1cm
Sensor	6 Axis Mems Sensor
Payload	450g
Working Range	50-350mm
Max Speed	0.16s per 60 degrees (RC Servo angular speed)
Connection	USB
Motherboard	Arduino UNO R3
Power Adapter	Input 100-240v 50/60 Hz; Output 12v / 3a 30w
Working Temperature	0°C-40°C
End Effector	Multi Gripper Assembly: Soft Origami Zigzag Gripper or hard gripper

The parallelogram robot arm has a multifunction end effector which allows different gripper designs. We started with a simple hard gripper. The end effector has a carrier that allows any gripper designs. We can apply a soft origami zigzag gripper or hard gripper on the end effector for our studies.

We designed a hard gripper based on a parallel link gripper that will help to evaluate the performance of a hard conventional gripper versus the soft origami zigzag gripper, see Figure-6. The design was done in Autodesk Fusion360 and printed out on PLA+ which has high rigidity and accuracy.

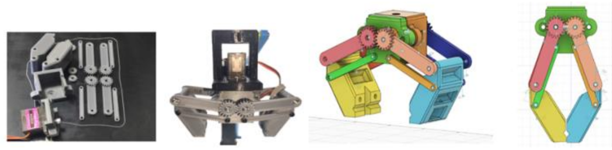

Figure-6. Autodesk Fusion360 Design of a parallel gripper (Left), the 3D printed multiple parts (Middle) and the completed assembly gripper (Right).

Software for the Robot arm on Arduino and Jupyterlab Notebook:

- The robot arm's Arduino UNO board with serial command g-code control.
- Using inverse kinematics for robot arm positioning in the X Y Z environment.
- Very convenient and simple robot arm gripper task control in Jupyterlab Notebook.

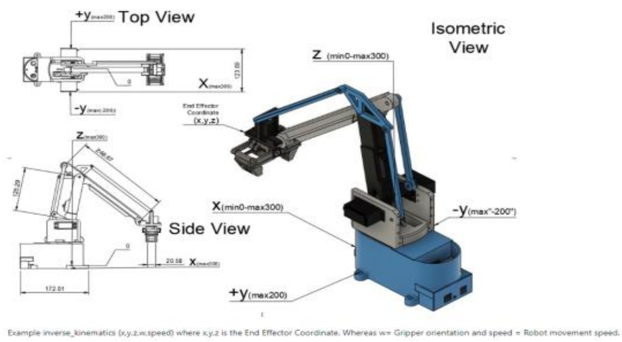

Figure-7. Inverse kinematics (X, Y, Z, W, Speed) where X, Y, Z is the end effector coordinate, whereas W = Gripper orientation and Speed = Robot movement speed.

2.3 Grasping Performance Evaluation

We have selected 10 objects with various types of surfaces, flexibility, shapes, weight, and volume as listed in Table-4.

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Table-4. List of objects for grasping performance evaluation.

No	Object	Object Characteristics			Weight (in grams)	Volume (in cm^3)	Density (in gcm^{-3})
		Surface	Texture	Shape			
1	Marble	Glass	rigid	Sphere	5	2.8	1.786
2	Sponge	Perforated	soft	Cuboid	3	135.52	0.022
3	Pen	Plastic	rigid	Cylinder	8	12.37	0.647
4	Cherry Tomato	Skin	soft	Ellipsoid	7	10.5	0.667
5	Egg	Grainy	rigid	Ellipsoid	61	60	1.017
6	Teddy bear	furry	soft	Uneven	9	55.90	0.161
7	Bun	Grainy	soft	Square	15	15	1.000
8	Garlic clove	skin	rigid	Crescent	4	0.3	13.333
9	French Fries	grainy	Soft	Cuboid	6	9.95	0.603
10	Lego axle	Smooth	rigid	Cylinder	1	0.1	10.000

The 3D-printed robot arm was controlled by Arduino UNO R3 and the PWM Servo controller. A six-axis MEMS sensor with Gyro and Acceleration at three axes X, Y, and Z were added right at the base of the gripper assembly to measure angular velocities that may affect the gripper and the object it was grabbing.

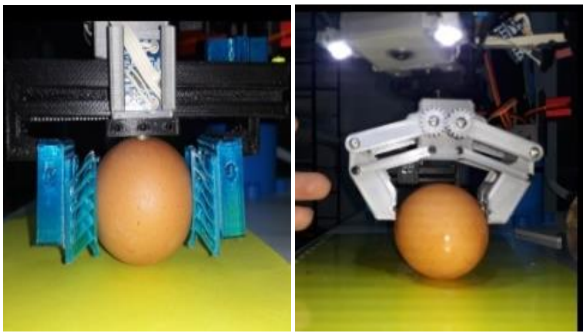

Figure-8. Grasping performance evaluation using two types of grippers: the Soft Origami Zigzag Gripper (left) and hard gripper (right)

The experimental evaluation focused on examining the following three motion characteristics:

a) Grasping performance in terms of object grasping against robot arm speed.

b) Grasping performance in terms of object grasping against gripping force.

c) Grasping performance in terms of object retention on the gripper during movement.

While the presented gripper can be attached to an articulated robotic arm for fully autonomous object grasping and manipulation, this evaluation focused on validating the effectiveness of the hard grasping objects with different sizes, shapes, and textures without sensor-based control. The gripper was moved by a robot arm to the target object and pre-programmed in opening and closing of the gripper and then subject to different angular velocities in 3D space, as shown in Figure-9. For the parallel gripper, an applied actuation of 85 is used to produce an average of 1.48N of gripping force throughout the whole procedure.

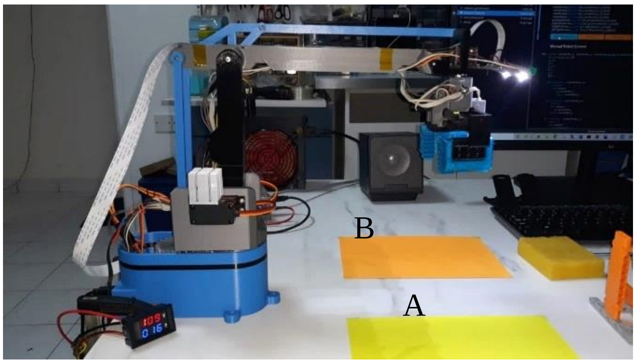

Figure-9. Grasping evaluation setup for both origami compliance zigzag soft gripper and parallel hard gripper

2.4 Artificial Intelligence - Object Classification for Upfront Grasping Awareness

Artificial intelligence (AI) gives robots computer vision to navigate sense and calculate their reaction accordingly. Soft origami zigzag gripper has built-in pressure sensors to determine the force exerted by the gripper, which is the gripping force. Once the object is identified, the robot arm can change the setting for the gripping force based on the object classification. The robot arm settings will change upon the object classification, including the changes in the gripping force, gripper positioning, and the robot arm speed. This allows a higher

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probability of grasping an object without damaging the object in contact. Combining AI with object classification will further enhance our soft origami zigzag gripper to be fully compliant. The AI object classification is completed using the two setups below:

A. Artificial intelligence object classification using Jetson Nano

Aim: Train and classify objects using Jetson Nano

Hardware: Nvidia Jetson Nano, 8Mp camera, computer, 3D Robot Arm, Soft Origami Zigzag Gripper

Software: Jupyterlab Notebook trained with convolution neural network (CNN) Resnet18 230x230 in Python

B. Artificial intelligence object classification using edge impulse

Aim: Train and classify objects using a smartphone and later deploy into Jetson Nano for object classification

Hardware: Computer and smartphone with a camera (for training) Nvidia Jetson Nano, 8Mp camera (for classification)

Software: Edge Impulse trained with MobileNetV2 96x96 0.35 and deploy model file EIM into Jetson Nano

3 RESULTS AND DISCUSSIONS

The robot grasping performance using the soft origami zigzag gripper and hard gripper is presented in Section 3.1. A logistic regression model is used to calculate the probability of grasping in Section 3.2 for both the soft origami zigzag gripper and hard gripper. Section 3.3 discussed artificial intelligence analysis using Jetson Nano AI CNN Resnet 18 and Edge Impulse MobileNetV2 respectively. The object classification for upfront grasping awareness using artificial intelligence is shown in Section 3.4.

3.1 Grasping Performance of Soft Origami Zigzag Gripper and Hard Gripper

Soft origami zigzag gripper exhibited an underactuated effect with zigzag with 3 gripping forces with just one actuation. Each gripping force has a significant compliant effect from the logarithmic decaying grasp force of (-0.05ln x) with 0.9873 R^2 from Figure-10 below:

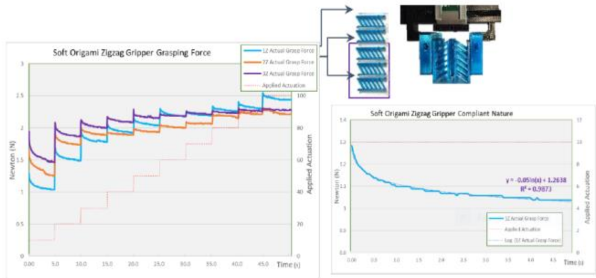

Figure-10. The grasping force of soft origami zigzag gripper is measured as applied actuation increases.

Hard gripper exhibits single gripping force with one actuation. Each gripping force has no compliant effect with 0 R^2 on logarithm decay from Figure-11 below:

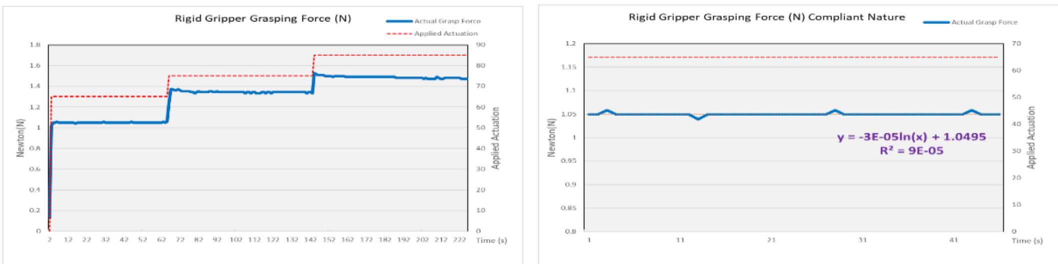

Figure-11. Grasping force of a hard gripper

The grasping performance between the soft origami zigzag gripper and hard gripper is collected from the 10 different objects with 10 attempts, as listed in Table-5:

Table-5. The grasping performance between the two grippers from the 300 collected data.

Grasping Performance	Mean	Variance
Soft Origami Zigzag Gripper	0.9333	0.0624
Hard Gripper	0.7667	0.1795

We used a paired *t*-test to compare the performance of the soft origami zigzag gripper and the hard gripper. Table-6 showed that H_0 is rejected as the *t*-Stat = 5.8692 > 1.6477 and the p-value is 1.37 x 10^{-6}. The paired *t*-test confirmed that the soft origami zigzag gripper has a better performance compared to the hard gripper.

Table-6. Paired t-test output.

Paired t-test Output			Alpha = 0.05	
	std err	*t*-stat	*p*-value	*t*-crit
One Tail	0.0284	5.8692	3.63E-09	1.6474

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3.2 Logistics Regression Analysis and Prediction

In this section, we showed logistic models that can be used to predict the grasping performance of the various objects for both the soft origami zigzag gripper and the hard gripper with the 3D robot arm.

A. Logistic regression for soft origami zigzag gripper

The *p*-values for the robot arm speed, gripping force, and weight are less than 0.05. The success rate of grasping using soft origami zigzag gripper is depending on the robot arm speed (*S*), gripping force (*F*), and weight (*W*) of the object based on the *p*-values in Table-7. Let $\hat{p}$ be the probability of grasping successfully.

Table-7. Logistic Regression data for Soft Origami Zigzag Gripper.

		# Iter	20		Alpha = 0.05		
	coeff	**s.e.**	**Wald**	**p-value**	**exp(b)**	**lower**	**upper**
intercept	-0.3075	0.6760	0.2069	0.6492	0.7353		
Robot Arm Speed, *S*	0.2104	0.0693	9.2135	0.0024	1.2341	1.0774	1.4137
Gripping force, *F*	0.1189	0.0299	15.793	7.07E-05	1.1263	1.0621	1.1944
Weight, *W*(g)	-0.0577	0.0132	19.013	1.3E-05	0.9439	0.9197	0.9687

Estimated logistic model (Log of Odds Ratio):

$$ln\left(\frac{\hat{p}}{1-\hat{p}}\right) = -0.3075 + 0.2104S + 0.1189F - 0.0577W$$

Estimated probability (predicted success rate probability):

$$\hat{p} = \frac{e^{(-0.3075+0.2104S+0.1189F-0.0577W)}}{e^{(-0.3075+0.2104S+0.1189F-0.0577W)}+1}$$

Table-8. Classification table of the logistic model with AUC = 0.91.

	Obs Suc	**Obs Fail**	**Total**
Pred Suc	278	16	294
Pred Fail	2	4	6
Total	280	20	300
Accuracy	0.9929	0.2	0.94

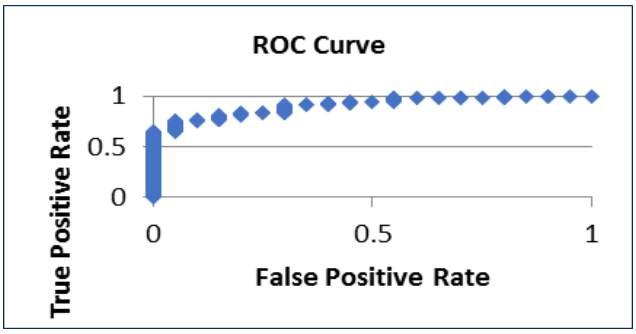

Figure-12. ROC curve of the logistics regression model (soft origami zigzag gripper).

The effectiveness of the prediction model is 0.940 (see Table-8) and the ROC curve is presented in are given, the logistic regression can be used to predict the success rate of object grasping with the soft origami zigzag gripper placed in the 3D printed robot arm.

B. Logistic regression for hard gripper

Table-9. Logistic regression data for the hard gripper.

		# Iter =20			Alpha = 0.05		
	coeff	**s.e.**	**Wald**	***p*-value**	**exp(b)**	**lower**	**upper**
intercept	1.8064	0.3050	35.0898	3.15E-09	6.0888		
Robot Arm Speed, S	0.0454	0.0338	1.8038	0.1793	1.0465	0.9793	1.1183
Weight, W(g)	-0.0792	0.0127	38.7150	4.9E-10	0.9239	0.9011	0.9472

The *p*-values for the robot arm speed, density, and contact coefficient are less than 0.05.

3.3 Estimating the Probability of Grasping by Using the Hard Gripper

The success rate of grasping using the parallel gripper is believed to depend on the robot arm speed (*S*), contact coefficient (*T*), and weight (*W*) of the object based on the *p*-values in Table-9.

Estimated logistic model (Log of Odds Ratio):

$$ln\left(\frac{\hat{p}}{1-\hat{p}}\right) = 1.8064 + 0.0454S - 0.0792W$$

Estimated probability (predicted success rate probability):

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$$\hat{p} = \frac{e^{(1.8064+0.0454S-0.0792W)}}{e^{(1.8064+0.0454S-0.0792W)}+1}$$

Table-10. Classification table of the logistic model with AUC = 0.6192.

	Obs Suc	**Obs Fail**	**Total**
Pred Suc	230	40	270
Pred Fail	0	30	30
Total	230	70	300
Accuracy	1	0.4286	0.8667

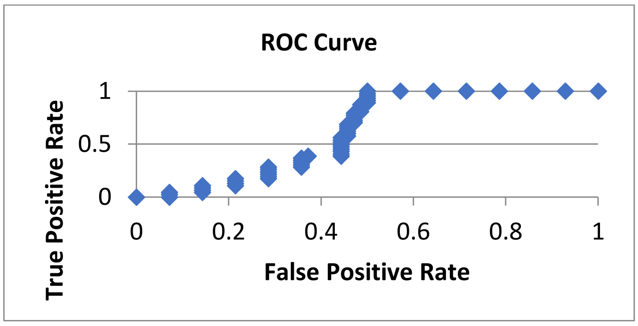


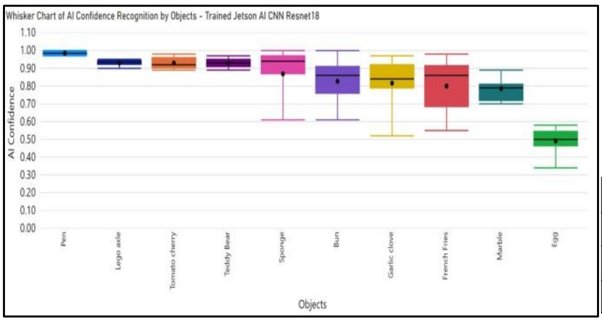
Figure-13. ROC curve of the logistics regression model (hard gripper).

The effectiveness of the prediction model is 0.8667 (see Table-10) and the ROC curve is shown in Figure-13. From the two prediction models for both grippers (soft origami zigzag gripper and hard gripper), we noticed that the prediction model for the soft origami zigzag gripper has higher accuracy as compared to the hard gripper.

3.4 Artificial Intelligence Analysis

3.4.1 Using Jetson Nano AI CNN Resnet 18

The image capturing for object classification training was performed on the cloud using external devices such as smartphones. This offloads the training computationally and allowed deployment remotely into Jetson Nano. This setup used the MobileNetV2 network as shown in Figure-14.



Source of Variation	SS	df	MS	F	P-value	F crit
Between groups	4.89	9	0.543	77.27	9.36E-72	1.91
Within groups	2.04	290	0.007			
Total	6.93	299				

	Suc-Obs	Fail-Obs
Suc-Pred	250	10
Fail-Pred	13	27

Figure-14. ANOVA showed the mean of object classifications is not equal, with the *p*-value 9.36E-72 < 0.05. AI adjusts gripping force, position & speed based on the object characteristics upon classification.

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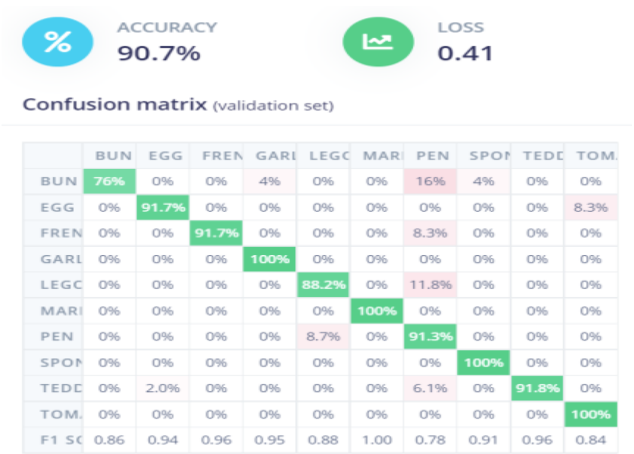
3.4.2 Using Edge Impulse MobileNetV2

The AI confidence recognition of various objects collected using a trained data set with Edge Impulse MobileNetV2 is presented in Figure-15.



	BUN	EGG	FREN	GARL	LEGC	MARI	PEN	SPON	TEDD	TOM.
BUN	76%	0%	0%	4%	0%	0%	16%	4%	0%	0%
EGG	0%	91.7%	0%	0%	0%	0%	0%	0%	0%	8.3%
FREN	0%	0%	91.7%	0%	0%	0%	8.3%	0%	0%	0%
GARL	0%	0%	0%	100%	0%	0%	0%	0%	0%	0%
LEGC	0%	0%	0%	0%	88.2%	0%	11.8%	0%	0%	0%
MARI	0%	0%	0%	0%	0%	100%	0%	0%	0%	0%
PEN	0%	0%	0%	0%	8.7%	0%	91.3%	0%	0%	0%
SPON	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%
TEDD	0%	2.0%	0%	0%	0%	0%	6.1%	0%	91.8%	0%
TOM.	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
F1 SC	0.86	0.94	0.96	0.95	0.88	1.00	0.78	0.91	0.96	0.84

Figure-15. Confusion matrix of edge impulse.

3.4.3 Summary

The AI confidence recognition of various objects was collected using a trained data set with Jetson Nano. ANOVA showed that the mean of object classifications was not equal, with the *p*-value 9.36E-72 < 0.05. Jetson Nano running AI CNN Resnet18 enhanced grasping performance with vision object classification and achieved an accuracy of 0.923 and an F1 score of 0.956.

AI confidence recognition of various objects collected using a trained data set with Edge Impulse MobileNetV2. Machine learning with an auto-tuner was used in various AI models to find the best inference time and accuracy. Edge Impulse Mobile Net V2 with vision object classification achieved an accuracy of 0.907 and an F1 score of 0.908.

We acquired at least 450 images from the Jetson Nano camera and smartphone on 10 objects. We trained object classification in the Edge Impulse cloud and deployed the neural network model.EIM into Jetson Nano. The average inference time was 10-20ms per image classification. This allowed upfront gripper actuation awareness in object grasping.

3.5 Object Classification for Upfront Grasping Awareness using Artificial Intelligence

Object classification using artificial intelligence-optimized robot grasping. Once the object was identified, the settings of the 3D robot arm were changed to cater to various objects before the 3D robot arm performed the pick-and-place operations. The settings of the 3D robot arm include the robot arm speed, position of the gripper, and gripping force, see Figure-16.

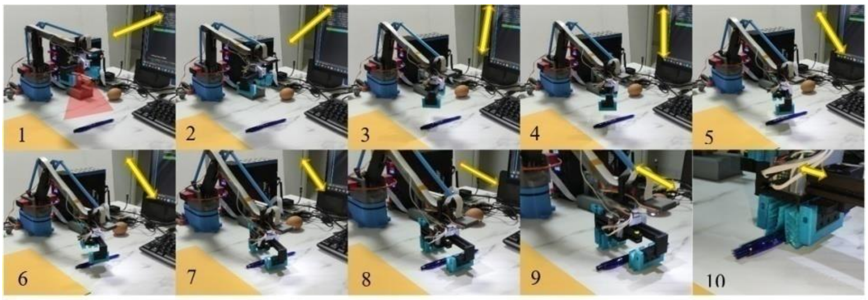


Figure-16. Upfront Awareness Gripping positioning based on AI Object classification. AI Camera classifies the object as a pen and a hard object. It will reorientate the gripper based on the object before gripping. Yellow arrows showing gripper orientation.

4. CONCLUSIONS

In this project, we developed a 3D print-in-place under-actuated soft origami zigzag gripper using TPU with artificial intelligence object pose estimation to grasp objects with high repeatability of success under different conditions. A self-designed 3D robot arm is used for object grasping. Grasping performance tests were conducted using different gripper designs, and robot arm speed on objects with different mass and morphology. The soft origami zigzag gripper has better-grasping performance than the hard gripper as analyzed by paired *t*-test. The logistic model of the soft origami zigzag gripper's grasping performance achieved an accuracy of 0.940 and AUC=0.911. Jetson Nano running AI CNN Resnet18 enhanced grasping performance with vision object classification and achieved an accuracy of 0.923 and F1 score of 0.9. The AI CNN MobileNetV2 is used for object classification and experimental results showed it had lower accuracy as compared to the AI CNN Resnet18. The object classification using artificial intelligence optimized the robot grasping performance by providing it with upfront actuator awareness.

By combining soft origami design, 3D print-in-place technology, and artificial intelligence, we developed a compliant, easy-to-assemble robotic gripper with object classification capability to improve automation in food processing, and food handling and to avoid contamination. This soft origami zigzag gripper can serve as a reference for the future development of other 3D print-in-place gripper designs in the quest of producing more affordable robotic grippers.

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