# Interaction Identification of a Soft Gripper Using LSTM Machine Learning Model

# 1. Introduction

## 1.1 Overview

The advancement in robotic grippers has led to the development of soft grippers that mimic the flexibility and adaptability of the human hand. This project involves a soft gripper with three soft fingers, which are actuated by cables. The objective is to train a machine learning model, specifically a Long Short-Term Memory (LSTM) network, to identify the interaction between the gripper fingers and objects, distinguishing between hard and soft objects.

## 1.2 Objectives

- To develop a soft gripper capable of safely handling objects of varying hardness.

- To train an LSTM model to classify objects as hard or soft based on interaction data.

## 1.3 Motivation

The primary motivation behind this study is to ensure safe interactions between the gripper and objects, particularly delicate materials that require a compliant gripper. Identifying the hardness or softness of an object is crucial for safe gripping.

# 2. Materials and Methods

## 2.1 Experimental Setup

The gripper comprises three soft fingers, each actuated by a cable. The cable is connected at one end to the top of the finger and passes through it, with the other end connected to a pulley. The pulleys are driven by a single motor via a bevel gear, ensuring equal torque distribution and simultaneous bending of the fingers when the motor is activated.

## 2.2 Sensors and Actuators

- Actuators: The soft fingers are actuated using cables and a motor with a bevel gear system.

- Sensors: Piezoelectric sensors are mounted at the tips of the fingers to collect interaction data. These sensors are chosen for their ability to accurately capture force and pressure variations during interactions with objects.

## 2.3 Data Collection

Data is collected from the piezoelectric sensors as the fingers interact with various objects. The objects used for data collection include glass bottles, steel water bottles, coffee mugs, sponge smileys, oranges, cloth balls, foam, very soft sponge balls, and 3D-printed objects. For each object, ten gripping experiments are conducted, with each experiment involving ten interactions. The data for all interactions is collected in real-time using Arduino Uno with Python at a baud rate of 250000.

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| A close-up of a graph  Description automatically generated |
| Fig 1. Fingertip interaction data with Hard surface. It shows larger peak with high frequency oscillation. |

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| A graph showing the different types of sensor  Description automatically generated |
| Fig 2. The combination of three fingers interaction data with hard for same interaction |

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| A close-up of a graph  Description automatically generated |
| Fig 3. Fingertip interaction data with soft surface. It shows smaller peak with lower frequency oscillation. |

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| A graph showing the number of sensors  Description automatically generated |
| Fig 3. The combination of three fingers interaction data with soft object for same interaction |

## 2.4 Data Processing and Model Training

The collected data is refined and classified to train the LSTM model. The data is labeled, with '0' representing soft objects and '1' representing hard objects. The LSTM network is implemented using the Keras library in Python. The model is trained to predict the classification of objects based on the time series data from the piezoelectric sensors.

## 2.5 Testing and Validation

The trained model is tested with new interaction data to evaluate its performance. The model achieved a prediction accuracy of 99%, demonstrating its effectiveness in distinguishing between hard and soft objects.

# 3. Results

## 3.1 Data Analysis

The data collected from the piezoelectric sensors showed distinct patterns for hard and soft objects. The LSTM model successfully learned these patterns and was able to accurately classify new interaction data.

## 3.2 Model Performance

The LSTM model was tested with new interaction data and achieved a 99% accuracy rate in classifying objects as hard or soft. This high accuracy rate indicates the model's robustness and reliability in real-world applications.

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| Fig 4. The result of prediction |

# 4. Conclusion

## 4.1 Summary of Findings

The study successfully developed a soft gripper capable of distinguishing between hard and soft objects using an LSTM machine learning model. The model achieved high accuracy in classifying objects, ensuring safe and effective gripping.

## 4.2 Future Work

Future work could involve improving the gripper design for better performance and exploring other machine learning models to further enhance accuracy. Additionally, testing the gripper with a wider variety of objects and conditions would help generalize the model for broader applications. Furthermore, applying transfer learning techniques to adapt the trained model for other types of grippers could be explored. Training the model to classify a range of soft and hard interactions, rather than just binary classification, would also be beneficial for more nuanced gripper control and object handling.

## All Resources:

All data and codes are available on [GitHub Repository](https://github.com/FirdausAcademic/IN-792-Making-Soft-Gripper-Smart.git)