Sensing a Physical Object Gripping using Haptic Technology and Machine Learning Algorithms

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Abstract: This study describes a new method for gripping and sensing a physical object (or material) with a prosthetic arm that uses haptic technologies, kinaesthetic communication, and machine learning. Haptic technology is a method of determining if an object is firm or soft as if it were gripped by a human and determining how much gripping force the object can withstand without crushing it. The bending moment and gripping force are measured using a flex sensor in human fingers and a pressure sensor applied by the tip of the human fingers. Three different types of objects (soft sponge, hard sponge, and plastic) are studied and tested in this work by pressing them with varying gripping pressures (soft, firm, and firmer). In addition, a model (Haptic Intelligence Recorder arm) is proposed that can anticipate the object type and gripping force based on the recorded intelligence data. The major goal is to educate our prosthetic hand to be able to grip various items with varying finger pressures, much like we can do naturally. Finally, a glove is created that is tailored to the intelligence arm's ability to anticipate grabbing items.

Keywords: Haptic technology, intelligent recorder arm, flex sensor, pressure sensor, machine learning.

1. Introduction

The science of using touch (tactile sense) to control and interact with computer programs is known as haptics. Haptical Technology, often known as haptics, is a type of feedback that uses the sense of touch to deliver forces, vibrations, and motion to the user. It can primarily sense and modify computer-generated worlds through touch. In the topic of haptics, there is currently a lot of study going on. Sensing items with robotic hands is doable using current feedback technology. A robotic arm's inability to anticipate the firmness of a substance when grasping it can result in the mutilation of delicate things by applying too much pressure. Furthermore, if the robotic hand is much larger than the thing it was intended to grip, the new object may be crushed under its weight, or the motors controlling the finger movements may be destroyed as a result of the stalled position. In the event of smaller things, the hand will not be able to secure a firm grip. These can cause the apparatus to be damaged or shorten its or the product's life. A Haptic Intelligence Arm is fitted with a flex sensor or bend sensor that measures the amount of deflection or bending to overcome all these problems.

In this paper, an artificial arm (Haptic Intelligence Recorder arm) is explored and trained to grip various items with varying finger pressures as if it were a person. Three different types of objects (such as a soft sponge, a hard sponge, and a plastic one) are considered and pressed on by different gripping forces (soft, firm, and firmer gripping), and the data is collected using sensors and fed into various machine learning algorithms to predict the gripping and bending forces applied by the specific object. Using the bend of the fingers as the independent variable and the force exerted as the dependent variable, the characteristics of the obtained data indicate a zone beyond which a material can be destroyed due to excessive application of pressure. For training and testing, a dataset is prepared and split 70:30. The major goal of this paper is to forecast how to grab different objects using different gripping strengths and finger bending. Flex sensors are important because the robotic arm cannot anticipate the material's stiffness, causing fragile objects to be mangled when too much pressure is applied. A gripping mechanism embedded within the usage of computer vision or dimension parameters that are fed into the system to hold on to specific items

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can be used to forecast the object in this study. Finally, several machine learning methods are used to assess its performance. As a result, the findings are compared within the datasets we generated, and all of them attain over 99 percent accuracy. A glove is being developed that will allow the haptic intelligence arm to anticipate grabbing objects.

This section introduces our research work and its goal. The remainder of the paper is structured as follows: The related work is discussed in part 2, and the dataset preparation is described in section 3, which is divided into two subsections. The first part of section 3 explains how the dataset was created by the robotic arm (Haptic intelligence recorder arm) to predict how to grip the object, and the second part explains how the dataset was analyzed by comparing the performance of various standard machine learning algorithms on the dataset. In section 4, we illustrate how a machine learning algorithm may anticipate an item, and in section 5, we have a critical debate to evaluate the performance of our work, followed by a conclusion in section 6.

2. Related work

Fingertip forces are used in a variety of everyday activities. The robotic arm's grip strength (the ability to exert a fingertip force) physically interacts with the surroundings, which is linked to improved quality of life (Weiner et al., 2018). Intelligent physical interactions with the environment are taking place by combining grip strength with a sophisticated touch sense (Cheng et al., 2017; Raspopovic 2014). Nonetheless, if the tactile sense is absent despite visual guidance, the work will be tough. To do this, technologies that study or develop tactile sensors must be used to duplicate the feeling of touch in artificial systems such as robotic and prosthetic hands (Quigley et al., 2014; Saudabayev et al., 2015; Jamali et al., 2015). For the control of artificial hands, force sensing is critical in comprehending the interaction between a mechanical hand and its environment. Joint angle sensors offer information about the shape of a grabbed object, temperature sensors measure the object's thermal conductivity, accelerometers detect slide, and distance sensors detect the presence of an object (Wottawa et al., 2016; McKinley et al., 2015).

Commercially accessible sensors sense the electronics and electric connections of the complicated mechanical structure of an artificial hand and its fingers when robotic and prosthetic hands are integrated into multi-modal sensor technologies (Yun et al., 2017; Polygerinos et al., 2015). Commercially available digital three-axis Hall effect sensors are used by the authors to measure forces through the displacement of a magnet embedded in flexible material (Bianchi et al., 2018). The authors (Conti et al., 2016) used a modular sensor to monitor the elastic deformation of the finger structure caused by applied forces. Natural tactile force sensors are created using a small barometric pressure sensor (Kang et al. 2019). For the artificial intelligence system for health monitor application and control, various sorts of sensor operations are shown (Wu et al., 2019). Although much effort has gone into developing a prosthetic arm that detects object by analyzing the image of the object (Zhao et al., 2016; Wang et al., 2021). However, the intelligent arm and sensor application are integrated here, and the intelligent arm detects the object using the sensor application. To predict the object, the proposed Haptic Intelligent Arm, flex sensor, and pressure sensor are integrated.

3. Dataset preparation

3.1. Data collection

We created an innovative device to collect data and generate a dataset linked to haptic technology gripping of various things. The prototype's major goal is to identify objects with varying gripping forces and finger bending movements, as well as vice versa, so it can quickly determine what type of object it is when gripping force is applied. There are several limits in sensing items using haptic technology of a robot until now. However, this proposed prototype (Haptic Intelligence Recorder arm) could be used in robots to overcome these obstacles. The prototype consists of a heavy-duty glove with two types of sensors for fitting into the human arm.

Each finger has a four-inch flex sensor attached to the back, which is used to measure the deflection or bending of the fingers. The resistance in the sensors is related to the angle at which the finger bends. Flex sensors have a resistance range of 14 to 40 kohm, but this varies from sensor to sensor due to inconsistency. The force of repulsion applied by the human arm to the piezo-electric force is recorded using fingertip sensors, whose resistance is inversely proportional to the force applied. Their resistance ranges from 1 Mohm to 16 kohm, but it is highly variable. Because piezo-electric force sensors are flat and can readily retain items, they are utilized on the fingertips instead of transducers. All the sensors are connected to an Arduino mega board through a potential divider circuit, which converts resistance changes into voltage changes that the Arduino board can read. The data from the sensors is read using a very basic code on the Arduino board, and the results are recorded in a spreadsheet using Tera Term software. We intend to apply reinforcement learning to test the feasibility of the concept in the first step. To do so, we took readings from flex sensors and force sensors attached to objects of varying tensile strength, as well as categorizing the pressure we applied into three categories: mild, hard, and firmer. As illustrated in Figures 1a and 1b, the flex sensors are located on the backside of the robot arm, while the pressure sensors are located on the frontside.

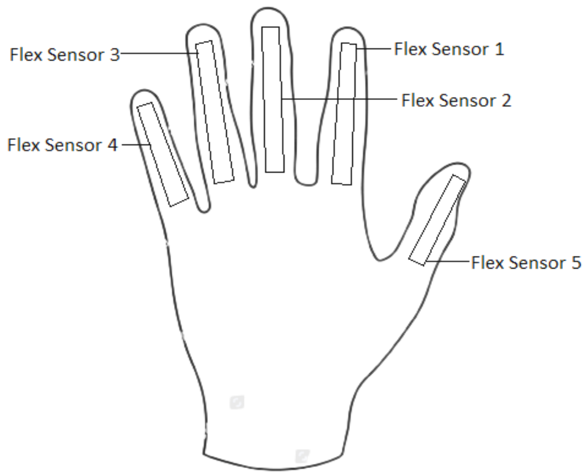


Figure 1a. Pictorial representation of the Robot Arm (Back side)

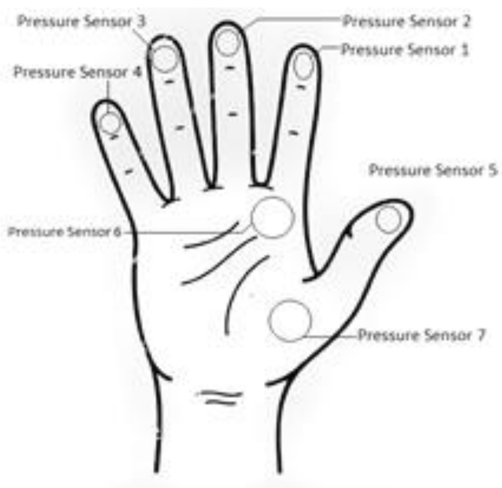


Figure 1b. Graphic representation of the Robot Arm (Front side)

The flowchart of the data collection is shown in Figure 2.

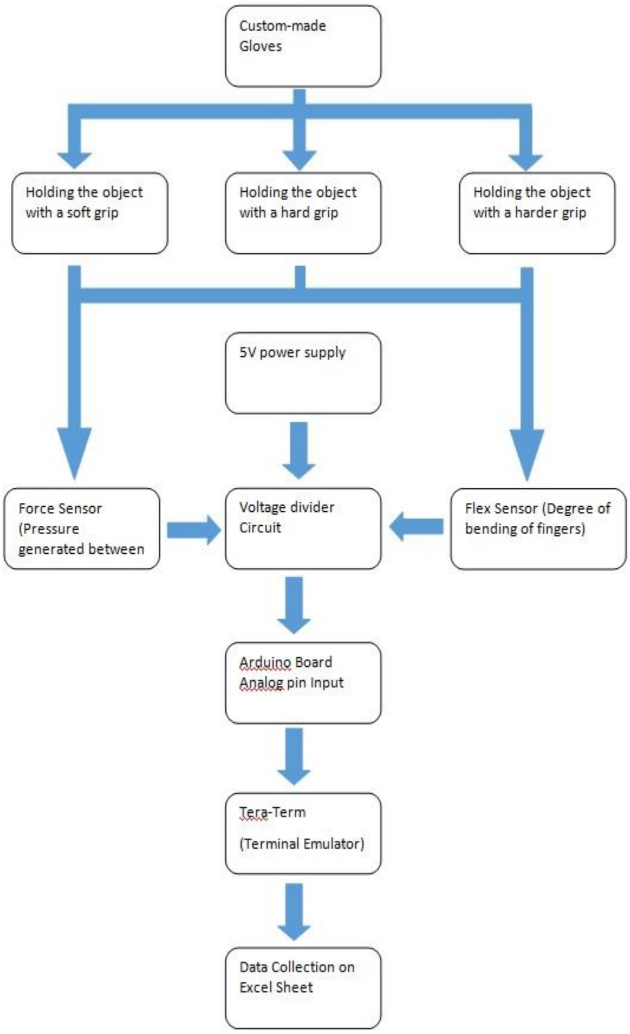


Figure 2. Flowchart of the prototype implementation

3.2. Data analysis

We built a dataset for three various sorts of objects: 'soft sponge,' 'hard sponge,' and 'harder plastic,' all of which have varied gripping forces such as soft, firm, and firmer. Various objects and gripping forces are divided into nine categories: soft-soft, soft-hard, soft-harder, hard-soft, hard-hard, hard-harder, and harder-soft, harder-hard, harder-harder. We looked at a total of 15352 samples in the dataset, which had 10 features and 9 categories. There is a big difference between soft, firm, and firmer grip when considering flex sensors with soft ball. There is a significant difference in grip between soft and firm for hard balls, but not between hard and harder. Finally, there is no discernible difference between soft, firm, and firmer grips for the harder ball. Similarly, there is no substantial difference (where the pressure reading is practically the same) between soft, firm, and firmer grip when using a pressure sensor with a soft ball. There is a difference in pressure value between soft and hard grip for hard balls, but not between hard and harder grip. Finally, there is a substantial difference between soft, firm, and firmer grip for harder balls. The goal of this data analysis is to figure out how the flex sensor resistivity rises when the sensor bends further, reducing current flow through the sensor. When too much pressure is applied, however, the resistivity of the pressure sensor drops, causing current flow through the sensor to increase. The hypothesis is tested using the dataset, although some results vary due to factors such as circuit current loss, analog sensors that are not properly calibrated, and the varying strength of the human grasp during the experiment.

The dataset we developed has 15352 samples with 10 features specified in the previous sections and 9 categories. Figure 3 depicts the categorical distribution of samples across the dataset, with the 'HARD-HARD' category having the most samples at 2217 and the 'HARD-SOFT' category having the fewest at 1285.

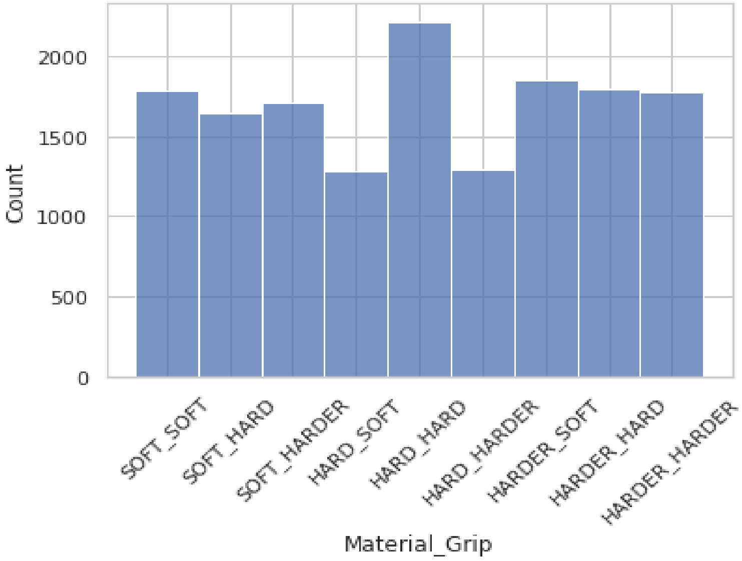


Figure 3. Distribution of samples taken for all the categories

The figures below illustrate some exploratory data analysis (EDA) on the dataset we created to gain a sense of the distribution of the features' values.

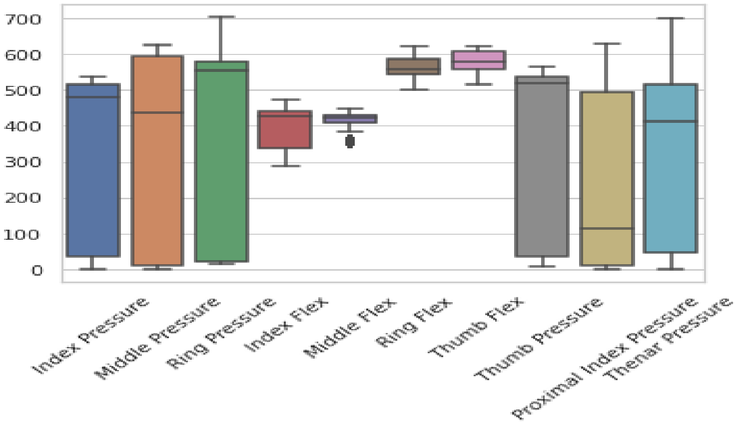


Figure 4. Distribution of range of features' values in the dataset

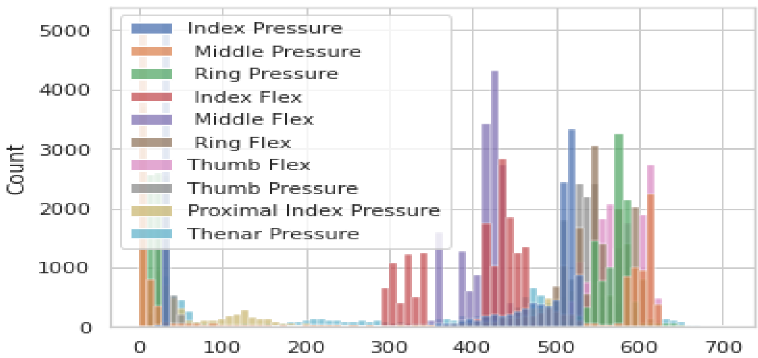


Figure 5. Categorical data distribution of the features' values in the dataset

4. Classification and prediction using machine learning algorithm

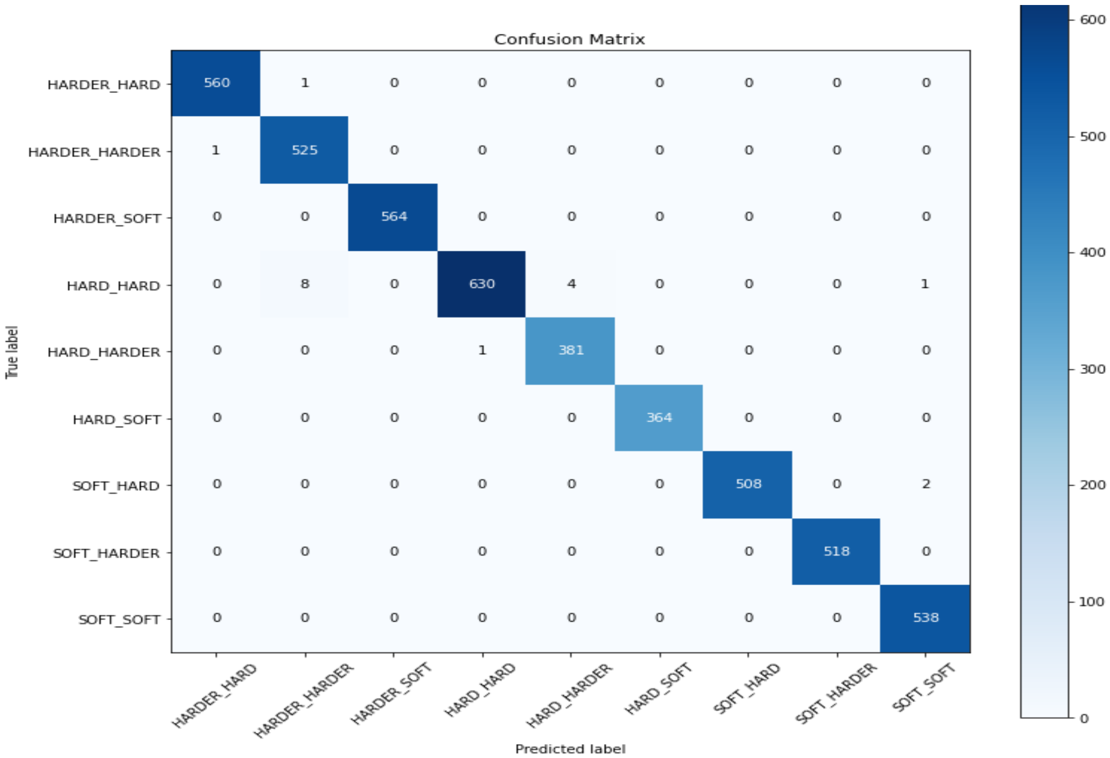
The dataset we developed is then put to the test with six well-known machine learning methods (Huang et al., 2003; Williams et al., 2006) that are discussed in the following sections. The dataset was split 70:30 into a train and test set. We tested the effectiveness and accuracy of all six well-known machine learning methods on the dataset. We used 'Logistic Regression' (LR) (Osisanwo et al., 2017), 'Linear Discriminant Analysis' (LDA), 'K-nearest neighbors' (KNN) (Loh et al., 2011), 'Decision Tree' (DT), 'Naive Bayes' (NB), and 'Support Vector Machine' (SVM) (Breiman et al., 1984; Zhang et al., 2005; Schein et al., 2007) on our dataset with 10-k cross-validation techniques and achieved 99% to 100% accuracy.

The final accuracy of the algorithms is shown in Table 1. Table 2 illustrates the dataset's confusion matrix using the LR technique. On the dataset, Table 3 displays the precision and recall for the same LR method. NB performs flawlessly in the classification job, demonstrating the range of variance present in the dataset we created. The data is well recorded and evenly distributed over the dataset employing haptic technology-based sensors. The dataset is publicly available at (GitHub, n.d.) for further research.

Table 1. Various classification models and their accuracy

Algorithms	LR	LDA	KNN	DT	NB	SVM
Accuracy (%)	99.6	99.8	99.9	99.7	100	99.9

Table 2. Confusion matrix for LR algorithm



True label \ Predicted label	HARDER_HARD	HARDER_HARDER	HARDER_SOFT	HARD_HARD	HARD_HARDER	HARD_SOFT	SOFT_HARD	SOFT_HARDER	SOFT_SOFT
HARDER_HARD	560	1	0	0	0	0	0	0	0
HARDER_HARDER	1	525	0	0	0	0	0	0	0
HARDER_SOFT	0	0	564	0	0	0	0	0	0
HARD_HARD	0	8	0	630	4	0	0	0	1
HARD_HARDER	0	0	0	1	381	0	0	0	0
HARD_SOFT	0	0	0	0	0	364	0	0	0
SOFT_HARD	0	0	0	0	0	0	508	0	2
SOFT_HARDER	0	0	0	0	0	0	0	518	0
SOFT_SOFT	0	0	0	0	0	0	0	0	538

Table 3 shows the table of Sensitivity (Recall) and Precision for the Logistic Regression (LR) algorithm, and Table-2 shows the confusion matrix. It tends to be NOT CLEAR, REPHRASE PLEASE! comparative information as given in Table - 2 and Table - 3 for other 5 algorithms ('Linear Discriminant Analysis' (LDA), 'K-closest neighbors' (KNN), 'Choice Tree' (DT), 'Credulous Bayes' (NB), and 'Backing Vector Machine' (SVM)).

Table 3. Precision and recall for the LR algorithm

Category	Precision	Recall
SOFT_SOFT	0.99	1.00
SOFT_HARDER	1.00	1.00
SOFT_HARD	1.00	1.00
HARD_SOFT	1.00	1.00
HARD_HARDER	0.99	1.00
HARD_HARD	1.00	0.98
HARDER_SOFT	1.00	1.00
HARDER_HARDER	0.98	1.00
HARDER_HARD	1.00	1.00

5. Design and discussion of prototype

We created a dexterous prosthetic arm with a rounded shape and profile that provides the hand a natural appearance, especially when covered with the lifelike silicone skins illustrated in Figure 6. The robotic hand can perform daily tasks like eating, carrying bags, opening doors, turning on lights, and typing. The dexterous control feedback system for grabbing items is created by placing flex sensors on the fingers inside the palm. The pressure force sensor meets the object as the fingers grab it with full dexterity, and after receiving data, the servo motor begins its operation, and the feedback loop begins. The servo motor continues to work after detecting the object until the pressure sensor reaches the optimal level. If the object begins to flex, the feedback is delivered to stop the servo motor's grabbing mechanism and decides to position the object in the desired location. Figure 7 shows a block diagram of the prosthetic arm.

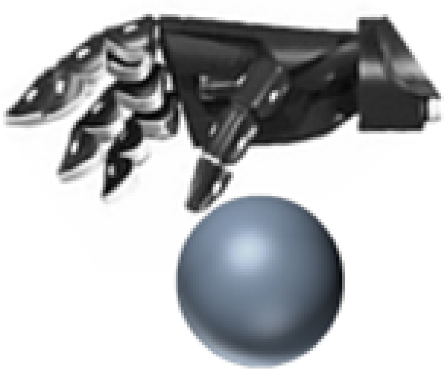


Figure 6. Design of prosthetic arm

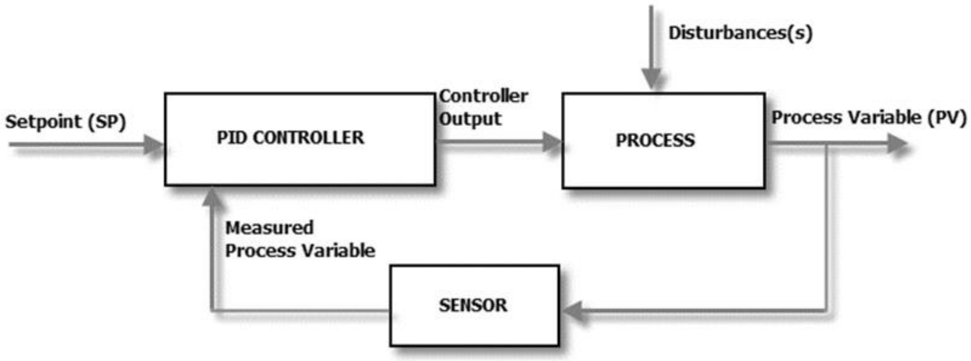


Figure 7. Block diagram representation of the function of arm

The hand glove for the prosthetic arm (shown in Figure 8) is already designed and used for handling real-life objects. The force sensor exerts pressure to the object to keep it firmly in place, and the flex sensor provides the appropriate degree of finger flexion while holding the object (see Figure 8). Objects used in daily life such as a marker pen, television remote, duster, water bottle, and smartphone are called holding objects. We've already generated a gripping dataset for four distinct types of objects, which we may use for future projects.

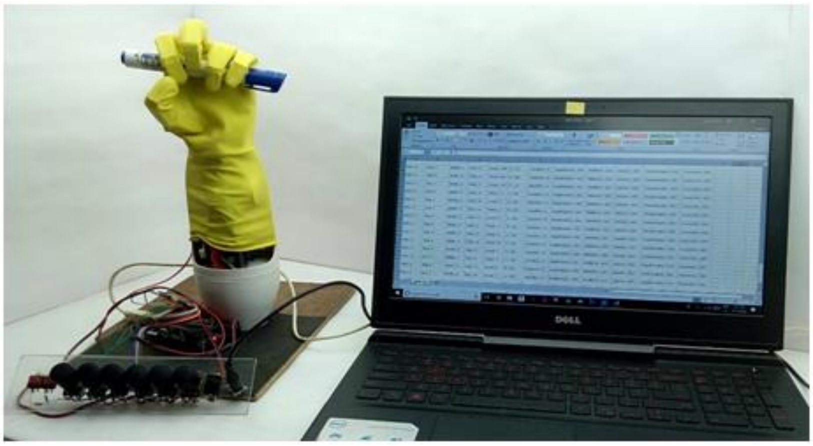


Figure 8. Prosthetic Arm Holding Marker Pen Showing Pressure and Flexion Values

6. Conclusion

By tracking the recorded data and applying various machine learning methods for prediction, we can anticipate the physical object type and the corresponding gripping in this study. An alternate solution to this challenge is to give the robotic arm a sense of touch instead of fingers so that it can learn to feel the object and calculate/predict its size and rigidity. In the future, the same approach might be applied to a prosthetic hand that grips an object with varying degrees of pressure to determine how much gripping force to apply. Furthermore, neural networking allows machine learning to recognize and classify distinct objects.

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