Actuator Selection using SVMs and Neural Networks

Nomenclature

SVM: Support Vector Machines

NN: Neural Network

GANN: Generative Adversarial Neural Network

Introduction

Soft Actuators are artificial muscles which are used to provide different motion capabilities using self deformation.

Problem: Classify actuators suitable for a specific working parameter/use case.

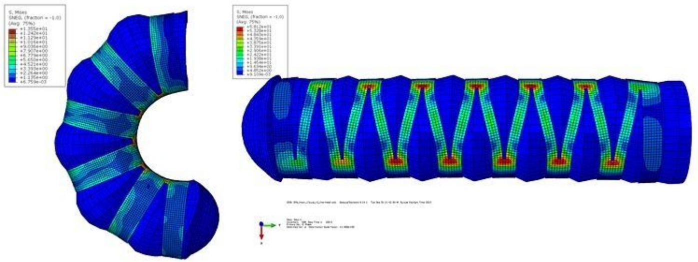
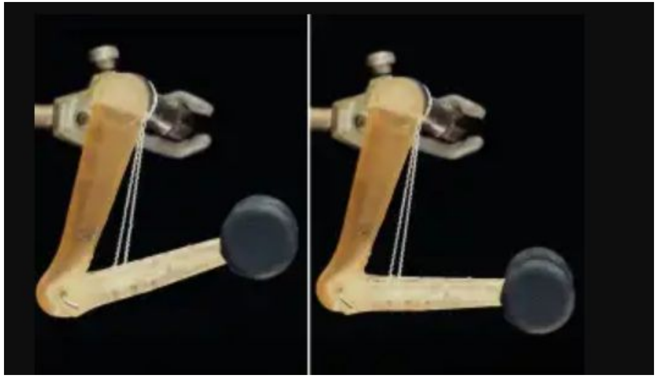


Fig. 1 Soft Pneumatic Actuator | Soft Robotics Toolkit



As biological muscles are for animals, artificial muscles are for robots.

Dataset

- There are seven types of muscle actuators : PZT, DEA, IPMC, SMA, SFA, SCP, TSA.
- Five physical properties : Bandwidth, Strain, Stress, Efficiency, Power Density.

Reference	Actuator T	Bandwidth	Strain (%)	Stress (MP	Efficiency	Power Density (W/g)
[1]	PZT	10000	0.2	110	90	0.2
	PZT	100			90	
	DEA	100	200	8	85	0.2
	IPMC	10	40	0.3		0.02
	SMA	3	5	200	1.3	50
	SMA	0.5	250	2	10	0.03
	SFA	130	50	10	30	11
	SFA	100	300		30	22
	SFA				30	10
	TSA	5	50	80	76	0.5
	SCP	3	49	11	1.02	27
[2]	SMA	3	10	200	3	4.3
	PZT	5000	0.2	35	50	

SVM Confidence Scores

If more than 1 model can be used; i.e. 3/5 features are available [a, b, c], then we need to select the better model:
a+b or a+c or b+c: Confidence score maps the performance of the models, giving the more reliable model for selection.

Classifier

Label

```
[  3   3   0   2  13  13   8  14   5   6]
[ 10   3   0   7  12  12   7  12   4   0]
[  0   0   0   0   0   3   0   3   0   4]
[  9   8   8   0 188  13  10  12   6  10]
[  2   0   4   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   6   0   0   0]
[  0   4   1   1   0   1   8   0   8   0]
[  0   0   0   0   0   0   0   0   0   0]
```

Predicted

Classifier

Label

```
[  3   3   3   2  18  15   9  16   9   9]
[ 11   6   3   7  15  13  10  12   8   5]
[  3   2   1   2  11   6   3   5   4   4]
[ 11  10   8   3 194  14  12  13   9  12]
[  6   3   4   2   6   6   7   2   5   4]
[  2   2   1   1   1   1   1   1   1   1]
[  2   2   1   1   5   4   9   1   2   4]
[  8   7   3   4  24  10  11   9  12   5]
[  0   0   0   0  26   0   0   0   0   0]
```

Actual

Accuracies

```
[0.522 0.514 0.542 0.455 0.71  0.609 0.629 0.695 0.46  0.455]
```

```
[0.43, 0.38, 0.12, 0.44, 0.07, 0.  , 0.04, 0.15, 0.  ]
```

Confidence

SVM Code: SVM architecture: Scikit Learn

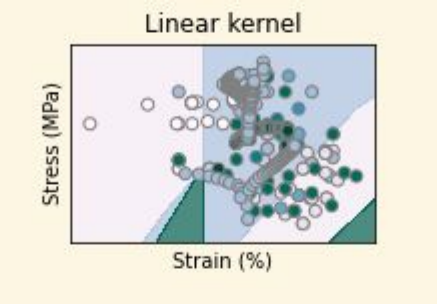
```
data = pd.read_csv("data/original_data.csv")
cols = list(data)[2:]
column_pairs = []
for i in range(len(cols)):
    for j in range(len(cols)):
        if i<j:
            column_pairs.append((cols[i],cols[j]))
accuracies = []
kernels = ['linear', 'poly', 'rbf', 'sigmoid']
for j in range(len(kernels)):
    print("Kernel = {}".format(kernels[j]))
    accuracies.append([])
    for i in range(len(column_pairs)):
        column1,column2 = column_pairs[i]
        X,y = Functions.data_clean(data, column1, column2)
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
        svc = SVC(C=0.1, random_state=1, kernel=kernels[j], degree= 3)
        svc.fit(X_train, y_train)
        y_predict = svc.predict(X_test)
        accuracies[j].append(np.round(metrics.accuracy_score(y_test, y_predict),3))
        print("Accuracy of Pair - {} and {} = {}".format(column_pairs[i][0],column_pairs[i][1],accuracies[j][i]))
    print()

```

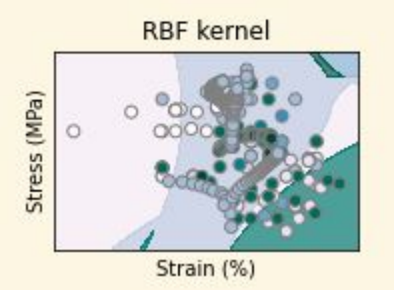
SVM Code: PlotMultilabel Boundaries

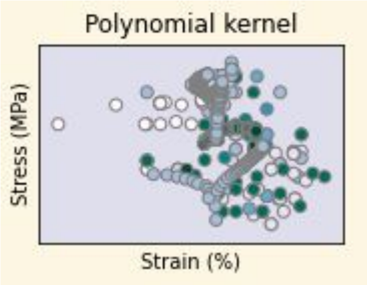
```
def plot_multilabel_boundary(X,y,linear, rbf, poly, sig,column1,column2):
    h = .01
    x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
    y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h),np.arange(y_min, y_max, h))
    titles = ['Linear kernel','RBF kernel','Polynomial kernel','Sigmoid kernel']

    for i, clf in enumerate((linear, rbf, poly, sig)):
        plt.subplot(2, 2, i + 1)
        #plt.subplots_adjust(wspace=0.1, hspace=0.1)
        Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
        y_map = {'PZT':0, 'DEA':1, 'IPMC':2, 'SMA':3, 'SFA':4, 'TSA':5, 'SCP':6, 'EAP':7, 'SMP':8}
        for j in range(len(Z)):
            Z[j] = y_map[Z[j]]
        Z = Z.reshape(xx.shape)
        plt.contourf(xx, yy, Z, cmap=plt.cm.PuBuGn, alpha=0.7)
        plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.PuBuGn,     edgecolors='grey')
        plt.xlabel(column1)
        plt.ylabel(column2)
        plt.xlim(xx.min(), xx.max())
        plt.ylim(yy.min(), yy.max())
        plt.xticks(())
        plt.yticks(())
        plt.title(titles[i])
        plt.show()
```

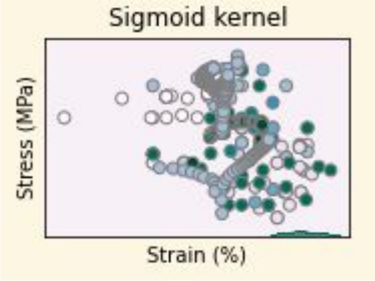
SVM output

Bivariate model accuracies










```
Output exceeds the size limit. Open the full output data in a text editor
Kernel = linear
Accuracy of Pair - Bandwidth (Hz) and Strain (%) = 0.5
Accuracy of Pair - Bandwidth (Hz) and Stress (MPa) = 0.333
Accuracy of Pair - Bandwidth (Hz) and Efficiency (%) = 0.167
Accuracy of Pair - Bandwidth (Hz) and Power Density (W/g) = 0.167
Accuracy of Pair - Strain (%) and Stress (MPa) = 0.697
Accuracy of Pair - Strain (%) and Efficiency (%) = 0.722
Accuracy of Pair - Strain (%) and Power Density (W/g) = 0.438
Accuracy of Pair - Stress (MPa) and Efficiency (%) = 0.6
Accuracy of Pair - Stress (MPa) and Power Density (W/g) = 0.385
Accuracy of Pair - Efficiency (%) and Power Density (W/g) = 0.417

Kernel = poly
Accuracy of Pair - Bandwidth (Hz) and Strain (%) = 0.417
Accuracy of Pair - Bandwidth (Hz) and Stress (MPa) = 0.222
Accuracy of Pair - Bandwidth (Hz) and Efficiency (%) = 0.167
Accuracy of Pair - Bandwidth (Hz) and Power Density (W/g) = 0.333
Accuracy of Pair - Strain (%) and Stress (MPa) = 0.658
Accuracy of Pair - Strain (%) and Efficiency (%) = 0.5
Accuracy of Pair - Strain (%) and Power Density (W/g) = 0.375
Accuracy of Pair - Stress (MPa) and Efficiency (%) = 0.467
Accuracy of Pair - Stress (MPa) and Power Density (W/g) = 0.231
Accuracy of Pair - Efficiency (%) and Power Density (W/g) = 0.417

Kernel = rbf
...
Accuracy of Pair - Stress (MPa) and Efficiency (%) = 0.333
Accuracy of Pair - Stress (MPa) and Power Density (W/g) = 0.308
Accuracy of Pair - Efficiency (%) and Power Density (W/g) = 0.25
```

Support Vector Machines

- Equation of Hyperplane: $w^T(x) + b = 0$
- where: b = Intercept and bias term of the hyperplane equation
- In D dimensional space, the hyperplane would always be D -1 dimensional.

- The goal of the support vector method approach is to maximize the minimum distance d between the hyperplane and the support vectors.
- For perfectly separable datasets, there are no issues, but for non perfectly separable datasets we can introduce a penalty for every misclassified datapoint to smoothen the learning curve,

$$d_H(\phi(x_0)) = \frac{|w^T(\phi(x_0)) + b|}{||w||_2}$$

$$||w||_2 =: \sqrt{w_1^2 + w_2^2 + w_3^2 + \dots w_n^2}$$

Performance of Supervised Learning Methods other than SVMs

Sparse Data leads to network stagnancy during training[1];

i.e. network learns working with zeroes.

Unable to perform with data in the sparse fields.

SVMs:

The research used 10 SVMs; each for any two features; i.e. No sparse data problem.

[1] Curci. S. et al; *"Truly Sparse Neural networks at Scale"*; 2021; arxiv.2102.01732;

NN code: Used Tensorflow.keras()

NN Architecture: L x 25 x 25 x 15 x 9
L = 2 for bivariate model;
L = 5 for multivariate model;

```
# for i in range()

model = tensorflow.keras.Sequential([
    tensorflow.keras.layers.Flatten(input_shape=(2,1)),
    tensorflow.keras.layers.Dense(25, activation='relu'),
    tensorflow.keras.layers.Dense(25, activation='relu'),
    tensorflow.keras.layers.Dense(15, activation='relu'),
    tensorflow.keras.layers.Dense(9, activation='relu')
])

model.compile(optimizer='adam', loss=tensorflow.keras.losses.SparseCategoricalCrossentropy(from_logits=True), metrics=['accuracy'])

model.fit(X[:,1:3], labels, epochs=10)
```

Our Approach to counter Data sparsity.

Methods Tested:

1. Generative Algorithm for generating similar data.
2. Data Imputation
3. Data augmentation with Real-life-parameters

Generative Algorithm: Tabular GANN[2][3]

Used GANN for generating a tabular database to fill gaps in the training data.

Issue: To generate feature "x1" for class "A", some data of "x1" should be available.

Due to the missing values in multiple classes, An All-feature classifier was not possible with this method.

Result: Model ran partially; Output data showed negligible accuracy.

[2] Xu, L., Veeramachaneni, K.; *"Synthesizing Tabular Data using Generative Adversarial Neural Networks"*; 2018; arxiv.1811.11264;
[3] Goodfellow, I., et al; "Generative Adversarial Neural Networks"; 2014; arxiv.1406.2661

Data Imputation: Statistical Method of Data Generation[4][5]

- There are seven types of muscle actuators : PZT, DEA, IPMC, SMA, SFA, SCP, TSA.
- Five physical properties : Bandwidth, Strain, Stress, Efficiency, Power Density.

Reference	Actuator T	Bandwidth	Strain (%)	Stress (MP	Efficiency	Power Density (W/g)
[1]	PZT	10000	0.2	110	90	0.2
	PZT	100			90	
	DEA	100	200	8	85	0.2
	IPMC	10	40	0.3		0.02
	SMA	3	5	200	1.3	50
	SMA	0.5	250	2	10	0.03
	SFA	130	50	10	30	11
	SFA	100	300		30	22
	SFA				30	10
	TSA	5	50	80	76	0.5
	SCP	3	49	11	1.02	27
[2]	SMA	3	10	200	3	4.3
	PZT	5000	0.2	35	50	

EAP	20223.17	10	34	41.12	0.15
EAP	20223.17	4	0.8	41.12	0.134947
IPMC	10	40	0.3	2.45	0.02
IPMC	49.37778	2	15	2.9	0.039594
IPMC	49.37778	40	11.91769	2.45	0.039594
IPMC	100	3	30	3	0.0026
IPMC	33	8.2	4.7	2.45	0.244
IPMC	49.37778	10	20	2.45	0.039594
IPMC	49.37778	0.5	3	1.5	0.00256
IPMC	1	5	11.91769	2.45	0.039594
IPMC	0.2	0.5	11.91769	2.45	0.039594
IPMC	0.2	2.1	11.91769	2.45	0.039594

Fig. 2a. Original Data b. After statistic data imputation

[4] Data Imputation; SciKit Learn https://scikit-learn.org/stable/modules/impute.html
[5] Khan, S., Hoque; "Improved Missing Data Imputation"; Journal of Big Data–Springer; 37(2020)

```python
# Imputing Mean Values in PZT.csv
df = pd.read_csv('PZT.csv')
del df["Actuator Type"]

df.fillna(-999, inplace = True)
numpy_data_PZT = df.to_numpy()
imp = SimpleImputer(missing_values=-999, strategy='mean')
imp.fit(numpy_data_PZT)
imp = imp.transform(numpy_data_PZT)
new_column_values = ['PZT'] * 32

df = pd.DataFrame(imp, columns = [ 'Bandwidth (Hz)',  'Strain (%)', 'Stress (MPa)', 'Efficiency (%)', 'Powe
df["Actuator Type"] = new_column_values
df = df[['Actuator Type', 'Bandwidth (Hz)', 'Strain (%)', 'Stress (MPa)', 'Efficiency (%)', 'Power Density
df.to_csv('PZT_mean.csv', index=False)
display(df)
```

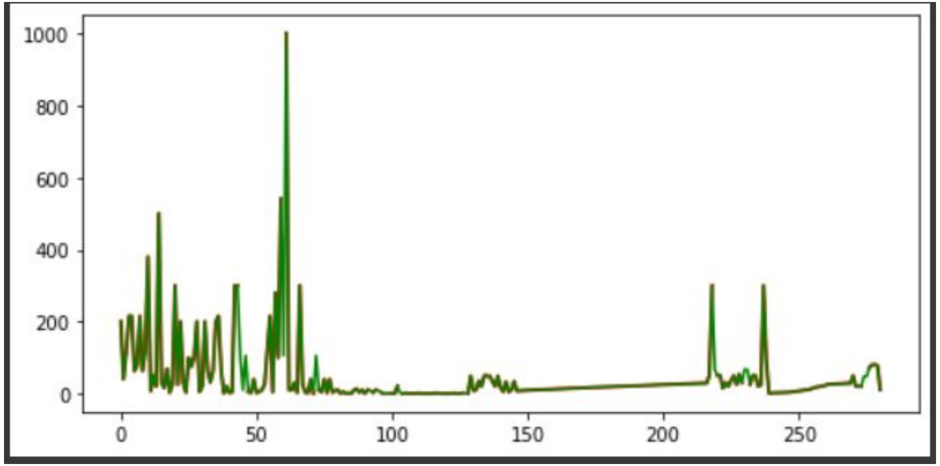
	Actuator Type	Bandwidth (Hz)	Strain (%)	Stress (MPa)	Efficiency (%)	Power Density (W/g)
0	PZT	10000.0	0.200000	110.000000	90.0	0.200000
1	PZT	100.0	1.242103	83.246154	90.0	0.230783
2	PZT	5000.0	0.200000	35.000000	50.0	0.230783
3	PZT	5800.0	1.700000	300.000000	90.0	0.230783
4	PZT	5650.0	0.100000	83.246154	72.6	0.230783

Fig 3. Data imputation using SciKit Learn

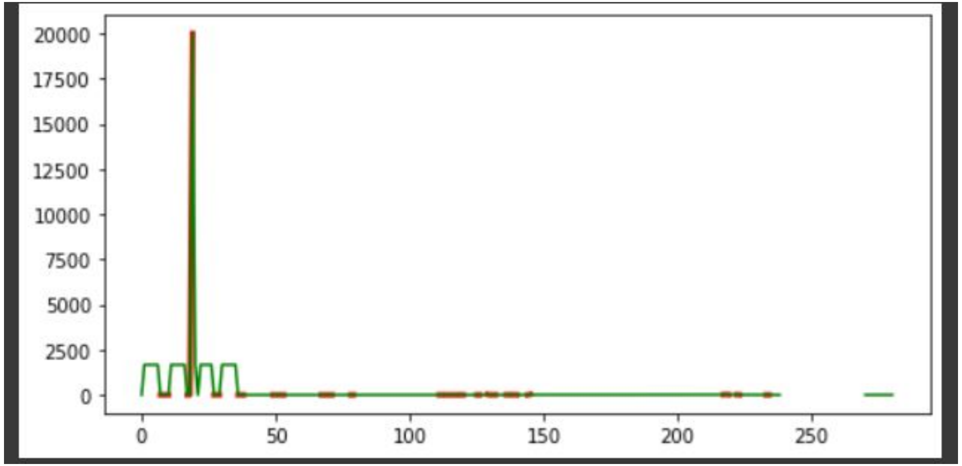
https://colab.research.google.com/drive/1bd7vZES_R0FRgQWzo-pehM4lc-56Ugrg?usp=sharing

Problem :

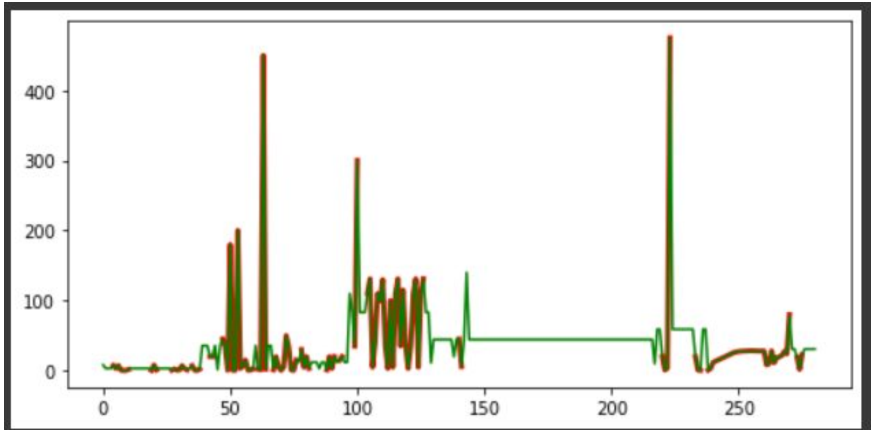
Columns for some actuators were almost empty, and there seemed no way to get imputer relevant data like mean etc.



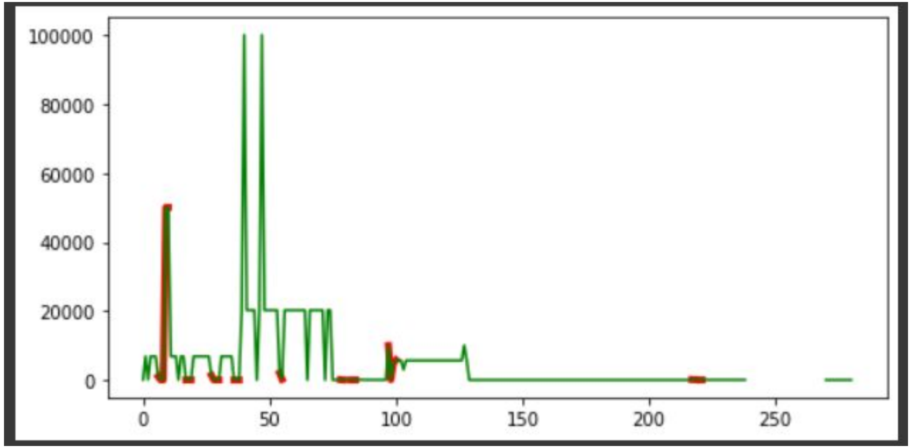
Strain (%)



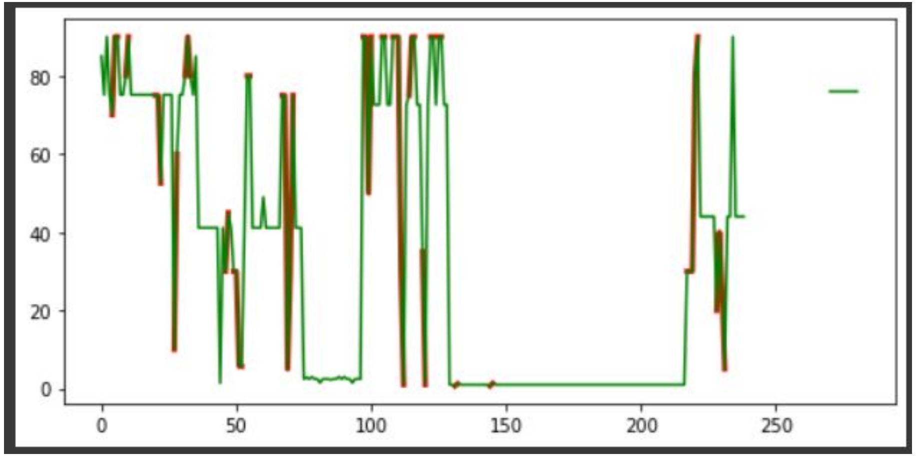
Power Density (W/g)



Stress (Mpa)



Bandwidth (Hz)



Red : Original
Green : Imputed

Efficiency (%)

Data Imputation: Statistical Method of Data Generation[4][5]

Results showed low accuracy on validation set: 43% [Best Model]

Reason deduced: The imputed data showed little to no coherence with the actual/original working parameters of the actuators.

```
9/9 [==============================] - 0s 2ms/step - loss: 4.1923 - accuracy: 0.2242
Epoch 9/10
9/9 [==============================] - 0s 2ms/step - loss: 3.8033 - accuracy: 0.2100
Epoch 10/10
9/9 [==============================] - 0s 3ms/step - loss: 3.5285 - accuracy: 0.1993
```

```
Epoch 9/10
9/9 [==============================] - 0s 3ms/step - loss: 2.2581 - accuracy: 0.4306
Epoch 10/10
9/9 [==============================] - 0s 416us/step - loss: 2.1953 - accuracy: 0.4270
```

Fig. 4a. accuracy(22%) before imputation, b. accuracy (43%) after imputation

Data Augmentation: Actual Data of Actuators used

Replaced missing data with actual work parameters of the given actuators.

Actuator type	ε_{max}	σ_{max} (MPa)	E (MPa)	ρ[W/kg]	Efficiency	f_{max} (Hz)
Muscle	0.3-0.4	0.1-0.4	5-20	50-284	0.2-0.4	50-500
DC Motors	0.4	0.1	--	100	0.6-0.9	---
Pneumatic	0.1-1	0.5-0.9	50-90	4000	0.4-0.5	50-300
Hydraulic	0.1-1	20-70	2 - 3 x 10^3	1600-2000	0.9-0.98	50-300
SMA	0.07	100-700	3 - 9 x 10^4	6400-6600	0.01-0.02	0.02-0.07
SMP	1.0	2-14	4 - 12 x 10^3	850-880	< 0.1	< 0.01
EAP (I)	0.02-0.4	5 - 34	0.2 - 3 x 10^3	150	<0.01	1-500
EAP (N/I)	0.2-3.8	5-6	1	1000-2500	0.15-0.9	1-2000
MREs	0.005	0.1-10	1-10	3 - 4 x 10^3	0.6-0.8	--
MRFs	0.002	0.1	--	3 - 4 x 10^3	--	--

G. Alici; *"Soft Robotics vs Hard Robotics",* 2018, Semantic Scholar; 2018.158

Data Augmentation: Actual Data of Actuators used

Replaced missing data with actual work parameters of the given actuators.

Result: 52 % accuracy [best model]

Reason: Better Data distribution should be selected.

```
9/9 [==============================] - 0s 3ms/step - loss: 1.8207 - accuracy: 0.5231
Epoch 9/10
9/9 [==============================] - 0s 2ms/step - loss: 1.8044 - accuracy: 0.5196
Epoch 10/10
9/9 [==============================] - 0s 3ms/step - loss: 1.7951 - accuracy: 0.5267
```

Conclusion

A bivariate model like SVM is really performant as the data sparsity problem is solved, removing stagnancy.

The Augmented Dataset with NN has a comparable accuracy to the bivariate SVM avg. Thus it can be a potential method to do the classification.

A more rigorous search for a better NN architecture can be done by using Grid Search CV[6] to solve any NN-capacity problems.

[6]https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html

Thank You