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Design and Development of Machine Learning Projects for Engineering Students

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This research project presents a valuable educational opportunity for engineering students to gain hands-on experience in the application of machine learning algorithms to real-world engineering challenges. The study focuses on the development of a predictive model for Young's modulus and Poisson's ratio of Auxetic materials, known for their unique negative Poisson's ratio property, using the Python programming language in conjunction with Ansys Workbench. The project leveraged finite element simulations conducted on unit cells with hollow inclusions. The geometric parameters served as input features for the subsequent machine-learning model. Through the direct optimization feature in Ansys Workbench, a dataset comprising over 100 design points with randomized geometric parameter values was generated. The calculated Young's modulus and Poisson's ratio, obtained from the finite element simulations, were utilized as labels in the machine learning algorithm. The research culminated in the development of a linear regression model, trained on Ansys-generated data, with the primary objective of predicting the mechanical properties of each unit cell based on their geometric parameters. This project exemplifies a practical and interdisciplinary approach to teaching machine learning to engineering students, bridging the gap between theoretical knowledge and real-world applications in materials science and simulation technology.

Introduction

Developing machine learning projects for engineering education is of paramount importance in preparing the next generation of engineers for the challenges of the modern world. These projects offer students a unique opportunity to bridge the gap between theoretical knowledge and practical application, a vital component of their future careers. Machine learning, with its ability to make sense of complex data and make predictions, has become integral in engineering fields. It equips students with the skills needed to address real-world engineering challenges, enhancing their problem-solving abilities and fostering creativity [1, 2].

Poisson's ratio is a dimensionless parameter that characterizes how a material deforms perpendicular to the direction of applied stress [3]. Materials exhibiting negative Poisson's ratio characteristics are commonly known as auxetic materials [4,5]. The auxetic effect can be achieved by carefully designing the material's structure and deformation mechanisms [6]. Auxetic materials come in various structural forms, such as hollow rectangular unit cells which were used in this project [7].

The current project offers a notable advantage in the development of a machine learning project. This advantage stems from its independence from an external source dataset whose scope and definition may not align directly with the needs of engineering students. This independence reduces the potential ambiguity in data interpretation.

One of the project's key merits lies in the fact that each student has the opportunity to generate a distinct and personalized dataset. This dataset is created by the students themselves, resulting in a unique platform for each student to build their individual regression model. These personalized models are tailored for predicting mechanical properties based on specific design parameters, enhancing the educational experience and a deeper understanding of the subject matter.

Creating a machine learning dataset

Input features:

Input features in the machine learning algorithm are the design parameters. The design parameters for the hollow unit cell in this study are depicted in Figure 1. The thickness of the unit cell is *t*.

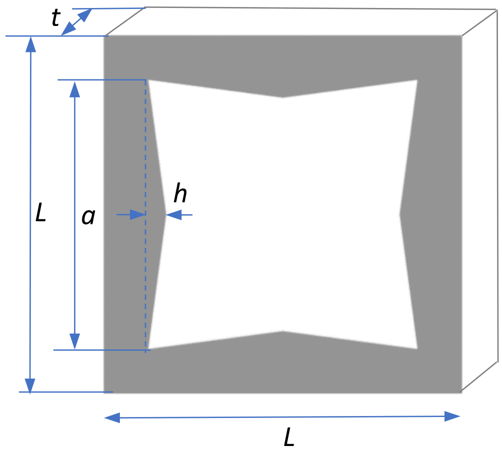

Figure 1: Design parameters of the unit cell

The limits and conditions that are applied to design parameters are

$$20\ mm \leq L \leq 50\ mm$$

$$20\ mm \leq a \leq 40\ mm\ \ ,\ \ a \leq 0.94L$$

$$1\ mm \leq h \leq 5\ mm\ ,\ \ \ h \leq 2a$$

$$1\ mm \leq t \leq 5\ mm\ ,\ \ \ 0.38h\ \leq t$$

The design parameters used in this study are the design points that were generated by Ansys during direct optimization. The optimization was conducted to determine the maximum lateral deflection.

Output labels:

The machine learning algorithm employs Poisson's ratio and the elastic modulus as its output labels. Poisson's ratio and Young's modulus of the unit cells can be determined by finite element analysis [8]. The finite element analysis is conducted using the Ansys 2023 version. The lower face of the unit cell is fixed, and a vertical deformation of δ is applied on the upper face of the unit cell, as illustrated in Figure 2. The overall lateral deformation, δ', is subsequently derived from the results of the finite element simulation.
The strains along the length of the plate, ε, and along the width, $\varepsilon^{'}$, are defined as

$$\varepsilon = -\frac{\delta}{L} \qquad \varepsilon' = -\frac{\delta'}{L}$$

The Poisson's ratio, ν, is determined as

$$\nu = -\frac{\varepsilon'}{\varepsilon} = -\frac{\delta'}{\delta}$$

The auxetic behavior of the unit cell can be observed in Figure 2.

To find Young's modulus of the plate, E, the reaction force, F, on the lower face of the unit cell is determined from finite element simulation. The amount of stress σ developed in the unit cell with the lateral cross-sectional area of A ($L \times t$) is determined as

$$\sigma = \frac{F}{A}$$

Then, Young's modulus is obtained as

$$E = \frac{\sigma}{\varepsilon}$$

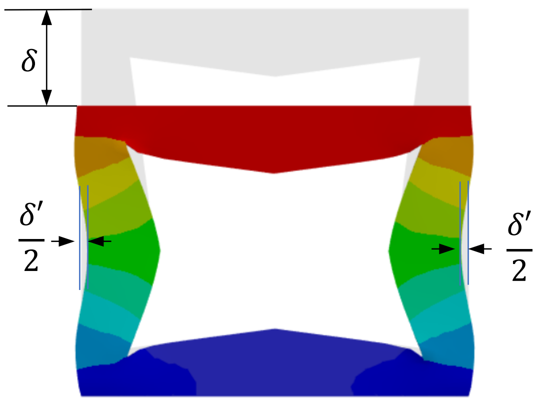

Figure 2: Longitudinal and lateral deformation of the unit cell

The Young's modulus of the base material is taken as 200 GPa in this study.

Results and discussion

133 design points were generated using the direct optimization technique in Ansys to obtain the maximum lateral deflection, as depicted in Table 1. These design points (L, a, h, t) will be used as input features in the linear regression algorithm. The modulus and Poisson's ratio of each design point will be calculated using the finite element method and utilized as outputs in the linear regression model. Employing the scikit-learn library in Python, a regression model was developed to predict each output of the dataset. The model was trained on a randomly selected 80% of the dataset and subsequently tested on the remaining 20% to evaluate the accuracy of the algorithm.

Table 1: Inputs and outputs of machine learning algorithm

	L (mm)	a (mm)	h (mm)	t (mm)	E (GPa)	ν
0	24.250000	21.416667	4.588889	3.593333	70.100241	-1.327436
1	26.250000	23.916667	1.625926	2.953333	47.906670	-2.097427
2	28.250000	20.791667	3.403704	2.313333	132.247160	-0.403942
3	29.250000	25.791667	1.329630	3.913333	59.449226	-1.198942
4	30.250000	23.291667	3.996296	1.673333	118.327670	-0.571395
...	...	...	...	...	...	...
129	30.950231	28.220290	2.394585	3.273333	48.898895	-2.131009
130	26.250000	23.935942	1.614032	2.953333	47.517654	-2.118993
131	26.250000	23.917733	1.614415	2.953333	47.844829	-2.096941
132	26.250000	23.935942	1.613840	2.953333	47.518125	-2.119223
133	26.254819	23.916667	1.716408	2.953333	48.302686	-2.101449

The linear regression model to predict Young's modulus was obtained as

$$E = 9.055035241544646\,(L) - 11.015679370106932\,(a) + 5.436545836286852\,(h) - 2.9852626206992605\,(t) + 75.63475764424173$$

The magnitude of the coefficient for each input feature indicates its impact on the predicted outcome. It can be seen that design parameters a and L have the greatest influences on Young's modulus.

The coefficient of determinations of the model for predicting Young's modulus was obtained as 0.9839 which shows a high level of accuracy for the developed model.

The obtained model for predicting Poisson's ratio using linear regression is as follows:

$$\nu = 0.1526150390972267\,(L) - 0.15903816345032598\,(a) + 0.15429292585890553\,(h) - 0.2137768369532793\,(t) - 1.9293367134164987$$

The coefficient of determination for the model predicting Poisson's ratio was determined to be 0.8128. The design parameter t is noted to have the most significant impact on Poisson's ratio. However, from the mechanics of materials perspective, it was expected that the thickness of the unit cell would not have a significant influence on the Poisson's ratio. That could be a contributing factor to the observed lower accuracy in predicting Poisson's ratio.

To robustly assess the performance of our predictive model, we also incorporated K-fold cross-validation into our evaluation strategy. Specifically, we set K to 5, leading to the systematic partitioning of our dataset into five equally sized folds. During each iteration, the model underwent training on four (K-1) folds, with subsequent performance testing on the held-out fold. This process iterated five times, guaranteeing that every data point was used for validation precisely once. The accuracy of the model was computed as the average performance across all five folds.

The coefficient of determination for the model, as determined through K-fold cross-validation, was found to be 0.9771 for predicting Young’s modulus and 0.7294 for predicting Poisson's ratio.

Conclusions:

In the proposed machine learning project, the geometric design parameters were input features for the machine learning model. A dataset, consisting of randomized geometric parameter values, was generated using the direct optimization feature in Ansys Workbench. Young's modulus and Poisson's ratio, calculated from finite element simulations, were employed as outputs in the machine learning algorithm. Finally, a linear regression model written in Python programming language was trained on data generated by Ansys, with the main goal of predicting the mechanical properties of individual unit cells based on their geometric parameters. The developed regression models exhibit a good level of accuracy in predicting Young’s modulus and Poisson's ratio. Through working on machine learning projects, students gain hands-on experience in tackling cutting-edge problems, helping them develop a deep understanding of data analysis, model development, and validation techniques. Furthermore, these projects promote interdisciplinary learning, which mirrors the dynamic, cross-functional collaborations seen in the industry.

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