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Machine-learning-accelerated design of functional structural components in deep-sea soft robots

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ABSTRACT

To explore the deepest regions of the ocean with high flexibility and environmental adaptability, deep-sea soft robots have been developed recently. One prominent example is the self-powered soft robot that successfully operated in the Mariana Trench at a depth of 11,000 meters. Notably, many functional electronic components such as resistive elements, capacitors, and crystal oscillators may fail under extreme hydrostatic pressure, posing significant challenges for the practical massive deployment of deep-sea soft robots. Consequently, designing miniature pressure vessels on the printed circuit board to protect these vulnerable electronic components is vital for enhancing the reliability of deep-sea soft robots. However, traditional structure design methods – which often rely on theoretical analysis, experimental testing and numerical simulations – are often costly and time-consuming, especially for design problems in high-dimensional design spaces. Herein, we demonstrate a machine-learning-accelerated design method for devising miniature pressure vessels for vulnerable electronic components in deep-sea soft robots. Machine learning algorithms including decision trees and neural network models are employed and compared. The resulting design algorithm can predict whether a specific design can survive the deep-sea hydrostatic pressure with high accuracy in $\sim$0.35 ms, roughly seven orders of magnitude faster than traditional design methods.

1. Introduction

Traditional robots are usually made up of rigid structures such as motors and bearings and have been widely utilized in industrial areas due to their high accuracy, ease of control, and strong output force. These rigid components, however, restrict robot flexibility and environment adaptation [1] and render traditional robots costly, highly noisy and less secure [2]. Inspired by nature, engineers have designed soft robots composed of compliant materials, which offer distinct benefits over traditional robots, including flexibility, lightweight, high environmental adaptability and human-machine safety [3–7]. In particular, underwater soft robots have garnered much attention in recent years [8–12]. In April 2021, a self-powered soft robotic fish that can function in the Mariana Trench under the extreme hydrostatic pressure of 110 MPa has been reported [13]. The soft robotic fish carries only batteries and transformers to support its basic function: wing-flapping actuation. In the future, soft robots are expected to be equipped with sensors, cameras, and other advanced electronic components to perform more complex tasks, such as deep-sea research and ocean development. However, the extreme hydrostatic pressure in the deep sea might limit the performance of these electronic components. For example, the resistance of resistive elements will change in the deep sea, because the resistive elements physically shrink under high hydrostatic pressure. The high-pressure conditions can also cause certain capacitors to lose their internal air space, leading to electrode short-circuit. In addition, electronic components containing internal cavities, such as crystal oscillators, may collapse and functionally fail under high hydrostatic pressure [14]. To this end, miniature pressure vessels on the printed circuit board (PCB) – a hollow structure that can hold delicate electronic components in its cavity – that can survive the mechanically demanding environment in the deep sea need to be designed to protect vulnerable electrical components in next-generation deep-sea soft robots.

It is worth noting that design problems of hollow structures are often defined in high-dimensional design space, with design variables of more than three. Take the spherical shell illustrated in Fig. 1, which has been widely used as conventional pressure vessels, as an example. In general, designing such a hollow spherical shell involves five design variables, including inner diameter

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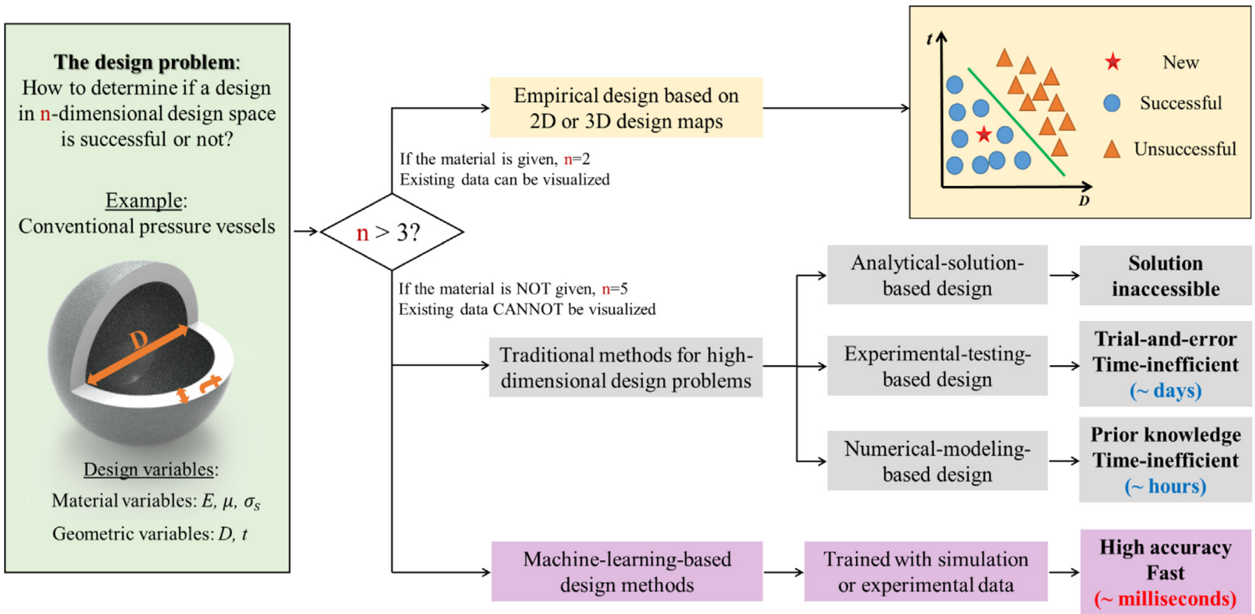

Fig. 1. Traditional design methods and machine-learning-based design methods. A structure design problem often involves multiple design variables. Take a hollow spherical shell as an example, if the material of the shell is given, the design problem has only 2 variables such that existing design data can be easily visualized in the Euclidian space as a design map to determine the rationality of a new design. However, if the number of design parameters is larger than three, the design problem cannot be displayed graphically. Traditional design methods for such design problems in high-dimensional space rely on analytical approaches, experimental tests and finite element simulations, which are either inaccessible for complicated cases or time-inefficient. Machine-learning-based design algorithms trained with offline simulation/experimental data can significantly accelerate the structure design in high-dimension design space.

(D), thickness (t), elastic modulus (E), Poisson's ratio (μ) and yield strength (σ_s) of the material. If the material of the pressure vessel is given, only two variables (D and t) remain so that the existing design data can easily be visualized in Euclidian space as a design map (see the design map in Fig. 1), which contains regions representing successful and unsuccessful designs, respectively. Then one can readily determine whether a new design is successful or not by referring to the map thereafter. However, in practice, the material of the pressure vessels also needs to be designed, thereby leading to a design problem with five design variables, which can hardly be displayed graphically. Traditional design methods for such design problems in high-dimensional design space rely on analytical solutions, experimental tests, or numerical simulations. For complex-shaped structures subjected to external mechanical loads, analytical solutions are usually inaccessible such that the analytical design method is inappropriate. The experimental-test-based design method, also termed the Edisonian approach, is often carried out in a trial-and-error fashion, which is costly and time-inefficient. With the improvement of computer performance, simulation-based numerical design becomes a powerful tool in industrial manufacturing today, which can drastically reduce the cost of experimentation. However, for complex 3-D simulation problems, design methods based on finite element method (FEM) rely on massive computing resources and require substantial prior knowledge of experienced designers. Notably, for both experimental and numerical design methods, it is essential to perform experimental tests or numerical simulations on every newly proposed design to determine whether the design is successful, which is time-consuming. To this end, how to efficiently and accurately design structures in n-dimensional design space ($n \geq 4$) remains an open question.

Machine learning (ML), as one of the cutting-edge research fields in artificial intelligence [15], is the study of how computers can imitate or actualize human learning processes. Machine learning has not only been applied in knowledge-based systems, but also in other fields such as natural language understanding [16], spam detection [17], computer vision [18] and image recognition [19]. In the field of mechanics and materials, machine learning has been widely employed in high entropy alloy development [20,21], structural damage site prediction [22], nano-mechanics [23,24], empirical formula verification [25], etc. In addition, researchers use machine learning to design structures with unprecedented properties [26–29]. For instance, Bessa et al. utilized Bayesian classification to design proper structure to make fragile material super compressible [30]. Ott et al. employed an algorithmic-driven method to optimize the shape of shark-denticle-inspired structures to acquire superior aerodynamic properties [31]. Kim et al. employed deep learning to accelerate the optimization of the shape of an adhesive pillar [32]. Oh et al. combined machine learning with topology optimization to automatically generate a wheel structure that is aesthetically superior and technically meaningful [33]. Wang et al. achieved the optimal workspace of magnetic soft continuum robots with the help of evolutionary design and genetic algorithm, providing an efficient tool to design and optimize the structure of magnetic soft actuators [34]. Sun et al. used the recurrent neural network model and evolutionary algorithm to design 4D-printed active composites. The method is developed for the forward shape-change prediction of the composite and solving the inverse problem to find the optimal design [35]. In the design of composite structures, machine learning has been used to predict the mechanical properties of the composites and generate designs with enhanced performance [36,37]. The machine-learning method is intrinsically suitable for capturing the relationship among a huge number of variables so that it naturally meets the requirement for structure design in high-dimensional design space.

In this paper, we use machine learning models – including decision trees and neural networks – to build ML-based design algorithms for miniature pressure vessels protecting vulnerable electronic components in deep-sea soft robots, with training data from offline finite element simulations. We first conduct finite element simulations to determine the deformation of miniature pressure vessels under 110 MPa hydrostatic pressure (i.e., the pressure at the Mariana Trench, the deepest part of the world's ocean), from which more than five thousand numerical examples are studied by varying four design variables. Then the obtained data set are used to train and test machine learning models including decision trees and neural networks implemented in the open-source package Scikit-learn [38]. The resulting design algorithms – namely, the trained and tested decision trees and neural networks – can assess whether a new design of miniature pressure vessels can survive the extreme hydrostatic pressure with high accuracy in ~0.35 millisecond, roughly seven orders of magnitude faster than traditional design methods based on finite element simulations. Compared with traditional design methods, the machine-learning-accelerated design approach presented in this work is experience-free and time-efficient, and can be easily generalized for designing other functional structural components in high-dimensional design space.

2. Model development

2.1. Description of the design problem

As shown in Fig. 2a, a hollow pressure vessel structure is needed on the PCB to protect vulnerable electronic components in the soft robotic fish. Considering the fact that most electronic components are thin, flat, rectangular pieces, the miniature pressure vessel is designed as a hollow box rather than a spherical shell, with the dimensions of the cavity being h (height) × L (length) × 0.8L (width). The pressure vessel and the PCB are further encased in a soft matrix, constituting the body of the soft robotic fish (Fig. 2a). The whole structure is subjected to the hydrostatic pressure of 110 MPa. Since the size of the body of the soft robotic fish is fixed, we fix the size of the entire structure. When the size of the miniature pressure vessel changes, the size of the soft matrix alters accordingly. Because the height of most vulnerable electronic components such as crystal oscillators is between 1 mm and 2 mm, we fix the height of the pressure vessel to be h = 2 mm. The pressure vessel is taken to be bilinear elastic–plastic material, with Young's modulus E, yield strength $0.001E$, and tangent modulus $E/140$. The soft matrix is considered as incompressible Neo-Hookean material, respectively. To this end, we take Young's modulus of the shell (E), the shear modulus of the soft matrix (G), the length of the cavity (L), and the shell thickness (t) as four design variables, which leads to a design problem in 4-dimensional design space. A successful design should be able to survive the extreme hydrostatic pressure of 110 MPa.

2.2. FEM simulations and data set preparation

In this work, the deformation of the miniature pressure vessel subjected to the hydrostatic pressure of 110 MPa is simulated by the commercial FEM package ABAQUS. Taking advantage of the symmetry, only a quarter of the pressure vessel is considered in the simulation to reduce the numerical cost. The model is meshed with tetrahedral elements. We set the criterion for successful design as follows: If the vertical displacement at the center point of the ceiling of the cavity is smaller than 10% of the cavity height (i.e., 0.2 mm), the design is considered successful and labeled "1" (Fig. 2b). Otherwise, the design is unsuccessful and labeled "0", since the ceiling of the cavity may fall onto the enclosed devices, damaging the device by transferring the high pressure.

To generate sufficient data set for training machine learning models, we explore the parameter space of the four input design variables, including the length of the cavity (L), the shell thickness (t), the shear modulus of the soft matrix (G), and Young's modulus of the pressure vessel (E). Specifically, we choose ten representative values for design variables t, L, and E: t and L range from 1 mm to 10 mm at a 1 mm interval and from 2 mm to 20 mm at a 2 mm interval, respectively; E increases from 50 MPa to 230 MPa with an increment of 20 MPa. Five representative values are selected for G, including 100 KPa, 1 MPa, 10 MPa, and 100 MPa for silicone rubbers with different compositions, as well as 1 GPa for epoxy. In the simulation, the overall size of the entire structure is 48 mm (Length)×40 mm (Width)×40 mm (Height). We utilize python script to explore the above parameter space and, for each combination of $\{L, t, G, E\}$, perform FEM simulations as described above to determine whether the design is successful or not. We run 5000 FEM simulations in total on ten computers in parallel and the entire data acquiring process takes about 5 days. To this end, a data set of 5000 samples is generated for training and testing appropriate machine learning models, with the input and target variables expressed as follows:

$$\begin{cases} \text{Input variables}: \quad X = \{L, t, E, G\} \\ \\ \text{Target variable}: \quad Y = 0 \text{ or } 1 \end{cases} \tag{1}$$

2.3. Machine-learning-based design algorithm

As illustrated in Fig. 2c, we use the data set prepared in Section 2.2 to train appropriate machine learning models, eventually obtaining a machine-learning-based design algorithm. The function of the design algorithm is to predict the value of the target variable Y based on input variables $X = \{L, t, E, G\}$. That is, given a proposed design of the miniature pressure vessel characterized by cavity length L, shell thickness t, Young's modulus of the shell E, and the shear modulus of the soft matrix G, the design algorithm can predict whether the design can survive the extreme pressure of 110 MPa.

Although there exists a myriad of machine learning models, according to the "no free lunch" theorem, researchers need to identify the most appropriate model for a particular problem. During training the design algorithm, we test various machine learning models, including the logistic regression model, decision trees, support vector machine, K-nearest neighbors' model and neural networks. The accuracy of these machine learning models for the structural design problem in this work is shown in Appendix A. By comparison, the decision-tree-based classification and the neural network model stand out, demonstrating higher accuracy than do other models.

2.3.1. Decision-tree-based algorithm

Decision tree learning is a supervised learning method used for classification and regression [39]. Tree models where the target variable takes a discrete set of values are called classification trees, which is suitable for this design problem whose target variable Y equals either 1 (successful design) or 0 (unsuccessful design). As illustrated in Fig. 3a, a classification tree is built by partitioning the input parameter space, which constitutes the root node of the tree, into subsets that are represented by a series of internal branch nodes, based on a set of classification rules (Details of the classification rules can be found in the literature [40,41]). This partitioning process is repeated on each derived subset recursively, growing the classification tree, until the subset at a node has all the same values of the target variable. Such nodes are termed leaf nodes and each leaf node represents a class label ($Y = 1$ or $Y = 0$ in our design problem). For the design problem of miniature pressure vessels, a given input $X = \{L, t, E, G\}$ flows from the root node, through the internal branch nodes according to the classification rules, and finally into a leaf node, producing a predicted target variable $Y = 0$ or 1 according to the label of the leaf node. To build the classification tree in Scikit-learn, the classification criterion is set to 'gini' and

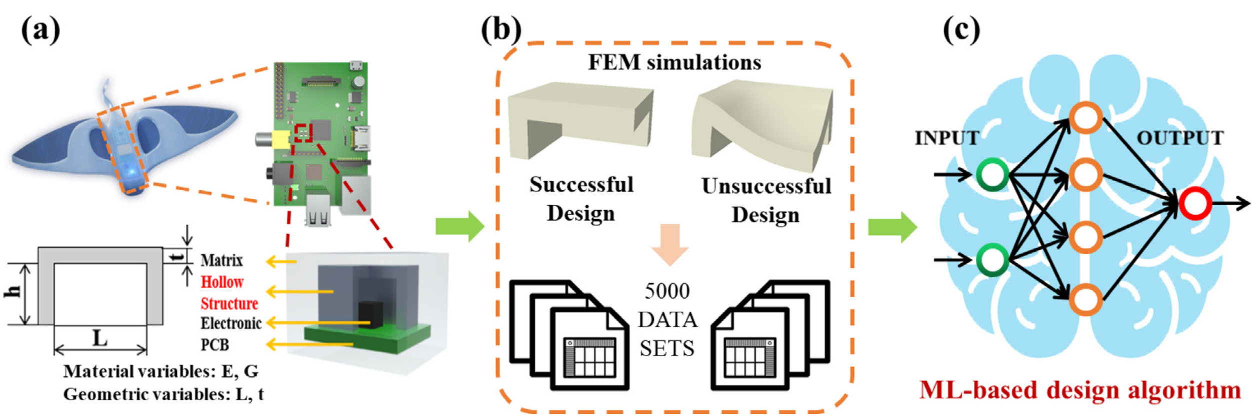

Fig. 2. Flowchart of the model development. (a) Schematics of the miniature pressure vessel. The miniature pressure vessel (dark gray part in the schematics at the bottom right corner) is designed to protect fragile electronic components (black part) on the PCB (green part) encased in the soft robotic fish. A box-shaped pressure vessel is chosen since most electronic components on PCB are thin, flat, and rectangular pieces. Input variables for the design problem include Young's modulus of the shell E, the shear modulus of the soft matrix G, the length of the cavity L, and the shell thickness t. (b) Data preparation based on FEM simulations. We perform FEM simulations to model the deformation of miniature pressure vessels with different design parameters. Based on the simulation result, each design is labeled either successful (1) or unsuccessful (0), generating a data set of 5000 samples. (c) A ML-based design algorithm can be obtained by training appropriate machine learning models using prepared data set. The resulting design algorithm can quickly determine whether a proposed design characterized by $\{L, t, E, G\}$ is successful or not. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the classification splitter is set to 'best'. The maximum tree depth (maximum number of splits from the root node to the leaf node) is limited to 4 to 8. We do not control the minimum leaf size (minimum number of samples required for each leaf node) since the number of features is only four such that overfitting is not an issue.

2.3.2. Neural-network-based algorithm

Neural networks, a machine learning technology inspired by biological neural networks in the brain and nervous system, excel at detecting complex nonlinear relationships among high-dimensional input and output variables [42], such that they naturally meet the requirement for the design problem in high-dimensional design space. A wide variety of deep learning models based on neural networks have been developed, such as convolutional neural networks [43], generative adversarial networks [44]. In this work, the original multilayer perceptron (i.e., a class of feedforward artificial neural network) is employed, which usually consists of several layers of nodes, including an input layer, an output layer, and hidden layers between them, with nodes in each layer connecting to all nodes in the adjacent layers through weight and bias (Fig. 3b). As the input layer receives external input data (e.g., $X = \{L, t, E, G\}$ for the design problem of miniature pressure vessel), each node in the hidden layers collects inputs from all nodes in the immediately preceding layer, and sends a single output by passing the weighted sum of the inputs through a nonlinear activation function to all nodes in the next layer. The output layer receives data from the last hidden layer and eventually produces the ultimate output ($Y = 0$ or 1 in the design problem). The complexity of the neural network depends on the number of hidden layers and neurons in each layer. In this study, the number of hidden layers is set to 1 or 2, the number of neurons in the hidden layers ranges from 4 to 12, the input layer is made up of 4 nodes since the input data $X = \{L, t, E, G\}$ contain four variables and the output layer has a single node for $Y = 0$ or 1.

3. Results

After training the ML-based design algorithm, we test the algorithm and evaluate its performance in terms of accuracy and efficiency. Furthermore, we summarize the mechanical rules for the design of the miniature pressure vessel in deep-sea soft robots based on predictions made by the ML-based design algorithm.

3.1. Accuracy

The ML-based design algorithm can achieve high prediction accuracy. For both the decision-tree-based and neural-network-based design algorithm, we use 80% of the data set prepared in Section 2.2 as the training data set and the remaining 20% (i.e., 1000 samples) as the test data set. After testing, the predictions – whether a design is successful or not, i.e., $Y = 0$ or 1 – made by the ML-based design algorithm are compared to the target value Y of the test data set, which is calculated by the FEM simulation (As described in Section 2.2). The accuracy of the design algorithm is measured by

$$Accuracy = \frac{n}{N} * 100\% \tag{2}$$

where n denotes the number of correct predictions and N the total number of predictions (herein, $N = 1000$). The accuracy of the decision-tree-based algorithm and the neural-network-based algorithm is summarized in Fig. 3c and d, respectively. Fig. 3c shows that the accuracy of the algorithm prediction improves as the depth of the decision trees increases, reaching 95.90% with a tree depth of 8. Fig. 3d shows the neural-network-based design algorithm can produce a high accuracy of 97.16% with 2 hidden layers and 21 neurons (4/8/8/1). The results demonstrate that the ML-based design algorithm can predict the rationality of a specific design of the miniature pressure vessel characterized by $X = \{L, t, E, G\}$ with high accuracy. We also evaluate the sensitivity of the accuracy to the size of the training data set. As shown in Fig. B.1 in the appendix, fewer training data lead to similar but relatively lower accuracy, the overall prediction accuracy is higher than 92% for data size larger than 1000.

3.2. Efficiency

To demonstrate the efficiency of the ML-based design algorithm, we randomly generated a group of design parameters $X_{new} = \{L = 7.9 \text{ mm}, t = 3.9 \text{ mm}, E = 67 \text{ GPa}, G = 59.8 \text{ MPa}\}$ using MATLAB, and feed X_{new} into the best performing ML-based design algorithms obtained in Section 3.1. Note that this set of parameters is not in the training data set and the test data set. Since the design problem of the miniature pressure vessel has four design variables and is difficult to be visualized, one cannot directly determine whether the design characterized

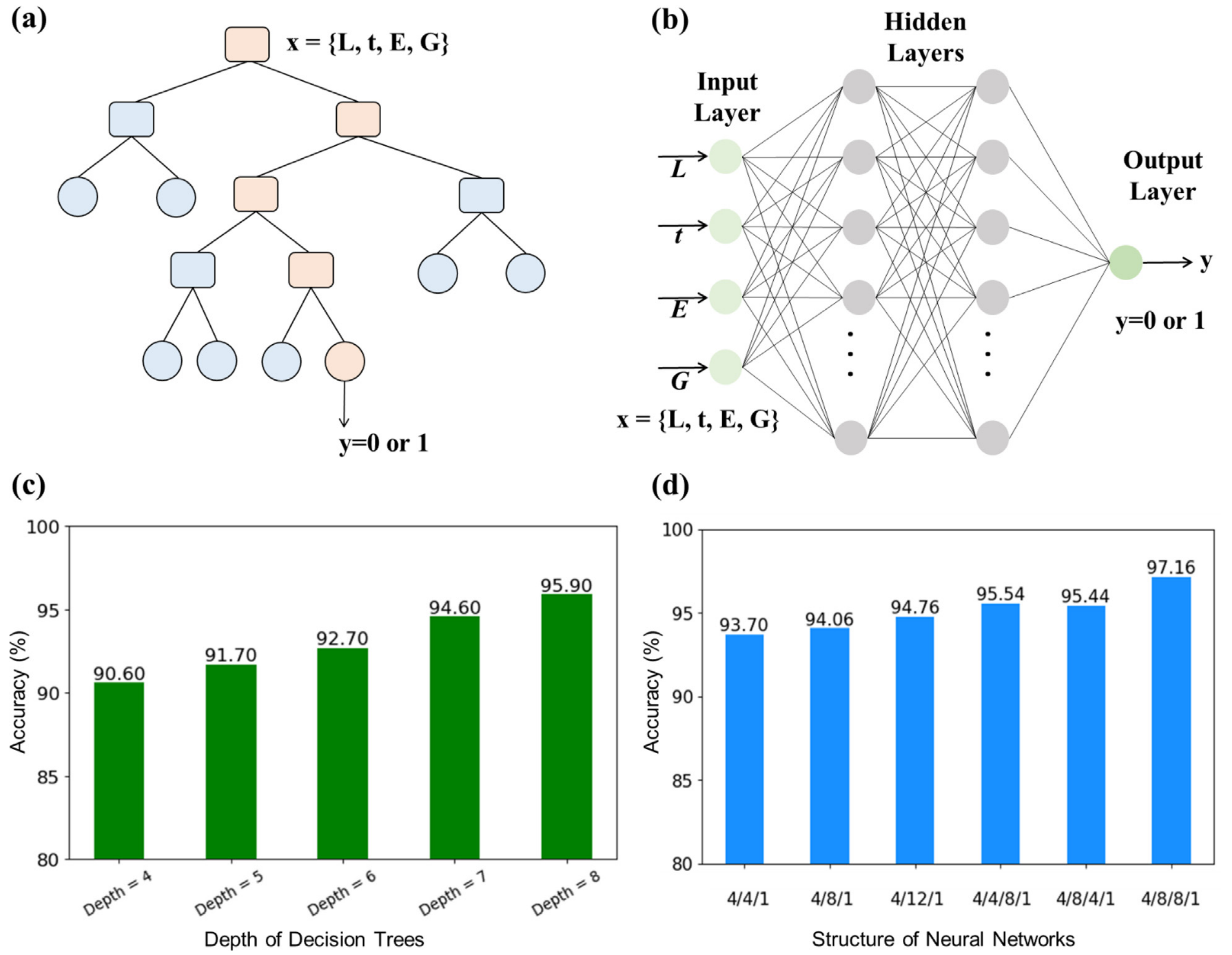

Fig. 3. Design algorithms based on decision trees and neural networks. (a) Schematics representing a decision tree model. As an input $X = \{L, t, E, G\}$ is fed into the decision-tree-based design algorithm, it flows from the root node, through the internal branch nodes based on classification rules, and finally into a leaf node. The value of the target variable ($Y = 0$ or 1) is given by the label of the leaf node. (b) The architecture of a neural network model. As an input $X = \{L, t, E, G\}$ is gathered by the nodes of the input layer of a neural network algorithm, it is successively passed to the nodes in the following hidden layers through an activation function, until the output layer receives data from the last hidden layer and produce the final output $Y = 0$ or 1. (c) Decision-tree-based design algorithm with high prediction accuracy. The tree depth that controls the complexity of the classification trees ranges from 4 to 8. (d) The neural-network-based design algorithm can achieve high accuracy with simple neural networks. "$n_i/n_1/n_o$" and "$n_i/n_1/n_2/n_o$" represents neural networks with one and two hidden layers, respectively; n_i, n_1, n_2, n_o are numbers of neurons in the input layer, 1st and 2nd hidden layers, and the output layer, respectively.

by X_{new} represents a successful design or not based on existing design experience. The decision-tree-based design algorithm (tree depth=8) and the neural-network-based design algorithm (4/8/8/1) can determine that the design is unsuccessful – i.e., the pressure vessel cannot survive a hydrostatic pressure of 110 MPa – in only 0.27 ms and 0.35 ms, respectively. FEM simulation verifies the prediction, but it takes 1.04 h (with 282 025 elements). To this end, we show the high prediction efficiency of the ML-based design algorithm, which can reduce the time needed to design the miniature pressure vessel from FEM by seven orders of magnitude.

3.3. Mechanical rules for the design of miniature pressure vessels

Mechanical rules for the design of miniature pressure vessels can then be summarized based on prediction results from the neural-network-based design algorithm (4/8/8/1), which is one of the best performing algorithms obtained in Section 3.1. In order to illustrate the prediction results graphically, we fix two out of the four variables at each time, reducing the design space to only two dimensions, which are easy to visualize. In this way, six two-dimensional design maps are generated and presented in Fig. 4, in which the regions of successful and unsuccessful designs are highlighted in green and red, respectively. Fig. 4a shows the influence of geometric variables by setting Young's modulus of the pressure vessel $E = 110$ GPa and the shear modulus of the soft matrix $G = 0.1$ MPa. As evident from the plot, increasing the thickness as well as decreasing the span length of the cavity is beneficial for limiting the structural deformation within the allowable range. Fig. 4b and c investigate the effect of Young's modulus of the pressure vessel E, demonstrating that the increase in the elastic modulus enhances the resistance of the structure to the extreme hydrostatic pressure. Results shown in Fig. 4d–f indicate that encasing the miniature pressure vessel with a stiff matrix such as epoxy makes the structure less prone to collapse under extreme pressure.

4. Discussion

It is worth noting that the ML-based design algorithm is not only valid for the 4-dimensional design problem of box-shaped structure discussed above, but can also be extended to design problems in higher dimensional space and other shapes. For instance, if we take the Poisson's ratio μ of the miniature pressure

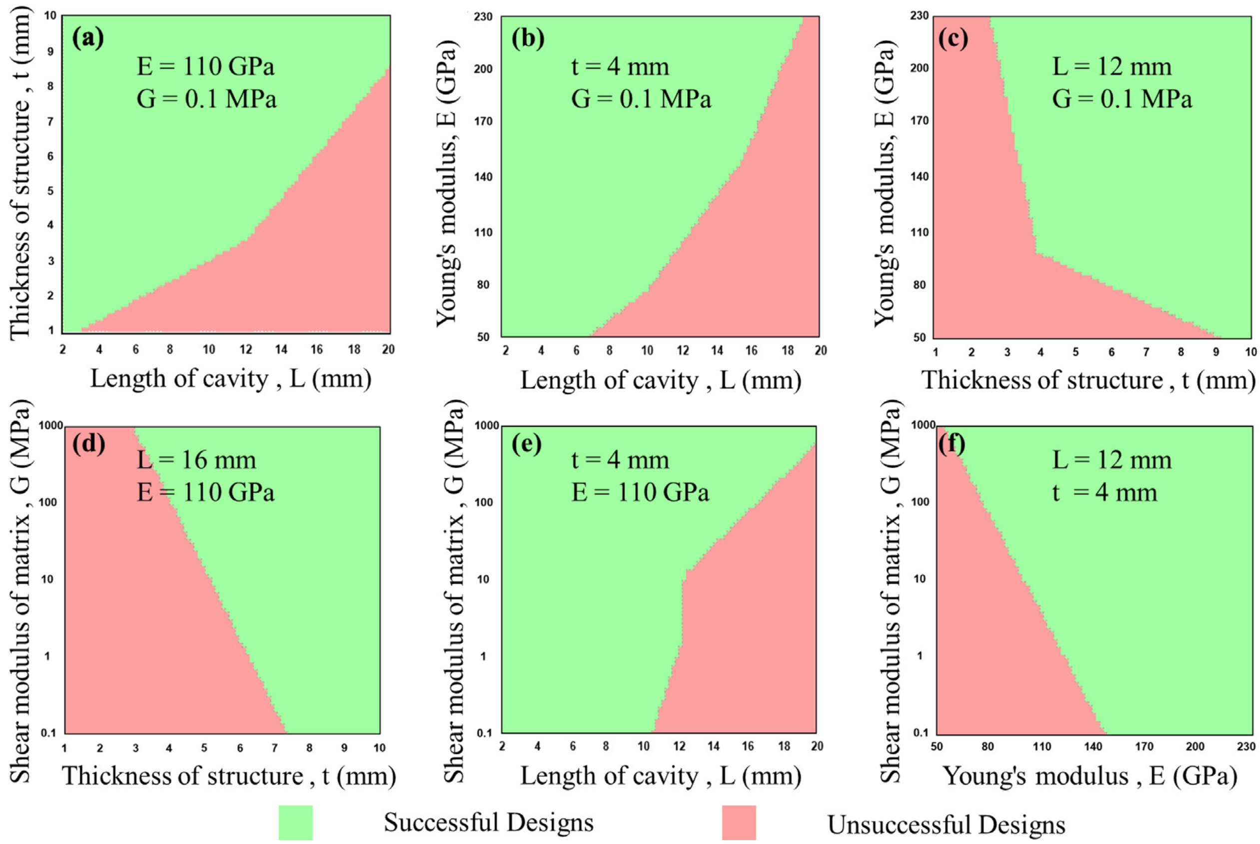

Fig. 4. Visualization of the prediction results. Two out of the four design variables are fixed at each time, so that the remaining two variables compose the two-dimensional design space. Prediction results are displayed graphically in the design space of (a) t vs. L, (b) E vs. L, (c) E vs. t, (d) G vs. t, (e) G vs. L, and (f) G vs. E. The regions of successful and unsuccessful designs are highlighted by green and red, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

vessel as the fifth design parameter, each design is now characterized by five parameters (i.e., L, t, G, E, and μ), thereby giving a 5-dimensional design problem. We can explore the parameter space of the five input design variables by following the procedure described in Section 2.2 (e.g., select 10 discretized values for parameters L, t, and E, and 5 discretized values for G and μ), and then conduct finite element simulations, getting a data set consisting of 25,000 samples. Machine learning models can then be trained/tested with the data set and used to guide the design of miniature pressure vessels in 5-dimensional design space. In general, since machine learning methods such as neural networks can recognize complex relationships between high-dimensional inputs and outputs, the ML-based method reported in this work is applicable to design problems in any n-dimensional space ($n = 1, 2, \ldots$). Moreover, for structural design of other shapes, one just needs to identify the n number of parameters that characterize the structural design, obtaining a n-dimensional design problem, which can be solved by the ML-based design method.

5. Conclusion

In summary, using machine learning models including decision trees and neural networks, we built two ML-based design algorithms for the four-dimensional design problem of miniature pressure vessels in deep-sea soft robots, of which the function is to determine whether a proposed design with four design variables is successful or not. It is worth noting that the best performing ML-based design algorithm can accelerate the design of miniature pressure vessels with high accuracy and high efficiency, drastically reducing the time needed to design the structure by seven orders of magnitude compared to the traditional FEM-based design method. Notably, if trained by appropriate data set, the ML-accelerated design approach presented in this work can be extended to higher dimensional design space and other shapes for practical applications.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. The accuracy of various machine learning models

For the structural design problem in this work, we test the prediction accuracy of different machine learning models. We run five tests on each model and average the results. All tests are carried out on Scikit-Learn, key model parameters are listed in Table A.1, and default parameters are chosen for the remaining parameters.

As shown in the table, logistic regression, supporting vector machines (SVM), and K-nearest neighbors (KNN) demonstrate

Table A.1
The accuracy of various machine learning models.

Machine Learning Model	Key Parameters	Accuracy(%)
Logistic Regression	N/A	92.4
Support Vector Machines	N/A	94.6
K-Nearest Neighbors	K=5	95.4
	K=10	95.2
	K=15	95.0
	K=20	93.9
Decision Trees	Depth=7	94.8
	Depth=8	95.8
	Depth=9	96.3
	Depth=10	97.1
Neural Networks	4/4/8/1	95.5
	4/8/4/1	95.4
	4/8/8/1	97.1

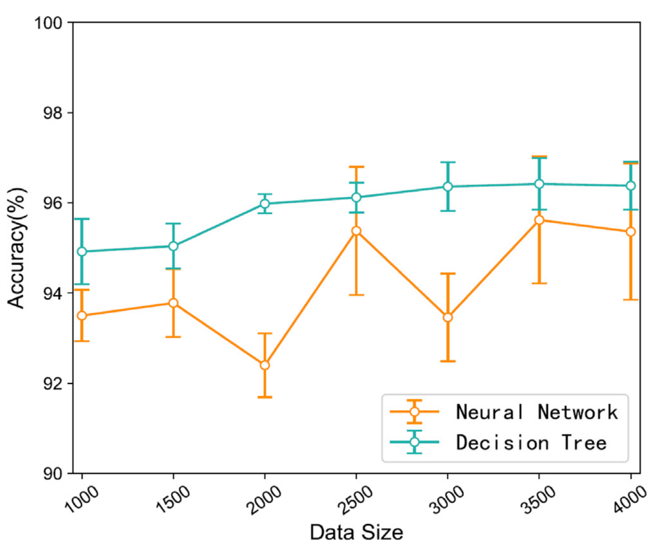

Fig. B.1. The sensitivity of the accuracy to the training set size.

accuracy up to 92.4%, 94.6%, and 95.4%, respectively. While the accuracy of decision trees and Neural Networks can be as high as 97.1% when the depth of the decision tree model is 10 and when the structure of the neural network is 4/8/8/1, exceeding that of the logistic regression, SVM and KNN model. To this end, we utilize the decision trees and neural network models in this work to achieve high design accuracy.

Appendix B. The sensitivity of the accuracy to the training set size

For this design problem, we tested the sensitivity of the accuracy to the training set size. We take 1000 data points for testing. The training set was randomly selected from the remaining 4000 samples and the size of the training set is increased from 1000 to 4000 at a 500 interval. For each training set size, five tests are conducted and the accuracy is evaluated by averaging the results from the 5 tests. As shown in Fig. B.1, fewer training data lead to similar but relatively lower accuracy, the overall prediction accuracy is higher than 92% for data size larger than 1000.

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