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SCAFFOLD DESIGN WITH NEURAL NETWORKS

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1 INTRODUCTION

Minimizing stress shielding is a key challenge in implant design, as it often leads to aseptic loosening, a major cause of revision surgeries. Since bone regeneration relies on mechanical stress, poor load transfer can result in insufficient stimulus, causing bone deterioration.
Advances in additive manufacturing have reduced implant stiffness by introducing porosity, allowing the creation of complex geometries. Porous designs are widely used in scaffolds to promote cell adhesion and fine-tune mechanical properties.
Neural networks, with their non-linear mapping ability, can be used to design unit cell structures with specific mechanical properties [1], [2]. In this study, one network is trained to predict the elastic tensor from unit cell geometries, which is then integrated into an optimization algorithm. A second network is trained to generate unit cell geometries based on the target elastic properties.

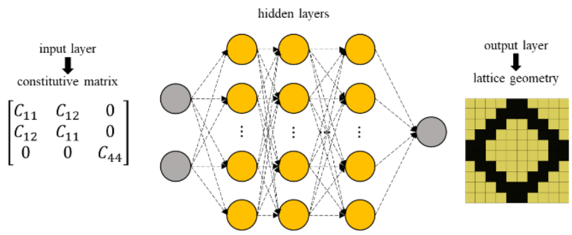


Figure 1 - Neural network scheme for reverse homogenization

2 MATERIALS AND METHODS

The surrogate model neural network has 400 input neurons, each representing an element of a uniform pixel grid, where 0 indicates a void and 1 indicates material. The output consists of four values, corresponding to the non-zero constants of the constitutive matrix.
The reverse homogenization network has 7 input neurons: 4 for the constitutive matrix constants, 1 for the volume fraction, and 2 for the pixel coordinates. It outputs the pixel density and must be run 400 times to generate a complete grid.
Both networks are tuned for optimal hidden layer configurations, using hyperbolic tangent activation functions and a linear output layer. The second network's continuous output is converted to binary (solid or void) using a 0.5 threshold.

3 RESULTS AND DISCUSSION

Regarding the surrogate homogenization network, the network with the lowest error had 4 hidden layers each with 40 neurons. The performance of the network for the direct task is shown in Figure

2, which shows the regression between the targets and the outputs of 50 separate instances in a test set.

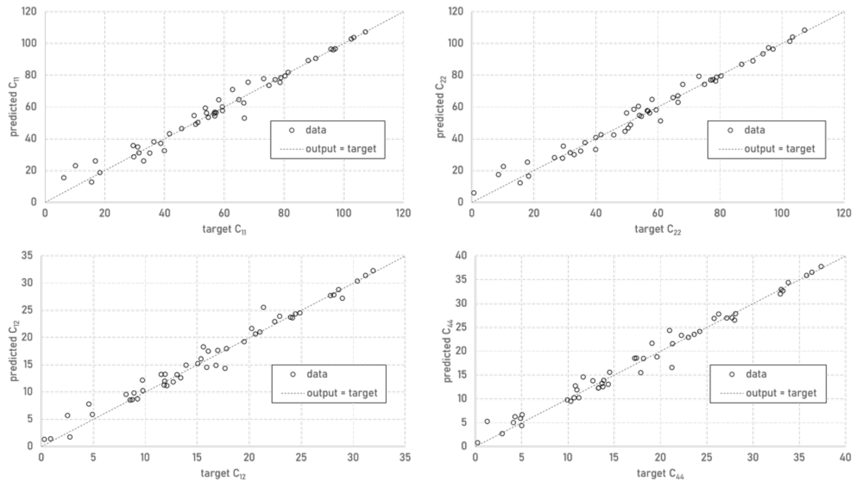
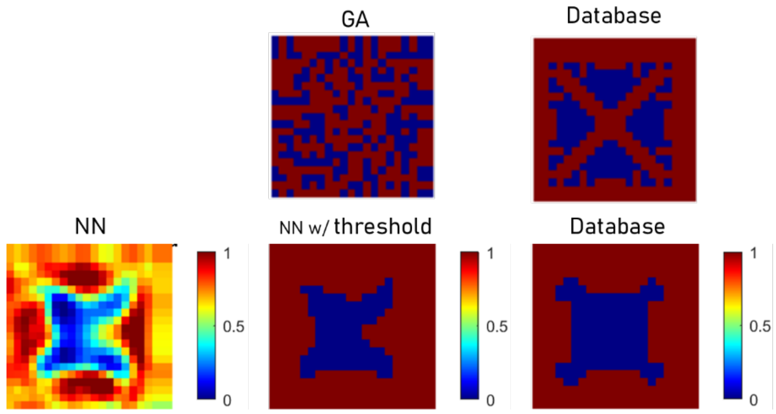


Figure 2 - Surrogate model for homogenization

The surrogate model was integrated into a genetic algorithm to minimize the difference between the unit cell properties and the target properties. Figure 3 (a) shows a unit cell generated through genetic optimization, which resulted in a random structure with mechanical properties significantly different from the target. Additionally, discrepancies between the homogenized properties predicted by the network and those calculated by FEM reveal model inaccuracies for geometries outside the testing set.

In contrast, the unit cell proposed by the reverse homogenization neural network, shown in Figure 3 (b) has a geometry more similar to the training database. The homogenized properties exhibit an average relative error of 34% compared to the target properties.



	target	surrogate homog.	FEM homog
C_{11}	36.431	30.948	16.837
C_{22}	36.431	38.069	17.265
C_{12}	12.681	13.001	3.791
C_{44}	10.305	13.831	5.882

(a)

	target	surrogate homog.	FEM homog
C_{11}	36.652	45.812	36.509
C_{22}	37.510	44.070	37.859
C_{12}	5.353	6.446	4.443
C_{44}	2.749	4.805	4.347

(b)

Figure 3 - Unit cell solutions using a surrogate model for homogenization and (a) a genetic algorithm (b) a neural network for unit cell design

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