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CONVOLUTIONAL NEURAL NETWORK AND HOMOGENIZATION BASED HYBRID APPROACH FOR LATTICE STRUCTURES

Abstract

This paper presents a novel methodology that utilizes the image processing based Machine Learning (ML) approach for the lattice structure design rather than using the traditional fine mesh based finite element method. The image processing based ML approach converted the lattice structures into binary matrices. The binary matrices are then used as a representation of the finite element mesh to calculate the material properties of the corresponding design, thereby alleviating the hassle of re-designing each configuration. Additionally, the study incorporated a Convolutional Neural Network (CNN) and Asymptotic Homogenization (AH) approach to reduce computational time further. Based on the training of 8,000 lattice designs, the developed hybrid model was found to have a mean absolute error of 1.60%. The approach also demonstrates the ability to predict the material properties of 1,000 lattice designs successfully in less time than it would take to perform the same task for a single lattice using an AH approach. As a result of previous efforts, the present study has conducted a parametric investigation to evaluate the generalization capability of the developed model. Consequently, the present strategy involves splitting the initially developed training dataset of 8,000 augmented lattice designs into three training subsets (e.g., 4,000, 2,000, 1,000) to explore whether the proposed model can maintain consistent prediction accuracy. Results indicate a significant reduction in prediction precision when the training set size falls below 50% of the original dataset, underscoring the critical role of training data volume. This study addresses a crucial challenge in determining the optimal amount of testing data for accurate predictions in novel ML models. The proposed approach facilitates a more realistic representation of material behavior, accounting for the variability observed in real-world scenarios.