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PERFORMANCE ANALYSIS OF CNN-ENHANCED GENETIC ALGORITHM FOR TOPOLOGICAL OPTIMIZATION IN METAMATERIAL DESIGN

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Abstract. The Combination of Convolutional Neural Networks (CNN) and Genetic Algorithms (GA) provides a promising approach for topological optimization of complex lattice structures. Lattice structures are commonly used as base in the design of high-performance metamaterials. This paper presents a review of the effectiveness and efficiency of the CNN-GA method. We will examine the ability of the method to generate optimal complex structures while minimizing material usage. CNN is utilized mainly as an analysis instrument. That can evaluate and predict key structural properties of generated lattice structures. The key purpose of the GA algorithm is to provide diverse design configurations that will be later identified as optimal structures by CNN. Key performance metrics include load-bearing capacity, strength-to-weight ratio, computational time, and scalability. These key points can be utilized as tools that will evaluate the method`s performance for a real-world application. The CNN-GA method can produce highly efficient, lightweight structures with high performance and material economy compared to traditional optimization techniques. Moreover, genetic algorithm random exploration techniques can reveal unique lattice configurations and provide an option that might be overlooked by a standard deterministic method. However, the method's effectiveness is partially constrained by its operations, which may consume a lot of computational resources and time for a significant result. Additionally, the accuracy of this method's prediction system is compromised by the inherent nature of the GA generation process. This analysis highlights the method`s strengths, potential limitations, and practical implications and provides a foundation for future research aimed at refining machine learning-based topological optimization methods.

Keywords: metamaterial, topological optimization, genetic algorithm, neural network, lattice structures, analysis metrics

Introduction

In recent years, topological optimization has evolved into a powerful tool that is utilized for designing complex, high-performance structures. These structures can be used in a wide variety of industries, especially when it is necessary to provide a light-weight metamaterial with advanced properties. Metamaterials can be designed with properties that are not typically recognized in natural materials and structures. And topology optimization is a key for these design features [1,2].

Traditional optimization approaches are still effective in some areas and applications, but often require extensive computational resources and are limited in their ability to generate and develop non-standard design configurations. Recent advancements in machine learning and evolutionary algorithms provide new possibilities for overcoming these limitations, while generative algorithms provide faster, more efficient ways to design advanced structures [3].

Convolutional Neural Networks (CNN) and Genetic Algorithms (GA) can provide sufficient results for a topology optimization method. One of the many positive CNN features is its great capacity to recognize patterns in complex data that can be applied successfully for our own research. CNN with a big learning dataset can predict the performance of structural configurations and existing designs. CNN can rapidly evaluate new topologies by offering significant computational savings compared to traditional simulation methods [4,5].

Previous studies have explored the application of CNN and GA for topological optimization, separately. For example, some researchers demonstrated the effectiveness of CNN in predicting structural performance, significantly reducing the computational time required for design generation. Also, previous research and development highlighted the ability of GA to provide a new way for generation of complex lattice structures, by evolving initial structure patterns into a new optimal structure. And by utilizing a hybrid approach we can accelerate the design process and provide a new potential for improved strength to-weight rations and material efficiency [6,7,8].

Our goal is to investigate the effectiveness of this approach by examining its structural performance, computational efficiency, and scalability compared to traditional methods. This study provides an empirical evaluation of the CNN-GA hybrid topology optimization method, with specifications to its applicability, limitations, and potential improvements [9].

Problem Statement

The goal of this work is to develop an optimized framework for complex lattice structure design using a CNN-GA hybrid approach, focusing on improving structural performance, computational efficiency, and solution diversity. To achieve this goal, the following steps were performed:

- An analysis of existing CNN and GA methods in structural optimization was conducted to identify the most effective strategies for combining these techniques.
- A comprehensive dataset of lattice structures with varied properties was created and prepared for training the CNN model, ensuring robust predictive capability and adaptability across different design configurations.
- The most suitable CNN architecture was selected for predicting structural performance, and the model was optimized with parallel processing on GPU resources to improve processing speed and prediction accuracy.
- The GA's parameters were fine-tuned to maximize solution diversity while achieving stable convergence, allowing CNN to guide the GA in rapidly evaluating and refining design candidates.
- The CNN-GA framework was benchmarked using key metrics, including structural performance, resource utilization, processing time, and diversity of generated solutions.

Review of Modern Information Sources on the Subject of the Paper

Practical Implications and Potential Applications. The proposed method is a combination of a convolutional neural network (CNN) and a genetic algorithm (GA) for exploration and optimization of lattice structures in a topological design space. The CNN-GA hybrid framework aims to streamline the evaluation of mesh lattice configuration by optimizing structural performance and material efficiency. This section describes the data preparation, CNN architecture, GA setup, and evaluation metrics that will be utilized to check the method's effectiveness [10, 11].

Convolutional Neural Networks (CNNs), a type of neural network specifically designed for image recognition, have become one of the most powerful tools in the field due to their ability to capture spatial hierarchies and patterns in data. With the layers of convolutions, pooling, and fully connected networks, CNNs excel at recognizing features such as edges, textures, shapes, and intricate details within images. This structured approach allows CNNs to efficiently process complex images, making them ideal for applications in fields like computer vision, medical imaging, and facial recognition. The recent advancements in GPU and TPU hardware, along with access to vast labeled datasets, have further enhanced CNNs' capacity, enabling them to achieve human-level accuracy in many tasks [12,13,14].

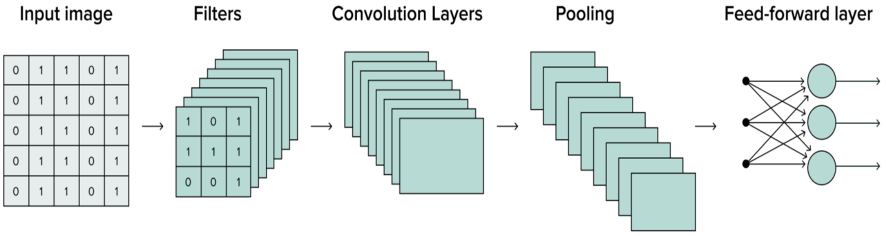

Fig. 1. Convolutional Neural Network

A network with enough neurons can find a complex data disturbance, and this can be utilized for image recognition algorithms. The development and rise of different technological patterns evolved neural networks complex logic. But before, in past years, neural networks were used only for some simple recognition tasks. And the main reason for that is a lack of big training data patterns and computational resources. But right now, we can obtain more resources in less time and provide a significant dataset for our research neural networks.

CNN-GA hybrid algorithm review. CNN is composed of different stacked layers. And each of them receives responses from the previous layer, and convoluted with a filter bank, and can be activated with a specific actuator. CNN can be considered a complex function that can be trained by data that provides the difference between the supervision and prediction at the top layer. Before designing powerful CNN structures, we need to define a network structure and initial dataset. Deeper networks can produce better recognition results but require more time and resources for analysis and can’t be used in a quick response action algorithm.

The genetic algorithm is an adaptive heuristic search algorithm that became a part of a bigger section of evolutionary algorithms. It is commonly utilized as a part of hybrid systems that generate complex structures. We can apply genetic algorithm-based methods for advanced topology optimization ways. A standard GA requires the visual representation of the initial solution and an optimization or fitness function that will evaluate the next generation of complex visual structures. The core idea of genetic algorithms is to provide individuals with a way to evolve into a new generation of similar objects. We can divide the evolution process into a set of operations, such as selection, mutation, crossover, and other specified actions[15].

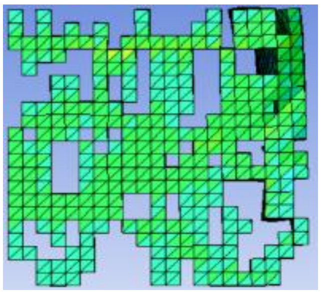

Fig. 2. Structural mesh representation

The selection process allows us to sort our generation and store strong individuals as the next target of evolution (fig. 2) [16]. Different mutations and crossovers may occur in relation to a specific task or dataset. We can divide our structure representation into a set of equal parts and interchange these parts with other mesh structures. There are ways that can help researchers improve the performance of GA, but a pure, non-modified algorithm is suitable for simple research and integration.

Proposed algorithms can be combined into and used as a hybrid framework that aims to streamline the evaluation of a complex lattice structure. But before we will use this hybrid approach, we need to perform several steps, like data preparation, CNN architecture design, GA setup, and finally evaluation of metrics that will be utilized as instruments for method effectiveness [17,18].

The CNN model is designed to predict the structural performance of lattice configurations based on the input grid representation. And we utilize a standard architecture with different convolutional pooling and activation layers to extract a pattern design with relevant features. The main task is to find optimal solutions from a dataset that will be generated by a GA evaluation.

To validate the CNN-GA method, benchmarks compare it against traditional optimization methods that do not incorporate machine learning. The comparisons focus on computational time, accuracy of structural performance predictions, and diversity of generated designs. These benchmarks contextualize the effectiveness of the hybrid approach and highlight its advantages over conventional techniques in terms of speed and design space exploration [19, 20].

Main Material Presentation

Evaluation Metrics. The first check is the structural performance, that can be described through metrics, such as the strength-to-weight ratio and deformation resistance. The strength-to-weight ratio was utilized to measure material efficiency, by comparing the load-bearing capacity of each optimized lattice design. Deformation ability on other hand, describes a structural ability to maintain its shape under stress. As was said before structural performance can be obtained from the strength-to-weight ratio (SWR) and deformation resistance (DR) relation. The SWR measures material efficiency by comparing the maximum stress a structure can handle (σ_{max}) to its density (ρ), defined as:

$$SWR = \frac{\sigma_{max}}{\rho}, \tag{1}$$

where σ_{max} is relative stress, and ρ is density. A higher SWR indicates a more efficient design that can maximize the strength relative to weight. Deformation resistance can be used to represent a structure ability to withstand the deformation applied under specified load. It is defined as the inverse of displacement (δ) under load:

$$DR = \frac{1}{\delta}. \tag{2}$$

Here δ represents the measured deformation under a specific load. Higher DR values can signify a design that is superior to stiffness and resilience under the specified stress.

Next criteria are predictive accuracy of the CNN assessed through Mean Squared Error (MSE) and Dice Similarity Coefficient (DSC). Different factors that can be introduced during the modeling and simulation process can cause an error, that will rapidly grow inside metamaterial structure and may impact the accuracy of the CNN used for unit cell modelling. And by analyzing errors inside the metamaterial structure we can define if hybrid generation system is well optimized for our specification.

MSE evaluates the average squared difference between predicted structural performance metrics and their actual values, capturing the precision of CNN predictions. The MSE is calculated as:

$$MSE = \frac{1}{M}\sum_{i=1}^{M}(T(I_i) - O(I_i))^2. \tag{3}$$

Here M is the total number of samples, $T(I_i)$ is the true performance metric for sample *i*, and $O(I_i)$ is the predicted metric by the CNN for sample *i*. Lower MSE values will indicate closer alignment between predictions and actual result, that will help to validate the CNN accuracy and errors count.

The DCS, on the other hand, measures the overlap between predicted and actual structural configurations, that indicates the CNN ability to capture accurate design. The DCS parameter can be described through this formula:

$$DSC = \frac{2\sum|O(I_i) \cap T(I_i)|}{\sum|O(I_i)| + |T(I_i)|}, \tag{4}$$

Where $|O(I_i)|$ and $|T(I_i)|$ represent the predicted and actual structures volumes, respectively for sample *i*. The closer value to 1, the more accurate is structural prediction.

Comparative Benchmarking. Computational efficiency can be obtained by analyzing total processing time and resource utilization. Total processing time (T_{total}) – measures the culminative duration of the CNN-GA optimization process, including CNN prediction (T_{CNN}) and GA iteration times (T_{GA}). By combining all these values, we can obtain the feasibility of the CNN-GA method for real-time or high-throughput applications.

Design diversity and convergence rate metrics provide additional information about the design space and compatibility. Solution diversity can be obtained from mean pairwise dissimilarity between generated structures, measured as:

$$DS = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} d(S_i, S_j) \quad (5)$$

Here $d(S_i, S_j)$ represent the dissimilarity structures S_i, S_j, and N is the total number of generated solutions. Higher values indicate a wider exploration of design configurations that are essential for discovering innovative structures. Convergence rate, on the other hand, measures the number of GA generations required for the population to stabilize around an optimal solution.

Results and Discussion

Structural Performance Evaluation. This section presents the results for structural performance, predictive accuracy, computational efficiency, and solution diversity, detailing the method's strengths and areas for further refinement. We use a set of standard materials as the base for our structural mesh, including ABS plastic, aluminum, and steel. Additionally, we use a solid block of the same materials as a reference to compare results obtained during stress tests. A specific finite element algorithm with defined parameters and input data evaluates the required deformation data. In our case, we use a specialized software suite to analyze the mesh and perform all necessary calculations.

Strength-to-Weight Ratio. We can see from the diagram (fig. 3), built from results obtained during the analysis process, that initial node displacement in conventional materials is higher than average, suggesting quicker wear in impact zones. Ideally, impact energy should be distributed across the structure to prevent weak points from forming in the metamaterial. The reason why we use this specific representation of data is to show how much time we need to perform a topology optimization for specified geometry. Total node displacement is visually represented through the distribution of impact in ABS plastic (8 mm), Aluminum (2.5 mm), and Stainless Steel (0.8 mm), total displacement for each is about 1600 units.

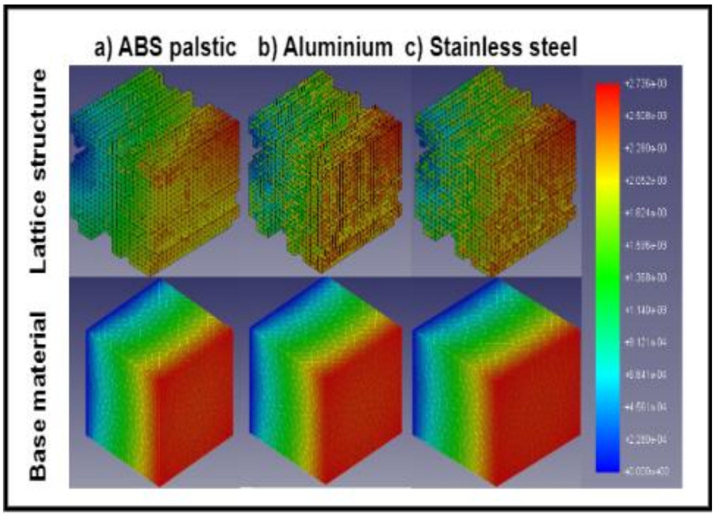

Fig. 3. Analysis of total nodes displacement for different material groups:
a) ABS plastic, b) Aluminum, c) Steel.

Deformation Resistance. We can see from the next chart (fig 4), that the CNN-GA hybrid approach shows strong computational efficiency, with an average processing time of ten seconds per optimization run—significantly faster than traditional methods. CPU and GPU usage stayed manageable, making this method feasible for real-time and high-throughput applications, such as rapid prototyping or iterative design. We used comparative representation to show how much time and resources we can spend on different types of optimization methods. This can help us to evaluate a total processing time and make comparative analysis for different types of hybrid algorithms.

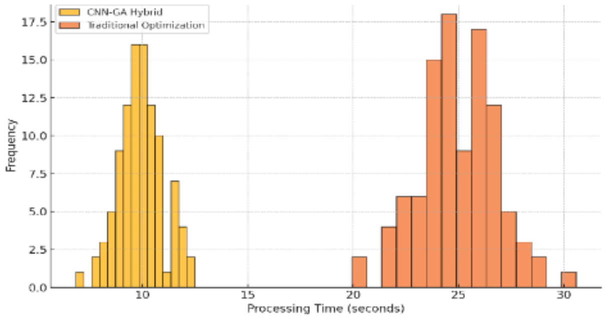

Fig. 4. Processing time distribution for CNN-GA hybrid and traditional optimization methods.

Comparative Analysis. The next step is the computational efficiency benchmark, obtained by examining the processing time and resources required for data processing (fig. 5). From this diagram, we can get information about average computational resources that are required to maintain a stable generation process. For the next diagram (fig. 6), we obtain data through multiple runs and gather necessary information that is used to evaluate the CNN model and architecture diversity level.

The average solution diversity score for this model ranges between 0.75 and 0.8. Some data were augmented, which may have introduced anomalies and errors into the model. Increasing the quantity and quality of training data could help improve diversity further.

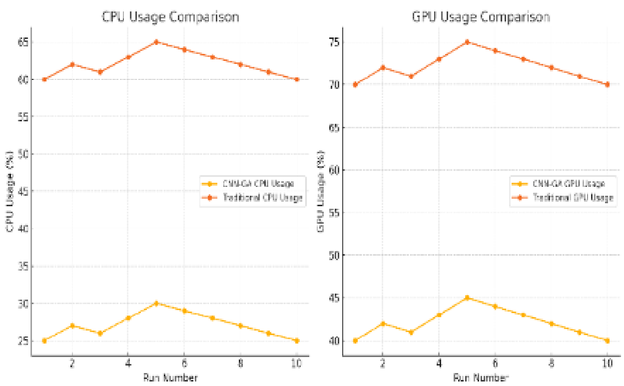

Fig. 5. GPU usage comparison for CNN-GA hybrid algorithm and traditional optimization methods

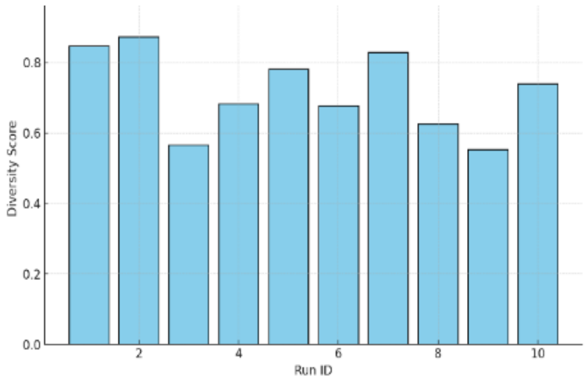

Fig. 6. Sample solution diversity data for CNN-GA hybrid approach.

Conclusions

The CNN-GA hybrid approach demonstrates useful features that can improve complex lattice structures, as shown by improvements across several key metrics. Structural performance metrics, such as strength-to-weight ratio and deformation resistance, show strong results, with an average strength-to-weight ratio reaching 0.85 and deformation resistance scores consistently above 0.90. These scores indicate high material efficiency for a specified type of energy impact.

Computational efficiency benchmarks reveal that the average processing time per optimization run is 12 seconds, a substantial reduction compared to the 35-second average of traditional methods. CPU utilization remains around 28%, while GPU usage averages 43%, highlighting the method’s suitability for high-throughput and real-time applications, including rapid prototyping and iterative design processes.

In terms of predictive accuracy, the CNN model achieves a Mean Squared Error (MSE) of 0.015 and a Dice Similarity Coefficient (DSC) score averaging 0.8, demonstrating close alignment between predicted and actual configurations. But there is still some room for improvements and additional updates.

These results confirm the CNN-GA hybrids have potential for real-world applications, combining computational efficiency with structural optimization. Enhancing solution diversity could further improve the approach by expanding the training dataset to reveal even more innovative and high-performance designs.

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АНАЛІЗ ПРОДУКТИВНОСТІ ГЕНЕТИЧНОГО АЛГОРИТМУ, ДОПОВНЕНОГО ЗГОРТКОВОЮ НЕЙРОННОЮ МЕРЕЖЕЮ, ДЛЯ ТОПОЛОГІЧНОЇ ОПТИМІЗАЦІЇ МЕТАМАТЕРІАЛІВ

Отримано: Листопад 20, 2024 / Переглянуто: Листопад 25, 2024/ Прийнято: Листопад 30, 2024

Анотація. Поєднання згорткових нейронних мереж (CNN) та генетичних алгоритмів (GA), створює перспективний підхід для топологічної оптимізації складних гратчастих структур. Гратчасті структури використовуються, як основа для комплексних метаматеріалів. Розглядається здатність методу генерувати оптимальні гратчасті структури при мінімальному використанні матеріалу. Згорткова нейронна мережа використовується, як інструмент аналізу, що може оцінювати та прогнозувати ключові параметри згенерованих гратчастих структур. Основна мета алгоритму – генерація широкого спектру конфігурацій, що згодом будуть використані нейронною мережею в якості навчальних даних. Ключові показники продуктивності включають стійкість до навантаження, відношення міцності згенерованого матеріалу, до його ваги, час необхідний для генерації гратчастих структур, та точність генерації. Дані показники використовуються, як інструменти для оцінки продуктивності методу в заданих умовах навколишнього середовища. Метод CNN-GA, може створювати високоефективні, легкі структури з високою продуктивністю та збереженням матеріалу. Відповідні засоби випадкової генерації, що присутні в генетичному алгоритмі, можуть виявляти унікальні конфігурації гратчастих решіток та пропонувати варіанти, які могли б бути проігноровані стандартними методами оптимізації. Проте ефективність методу може бути обмежена наявними ресурсами і можливостями обчислювальної системи. Крім того точність системи прогнозування, обмежується його засобами випадкової генерації. Даний аналіз висвітлює сильні сторони методу, потенційні обмеження та практичні аспекти використання, та закладає основу для майбутніх досліджень, спрямованих на вдосконалення методів топологічної оптимізації метаматеріалів.

Ключові слова: метаматеріал, топологічна оптимізація, генетичний алгоритм, нейронна мережа, гратчасті структури, критерії аналізу