Topology Optmization Using Machine Learning

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Student's Declaration

I hereby declare that the work presented in the report entitled **"Topology Optmization Using Machine Learning"** submitted by me for the partial fulfillment of the requirements for the degree of *Bachelor of Technology* in *Computer Science & Engineering* at Indraprastha Institute of Information Technology, Delhi, is an authentic record of my work carried out under guidance of **Dr.Kalpana Shankhwar**. Due acknowledgements have been given in the report to all material used. This work has not been submitted anywhere else for the reward of any other degree.

Aryan khatana, Aman Kudiyal

Chirag Madaan, Shantanu Prakash

Place & Date: 29 April 2024, Delhi India

Certificate

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Dr.Kalpana Shankhwar

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Abstract

This thesis presents a novel approach to structural design through the integration of topology optimization (TO) and machine learning (ML), aimed at enhancing the design efficiency and material utilization in engineering structures. Topology optimization is employed to systematically reduce material usage while preserving structural integrity, which is crucial in fields such as aerospace, automotive, and civil engineering. By leveraging machine learning, particularly convolutional neural networks, this project automates the optimization process, thereby significantly reducing the computational time and resources traditionally required. The methodology involves generating diverse datasets using TOPY, a popular topology optimization tool, and developing a U-Net-like neural network model to predict optimized material distributions from given load and boundary conditions. The machine learning model is trained and validated on datasets characterized by variations in loading conditions and material properties, created through simulations that include both 2D and 3D models. Preliminary results demonstrate that the ML-augmented topology optimization process can enhance the design accuracy and speed, proposing a scalable solution that can be extended to more complex structures and optimization scenarios. This integration not only streamlines the design process but also opens new avenues for innovation in structural optimization.

KeyWords: Topology Optimization, Machine Learning.

Contents

Chapter 1

Introduction

Topology optimization (TO) is a computational technique used to determine the optimal distribution of material within a given design space subject to specified loads, boundary conditions, and constraints. Its goal is to maximize or minimize a performance function, typically involving structural behavior such as stiffness or strength. This method is instrumental across various engineering disciplines, including aerospace, mechanical, and civil engineering, where material efficiency is crucial. However, conventional topology optimization processes are computationally intensive and can be time-consuming, especially when dealing with complex structures and high-resolution models.

The advancement of machine learning (ML), particularly deep learning, offers promising solutions to overcome some of the challenges faced by traditional TO methods. Machine learning algorithms can learn from data to make predictions or decisions without being explicitly programmed to perform the task. In the context of topology optimization, ML can be utilized to predict optimal material distributions faster than conventional iterative methods. This integration not only aims to reduce the computational load but also enhances the ability to handle complex optimization tasks that are otherwise impractical with standard approaches.

The motivation for this project stems from the need to improve the efficiency and effectiveness of structural designs, minimizing material use while ensuring structural integrity and functionality. The potential for significant reductions in time and resource expenditure makes this an attractive area for research and development.

This thesis explores the integration of topology optimization with machine learning techniques to create a hybrid approach that leverages the strengths of both fields. The project involves generating a dataset using topology optimization software, which is then used to train a machine learning model to predict optimized topologies.

The structure of this thesis will cover the development of the methodology, including dataset generation, model training, and integration of ML predictions back into the topology optimization process. The approach is tested on both 2D and 3D models to evaluate its effectiveness across different dimensions and complexities. Through rigorous testing and validation, this work aims to demonstrate the applicability of machine learning-enhanced topology optimization in real-world engineering problems, potentially transforming how structural designs are conceived and implemented.

Chapter 2

Models And Methods

2.0.1 Dataset Generation

Any sort of machine learning/AI task requires data. So, our first objective was to generate the data to train the machine learning model. So, we had to think about the type of data we needed since we needed both inputs and their corresponding for the model to learn how to optimize different types of topologies. We dove into several research papers and connected several authors from whom we got to know getting authentic real world data was impossible so we had to generate synthetic data which could be done through several ways -

1. Using a Generative Adversarial network/ Variational Autoencoder to generate lots of data using just a little data but that wouldnt have generated the correct input output topologies since we need the best optimized output for the input when all the stresses are applied and nodes are fixed.

2. Using SIMP based solvers to create random random problems and solve them to get the correct optimized solution with the intermediate states as the solver iterates to solve the problem, this is the only method which was used in all the different research papers since it was accurate. The only problem is it is "too slow". We used a library called "topy" after discussing with one of the first research paper authors in this field.

2.0.2 Two-Dimensional Topology Optimization Sampling

1. We sampled random topology optimization problems and performed 100 iterations using the Solid Isotropic Material with Penalization (SIMP) strategy. [2]

2. Each problem was loaded with random constraints, including several fixed points and forces applied along the x and y axes.

3. The topology was divided into a mesh of square elements, with each square considered as a node. Constraints and forces were applied to these meshed nodes. Figure 1 from the documentation clearly depicts these nodes and the applied strains and constraints.

4. Sampling of fixed and loaded nodes:

    a. Fixed nodes were sampled from a Poisson distribution with parameter $\lambda = 2$. Loads were also sampled from a Poisson distribution with $\lambda = 1$.

    b. The probability of a force being applied within the structure's interior was almost zero, hence more likely applied at the boundary.

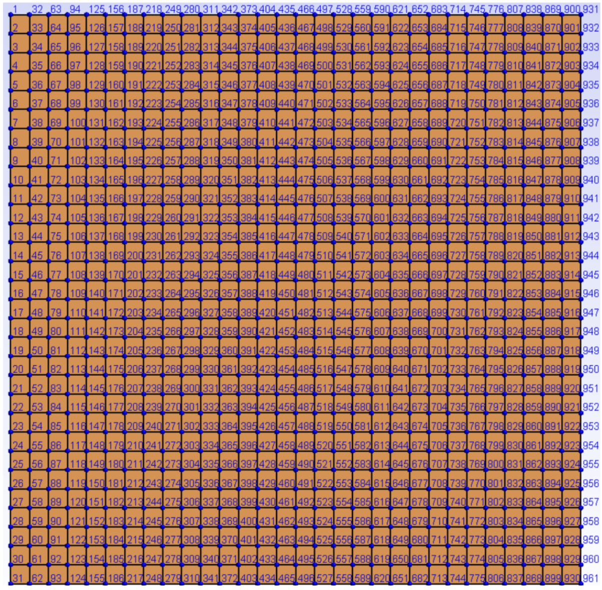

Figure 2.1: Depicts these nodes and the applied strains and constraints.

c. The volume fraction, which is the fraction of the original volume that the optimized structure will have, was sampled from a normal distribution with parameters $\mu = 0.5$, $\sigma = 0.1$.

5. This resulted in a numpy array of size $100 \times 30 \times 30$, representing the 100 iterations of each 30x30 sample, totalling 10,000 samples.

2.0.3 Three-Dimensional Data Sampling

1. Similar to the 2D case, but adjusted for three degrees of freedom: x, y, and z, while the rest of the details remained consistent.

2. The computational demand was significantly higher, with each problem taking over 45 minutes to solve. Thus, acquiring each data point took more than 45 minutes. The output was an array of dimensions $100 \times 30 \times 20 \times 40$, representing 100 iterations of 30x20x40 minimal bounding box (MBB) beam problems.

2.0.4 Model Architecture

In this study, a comprehensive literature review indicated a preference for encoder-decoder architectures in existing research. The model architecture developed for this research is implemented using PyTorch, following an encoder-decoder paradigm. The input is formatted as a tensor with dimensions (batch_size $\times\ 2 \times H \times W$), where H and W represent the height and width, respectively. The tensor comprises two channels: the first channel corresponds to either the 10th or 11th iteration from the Topology Optimization Process (TOPY), and the second channel delineates the optimization changes between two consecutive iterations, specifically between iterations n and $n-1$.

To exemplify, in the Figure 2.2 first channel could represent the topology at the 9th iteration, and the second channel could illustrate the differences between the 9th and 8th iterations. The

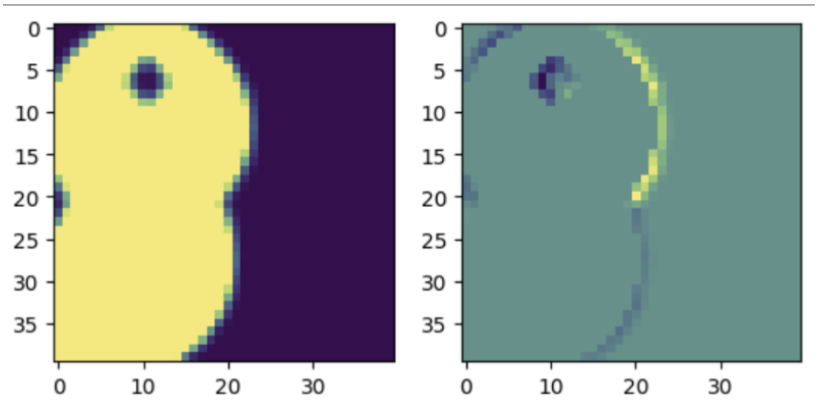

Figure 2.2: First channel could represent the topology at the 9th iteration, and the second channel could illustrate the differences between the 9th and 8th iterations. The model's output is the topology at the final or 100th iteration, which is then assessed using the defined loss function

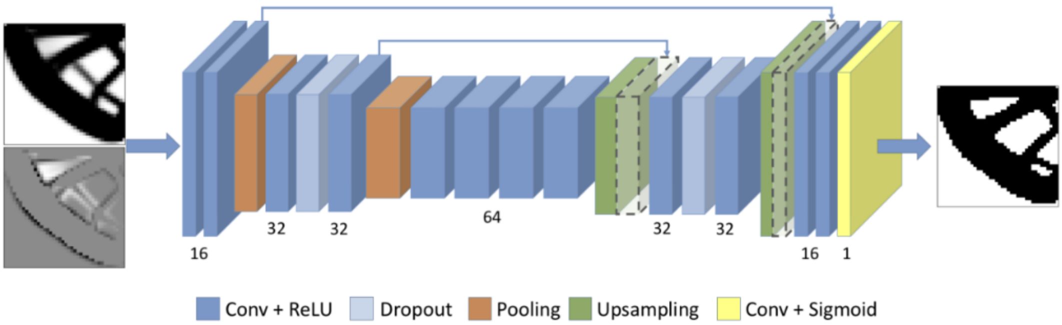

Figure 2.3: Model architecture for 2D samples:All kernels are of size 3x3. The number of kernels is represented by the number at the bottom of the layer. Blue arrows and opaque boxes represent the concatenation of the features from different layers

model's output is the topology at the final or 100th iteration, which is then assessed using the defined loss function.

Loss Function The loss function employed integrates Binary Cross-Entropy with Logits Loss (`BCEWithLogitsLoss`) and Mean Squared Error Loss (`MSELoss`), augmented by a volume coefficient (`vol_coeff`). The loss equation is given by:

$$\text{loss} = \text{BCEWithLogitsLoss}(\text{output}, \text{target}) + \text{vol\_coeff} \times \text{MSELoss}(\text{output}, \text{target}) \tag{2.1}$$

where *output* represents the model's predictions, *target* denotes the ground truth labels, and *vol_coeff* is a factor that modifies the contribution of the MSE loss to the overall loss. This composite loss function is designed to minimize both the binary cross-entropy, commonly used in segmentation tasks, and the mean squared error, with the influence of the latter scaled by the `vol_coeff` parameter. Figure 2.3 shows the Model architecture for 2D samples where all kernels are of size 3x3. The number of kernels is represented by the number at the bottom of the layer. Blue arrows and opaque boxes represent the concatenation of the features from different layers. [3] Figure 2.4 shows the Model architecture for 3D samples where architecture is similar to Sosnovik's but it works for 3D data.[1]

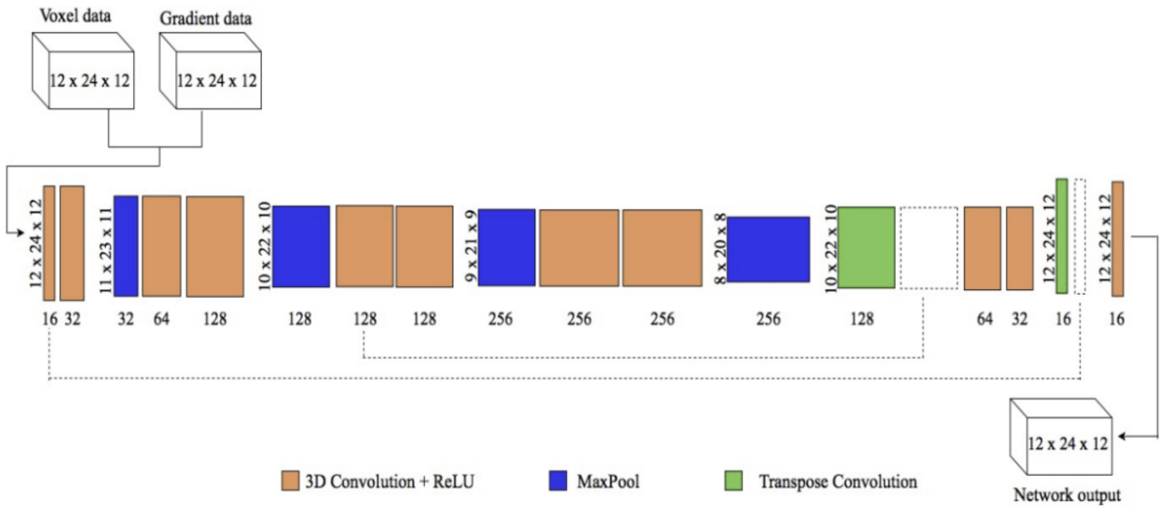

Figure 2.4: Model architecture for 3D samples:The above architecture is similar to Sosnovik's but it works for 3D data and the rest of the details are the same.

2.0.5 Integration of Topology Optimization and ML

Integrating ML predictions with traditional TO involved an iterative refinement process:

Feedback Loop: After initial topology optimization to generate training data, the ML model's predictions were used to refine the optimization in subsequent iterations. This feedback loop allowed for continuous improvement in topology design, reducing computational time and potentially uncovering more efficient design solutions than could be achieved through traditional methods alone.

The methodologies were applied to both synthetic and real-world scenarios to validate the approach. Testing involved comparing the results from the ML-enhanced TO process against those obtained from traditional TO methods, assessing improvements in terms of computational efficiency and the quality of the optimized designs.

Chapter 3

Results

3.0.1 Two-Dimensional Topology Optimization

The first set of results pertains to the two-dimensional topology optimization. By employing the TOPY optimization tool and a custom Python script, the optimization process generated various material layouts based on the specified load and boundary conditions. The 2D results, one of which is depicted in Figure 3.1, show the optimized topology of a rectangular design domain subjected to specific loading conditions.

Figure 3.1 Shows a Optimized 2D topology obtained from TOPY using a custom Python script. The yellow regions represent material presence, while the purple regions indicate material absence, demonstrating the algorithm's ability to reduce material usage while maintaining structural integrity.

The algorithm's efficiency is evident in the minimalistic yet structurally sound layout, with stress concentrations adequately addressed by the material distribution. This demonstrates the potential of machine learning to enhance traditional topology optimization techniques, streamlining the design process and enabling the creation of lightweight yet robust structures.

3.0.2 Three-Dimensional Topology Optimization

Advancing to three-dimensional topology optimization, the developed scripts facilitated the generation of datasets with 3D models, which were then used to train the machine learning model. Figure 3.2 Shows a 3D scatter plot visualization of the optimized topology at a certain threshold level, displaying a complex geometry that maximizes structural efficiency within a cubic design domain.

Figure 3.3 Shows Another 3D visualization from a different angle, highlighting the algorithm's capability to navigate and optimize within the three-dimensional space, addressing multi-axial loads and constraints. The 3D results underscore the model's ability to discern and implement intricate design features, optimizing material layout in three dimensions. This capacity to process and optimize 3D structures underscores the significant advantage of integrating machine learning with topology optimization, paving the way for advanced design methodologies in engineering applications.

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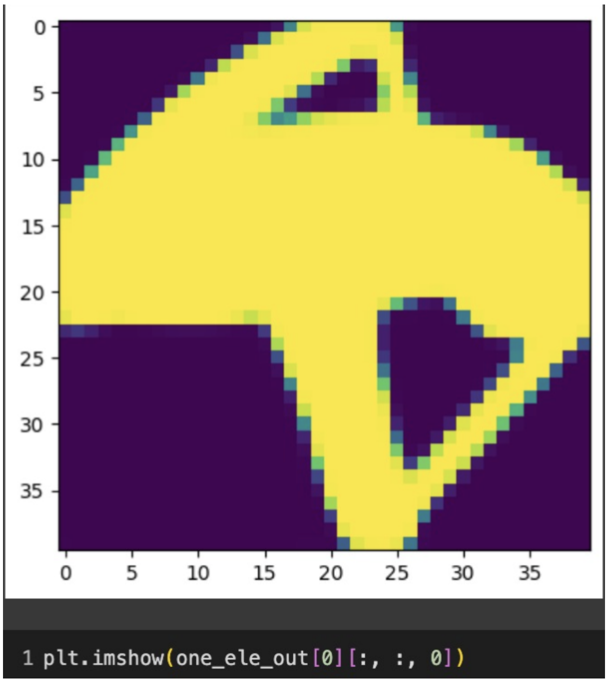

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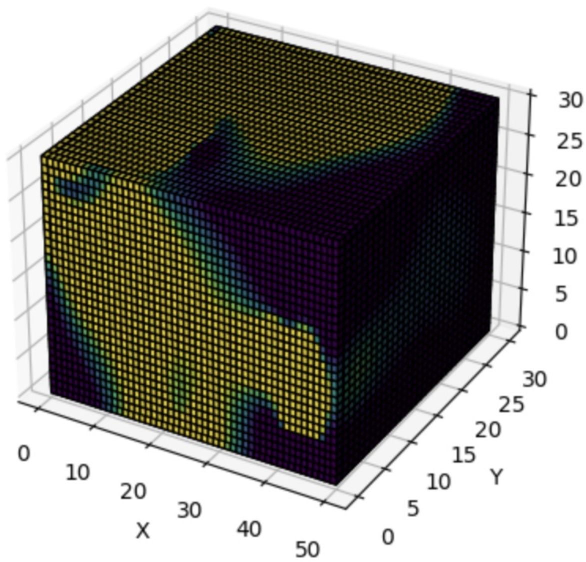

Figure 3.2: Shows a 3D scatter plot visualization of the optimized topology at a certain threshold level, displaying a complex geometry that maximizes structural efficiency within a cubic design domain

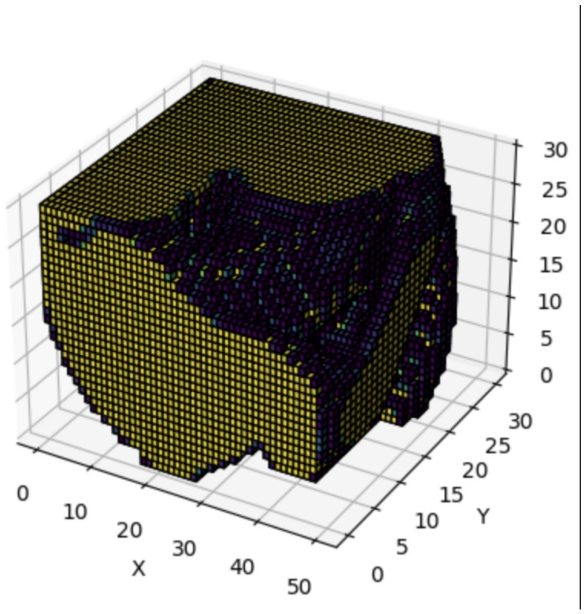

Figure 3.3: Shows Another 3D visualization from a different angle, highlighting the algorithm's capability to navigate and optimize within the three-dimensional space, addressing multi-axial loads and constraints.

Chapter 4

Discussions

The integration of machine learning (ML) with topology optimization (TO) represents a paradigm shift in structural design and optimization. The discussion is structured around the results obtained from the application of this integrated approach, emphasizing the advancements and challenges encountered during the research.

A. Efficiency of Machine Learning-Augmented Topology Optimization :

The ML-augmented TO process has demonstrated a notable increase in efficiency. The use of a U-Net-like convolutional neural network, trained on datasets generated by TOPY, enabled rapid predictions of optimized topologies. The two-dimensional results, as shown in the provided visual outputs (Figure 3.1), illustrate the ML model's capability to discern and predict material distribution efficiently. The three-dimensional visualizations (Figures 3.2 and 3.3) further highlight the model's proficiency in extending this capability to more complex structures, where traditional TO methods would require significantly more computational resources and time.

The Python scripts, part of the methodology, allowed for the automation of dataset generation and processing. The application of multiprocessing significantly improved the computational efficiency, a crucial aspect considering the voluminous data involved in 3D topology optimization.

B. Accuracy and Material Efficiency :

The results underscored not just the efficiency but also the accuracy of the ML-augmented TO approach. The 2D optimization outputs reveal material distributions that align well with load-bearing pathways, suggestive of an understanding of stress distribution principles by the ML model. Similarly, the 3D results show an optimized distribution of material that suggests a mature grasp of three-dimensional stress fields, pivotal for practical applications in engineering design.

The detailed geometries obtained from the ML-enhanced process also indicate the model's ability to create designs that potentially lead to material savings while maintaining or even enhancing structural performance—a critical goal in sustainable engineering practices.

C. Comparison with Traditional Methods :

Comparing the ML-augmented TO process with traditional TO methods reveals several advantages. Primarily, the ability to process large datasets and produce results within a shorter timeframe stands out. Furthermore, the ML model's predictions often presented novel solutions that were not immediately apparent through traditional optimization methods, suggesting that

ML can indeed discover innovative design paradigms.

D. Real-world Implications and Future Work :

The implications of this research are vast, extending to industries where material efficiency and innovative design are paramount. The aerospace, automotive, and civil engineering sectors stand to benefit significantly from the ability to generate optimized, lightweight structures rapidly.

Chapter 5

Conclusion

This project has successfully demonstrated the integration of machine learning (ML) with topology optimization (TO) to enhance the efficiency and effectiveness of structural designs. The utilization of a U-Net-like convolutional neural network to predict material distribution from generated datasets has shown considerable promise in reducing computational time and resource usage compared to traditional TO methods. The visual outputs obtained from both 2D and 3D models highlight the potential of this integrated approach to produce structurally sound and material-efficient designs. The adoption of parallel processing and Python computational capabilities further underscores the viability of scaling this approach for complex, real-world applications. Future work will focus on improving the accuracy and robustness of the ML model, experimenting with various neural network architectures, and extending the application of this research to practical, industry-specific challenges. The findings from this study pave the way for innovative approaches in engineering design, with the potential to revolutionize the field of structural optimization.

Chapter 6

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