Advancing Structural Design with Machine Learning: Stress Field Prediction in Plates with Cutouts

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Abstract. Machine learning techniques are creating disruptive approaches in diverse engineering fields, including in engineering and structural design, pushing the boundaries of performance and reliability. This presentation delves into the development of a machine learning model that accurately predicts stress fields in complex structures. By leveraging the SimuStruct dataset, encompassing diverse geometries and configurations, valuable insights are gained into the challenges faced in structural engineering.

Complex structures, especially those with holes, introduce complexities that affect structural behavior and integrity. Accurately predicting stress distribution in these configurations is crucial for ensuring safety and performance. The incorporation of hole-containing structures into the SimuStruct dataset enables training and evaluating machine learning models specifically tailored to address this critical aspect of structural design. This resource facilitates optimization and informed decision-making.

The application of machine learning in predicting stress fields in structures with holes holds promise for enhanced design and performance. By precisely capturing stress distribution, engineers can identify regions of heightened stress concentration, enabling informed choices in material selection, reinforcement, and weight reduction. These advancements lead to improved efficiency, reliability, and safety in structural operations. The focus on structures with holes in the SimuStruct dataset, alongside the development of machine learning models for stress prediction, significantly impacts the engineering industry, fostering innovation and optimization while ensuring structural integrity under complex loading conditions.

In conclusion, the integration of structures with holes or other discontinuities into the SimuStruct dataset directly addresses ongoing challenges in structural design. The remarkable development of machine learning models for stress prediction represents a significant leap forward, empowering researchers and engineers to optimize design and achieve substantial improvements in efficiency, reliability, and safety. With a focus on complex structures, machine learning techniques revolutionize the industry, paving the way for innovative advancements in structural integrity and performance.

Keywords: Machine Learning, Graph Neural Networks, Structural Design, Plates, Finite Element Modeling

1 Introduction

Predicting stress-strain distributions has become an increasingly critical and indispensable task, with wide-ranging implications spanning the domains of mechanical engineering and materials science. Achieving a nuanced and accurate comprehension of intricate physical fields, which encompass a multifaceted array of strain and stress tensors, holds the key to the success of complex design and engineering endeavors. In this context, the assessment of stress distribution and the potential for structural compromise under specific conditions, an intricate discipline known as structural stress analysis, assumes an irreplaceable role across a diverse spectrum of scenarios and applications [1]. While traditional methodologies undeniably offer a high degree of precision, they do, however, exact a substantial computational toll, stemming from the imperative need to meticulously solve sprawling linear systems. This computational challenge is further exacerbated when grappling with the intricate intricacies inherent in nonlinear materials and structures, characterized by multifarious phenomena such as post-buckling instability, hyperelasticity, and plasticity [2].

Amidst these challenges, the Finite Element Method (FEM) has emerged as a stalwart technique for structural and solids analysis, renowned for its capacity to deliver a harmonious blend of computational efficiency and analytical precision in stress analysis across a diverse array of applications. Its versatility in accommodating a wide gamut of constitutive laws, boundary conditions, and loading scenarios is a hallmark of its utility [3]. Nevertheless, it is imperative to underscore that FEM grapples with the aforementioned computational demands, underscoring the ongoing need for innovative and efficient methodologies.

The swift advancement of computational methods dedicated to stress analysis takes on a heightened significance in contemporary domains such as generative design and topology optimization. In such domains, the expeditious and accurate evaluation of structural integrity stands as a paramount requisite. Herein lies the compelling rationale for delving into the realm of Deep Learning (DL), an intrinsic subset of Machine Learning (ML), that exhibits a compelling aptitude for modeling intricate relationships between input and output parameters in FEM stress analysis, effectively serving as a surrogate for the FEM itself. The integration of DL techniques with physical field data holds the promise of augmenting the physical relevance of stress analysis and delving deeper into the underlying mechanisms that govern complex systems [4].

Within the expansive landscape of Deep Neural Networks (DNNs), characterized by a diverse array of architectural paradigms including but not limited to Feedforward Neural Networks (FFNNs), Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Graph Neural Networks (GNNs), and Hybrid Neural Networks. Engineered with a laser focus on graph-based data, GNNs stand as a quintessential embodiment of deep learning algorithms meticulously designed to unravel intricate patterns within datasets organized as interconnected nodes and edges [5, 6]. Particularly intriguing is the inherent compatibility between the conventional FEM domain, conventionally manifest as a mesh replete with nodes and elements, and the graph framework, thereby enabling a seamless transition for GNN integration into mesh-oriented quandaries.

In fact, one of the most compelling advantages conferred by the strategic integration of GNNs is their remarkable prowess in adroitly navigating through intricately refined meshes, particularly those contiguous to stress concentrations such as notches and material discontinuities. This remarkable attribute empowers GNNs to dispense highly accurate localized predictions, all while judiciously economizing on computational resources. Furthermore, GNNs operate with an admirable indifference towards mesh resolution, rendering them impervious to the fluctuating scales of mesh intricacy. This is a marked departure from their CNN counterparts, which often grapple with the constraints of fixed-domain contours, a testament to GNNs' agility in tackling the fluid contours of mesh-centric challenges.

In the dynamic arena of simulations, GNNs have witnessed a discernible shift in their application trajectory, assuming an increasingly central role in physics predictions rather than confining themselves to forecasting static scalar values. This intriguing shift is palpably evident in seminal works such as [7]. Notably, recent work by Maurizi et al. [8] has unveiled a pioneering GNN model, distinguished by its remarkable efficacy in prognosticating the nuances of displacement, stress, and strain distributions across material and structural systems.

This paper proposes utilizing a GNN model to predict von Mises stress fields under linear elastic conditions. Our research shows that our model can be robust enough to generalise to different geometries. The data used to train this model comes from a dataset, designed and filled for this type of cases. The case under study is a rectangular plate with six circular holes loaded biaxially. One thousand cases were used, containing variations on the geometry of the holes. An average R-square of 0.9 was obtained for the training data, and 0.6 and 0.5 for the model's interpolation and extrapolation, respectively. In future work, this model will be trained for a larger dataset, aiming to increase its robustness and evaluate its generalisation for different boundary conditions. By leveraging GNNs, we aim to improve the accuracy and scalability of stress prediction methods, enabling more efficient and effective engineering design and analysis.

2 SimuStruct Dataset

The Simulated Structural Parts Dataset (SimuStruct) is a valuable resource that offers comprehensive numerical solutions for various aspects of 2D structural components, with a particular focus on plates with holes. These thin plates with geometric discontinuities find widespread use in key industries such as automotive, aerospace, and maritime. The presence of holes in these plates, which come in diverse sizes and shapes, serves multiple critical purposes. Beyond reducing overall structural weight, these discontinuities allow for the establishment of bolted or riveted joints and enable access to specific regions within the structure. This classic 2D case in mechanical engineering has found applications in airplane doors and windows, fuselage plate joints using rivets, bolted beam joints, cooling holes in turbine blades, and plates for humerus fracture treatment. Incorporating plate examples into novel datasets holds substantial promise for advancing the fields of mechanical design and structural analysis.

The SimuStruct dataset includes a wide array of essential components. It provides numerical solutions encompassing displacement, stress, and strain fields, as well as the essential von Mises stress metric. Moreover, it offers detailed meshes and geometries for the 2D structural parts, with a specific emphasis on plates with holes. This dataset covers various geometric cases of plates with holes, each subject to different loading and boundary conditions, along with diverse mesh refinements. These elements collectively empower engineers and researchers with quick analyses and optimization capabilities for mechanical design tasks.

The creation of this dataset employs standard Finite Element Method (FEM) techniques, driven by scripted automation through FEniCSx [9], a powerful open-source Python library for FEM analysis. SimuStruct serves a dual purpose as both training and evaluation data for machine learning (ML)-based approaches aimed at computing stress-strain fields and refining mesh definitions. Its existence plays a pivotal role in the development of ML-powered solutions for optimal mechanical design. Furthermore, this dataset fosters collaboration between academia and industry, bridging the gap between the Mechanical Engineering and ML communities. This collaboration holds the promise of accelerating research in the realm of computational mechanical design, ushering in innovative advancements.

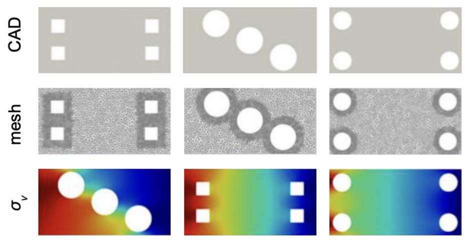

Figure 1. SimuStruct: a collection of geometry, meshes, and FEM simulations for plate with holes under different conditions of mesh refinement, linear and elastic material properties, and boundary and loading conditions.

3 Methodology

The dataset generation and processing procedure are thoroughly detailed in Fig. 2. The process commences by defining diverse geometric cases, inspired by Peterson's stress intensity factor compendium, encompassing rectangular plates with various hole shapes, orientations, and patterns. These geometry properties are stored in a JSON file. The subsequent steps involve specifying loading and boundary conditions, creating meshes of varying refinement levels, defining material properties, and constructing a numerical model solved using FEniCSx to obtain essential results such as displacement, stress, strain fields, and von Mises stress. This information is cataloged in CSV files, culminating in a comprehensive dataset for training and evaluating machine learning models, thereby presenting a versatile framework for enhancing structural analysis via ML-based approaches.

4 Application

To highlight the capabilities of SimuStruct and underscore the advantages of Machine Learning (ML) in predicting stress fields within structural analysis, we introduce a specific application. In this case, we employ a GNN model to predict the instantaneous von Mises stress field, and this model is meticulously trained and tested using the SimuStruct dataset.

Our study revolves around a plate featuring six circular holes arranged in a rectangular pattern, exposed to uniaxial loading. The load is applied to the top surface (σ_1), while the bottom side of the plate is simply supported.

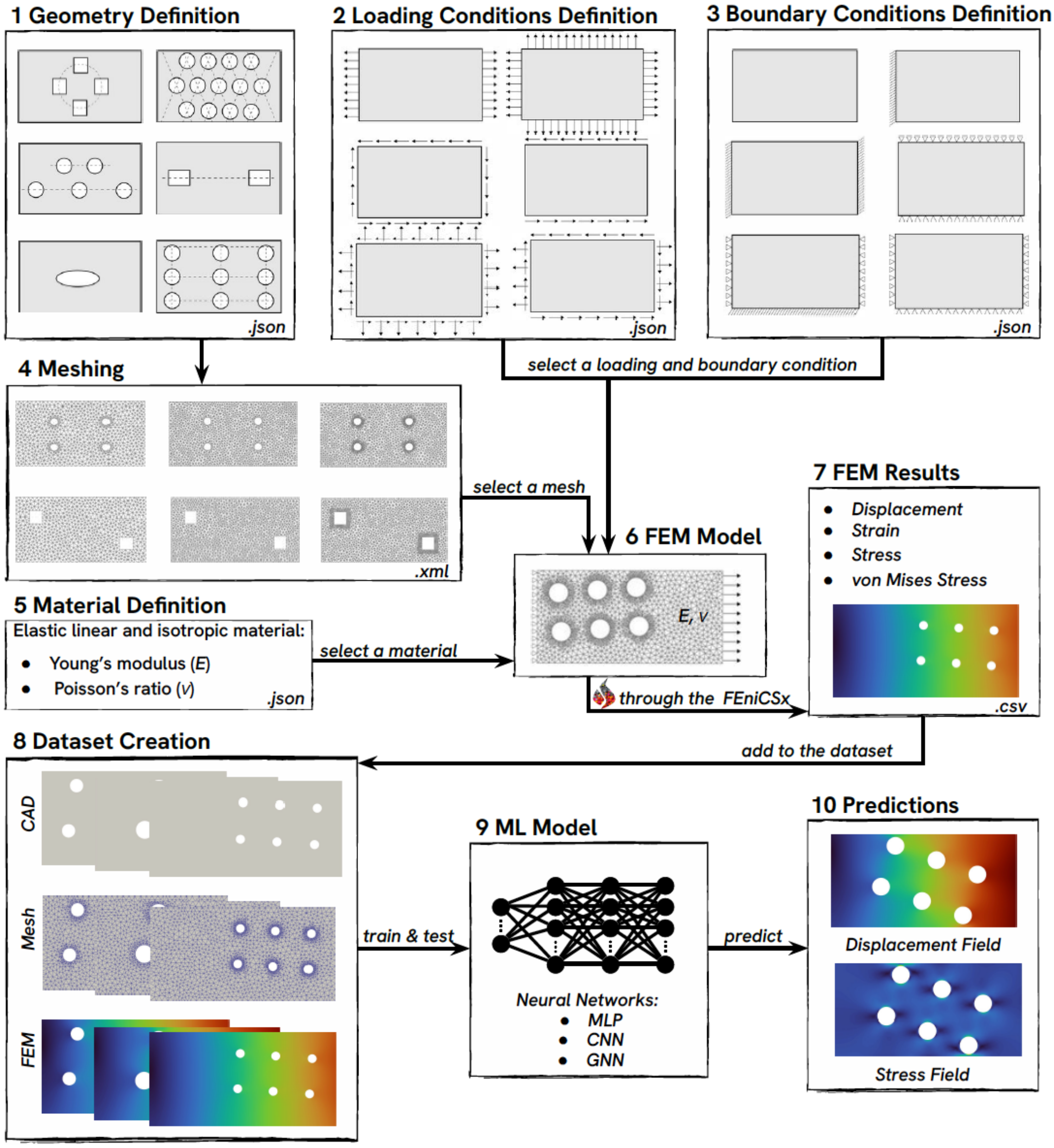

Figure 2. The SimuStruct generation process involves the following steps: (1) geometry definition, (2) loading condition definition, (3) boundary condition definition, (4) meshing, and (5) material definition. These inputs are used to create a (6) FEM model. The FEM results (7) are obtained using FEniCSx to build the dataset (8). This dataset can then be used to train and test machine learning models (9) to make predictions for the problem being analyzed (10).

Our analysis assumes a linear elastic material behavior, mirroring the traits of a typical steel alloy, with a Young's modulus of 210 GPa and a Poisson ratio of 0.3. Fig. 3 provides a visual depiction of the plate's properties.

To tackle this challenge, we've generated a comprehensive dataset containing 1000 distinct cases, all meticulously curated through SimuStruct.

Fig. 4 presents the results of our investigation. We observe a significantly diminished absolute difference and a notable R^2 value of 0.94, a value remarkably close to the ideal value of 1. This observation indicates that the predicted results from the GNN model are substantially more accurate, closely aligning with the outcomes of the Finite Element Method (FEM) results.

Drawing insights from these recent findings, it becomes evident that the SimuStruct dataset holds immense potential for use in structural analysis, demonstrating its adaptability across a diverse range of geometrical cases. This application not only showcases the efficacy of SimuStruct but also highlights the broader benefits of integrating Machine Learning into predicting stress fields in complex structural analysis, leading to enhanced accuracy and efficiency.

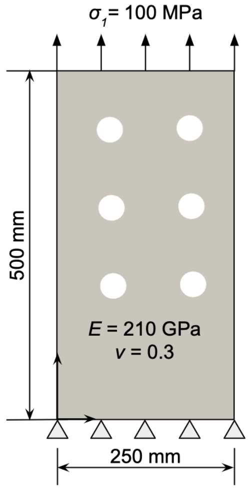

Figure 3. Schematic representation of a rectangular plate with circular holes under uniaxial loading at the top and simply supported at the bottom.

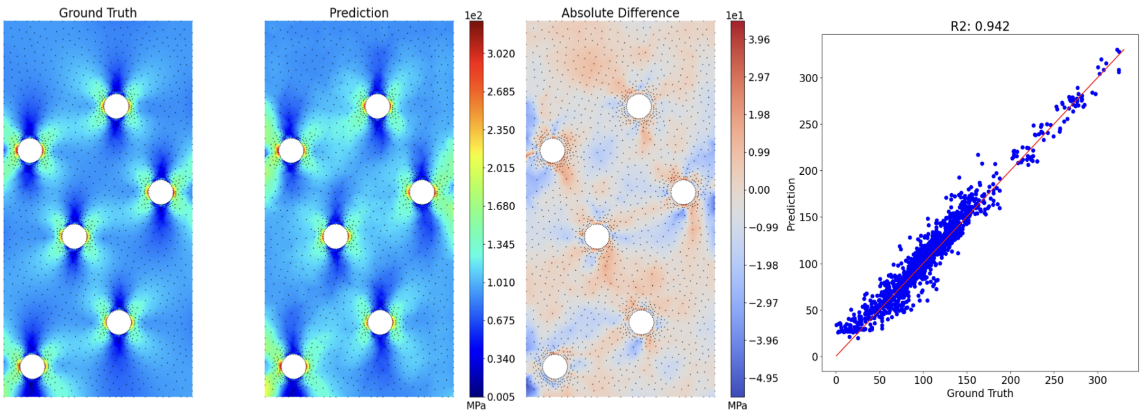

Figure 4. Comparison of ground truth (FEM results) and prediction (GNN results) for von Mises stress using the SimuStruct dataset. The results are shown through ground truth, prediction, and absolute difference fields, as well as a ground truth $vs.$ prediction plot, with an R^2 value provided.

5 Conclusions

The developed GNN model showed promising results, with an average R-square for the training of 0.89. However, when evaluating the interpolation and extrapolation of the model, predictions for smaller and larger circular holes, respectively, than those used in training, the model presented an average R-square of 0.6 and 0.5, respectively. It was possible to show the potential of scalar field prediction on structural analysis.

Future work will train the model for a larger dataset to improve the model's generalisation for different geometries. Furthermore, we will study the model's generalisation for different boundary conditions.

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References

[1] D. Wang, J. Lee, K. Holland, T. Bibby, S. Beaudoin, and T. Cale. Von Mises Stress in Chemical-Mechanical Polishing Processes. *Journal of The Electrochemical Society*, vol. 144, n. 3, pp. 1121. Publisher: IOP Publishing, 1997.

[2] M. Mozaffar, R. Bostanabad, W. Chen, K. Ehmann, J. Cao, and M. A. Bessa. Deep learning predicts path-dependent plasticity. *Proceedings of the National Academy of Sciences*, vol. 116, n. 52, pp. 26414–26420. Pub-

lisher: Proceedings of the National Academy of Sciences, 2019.

[3] L. G. Bradford, S. B. Dong, D. a. C. Nicol, and R. A. Westmann. Application of global-local finite element method to fracture mechanics. Technical report 1. [GLASS I]. Technical Report EPRI-NP-239, California Univ., Los Angeles (USA). School of Engineering and Applied Science, 1976.

[4] Z. Yang, C.-H. Yu, and M. J. Buehler. Deep learning model to predict complex stress and strain fields in hierarchical composites. *Science Advances*, vol. 7, n. 15, pp. eabd7416. Publisher: American Association for the Advancement of Science, 2021.

[5] J. Zhou, G. Cui, S. Hu, Z. Zhang, C. Yang, Z. Liu, L. Wang, C. Li, and M. Sun. Graph neural networks: A review of methods and applications. *AI Open*, vol. 1, pp. 57–81, 2020.

[6] I. Chami, S. Abu-El-Haija, B. Perozzi, C. Ré, and K. Murphy. Machine Learning on Graphs: A Model and Comprehensive Taxonomy. arXiv:2005.03675 [cs, stat], 2022.

[7] T. Pfaff, M. Fortunato, A. Sanchez-Gonzalez, and P. W. Battaglia. Learning mesh-based simulation with graph networks, 2020.

[8] M. Maurizi, C. Gao, and F. Berto. Predicting stress, strain and deformation fields in materials and structures with graph neural networks. *Scientific Reports*, vol. 12, n. 1, pp. 21834. Number: 1 Publisher: Nature Publishing Group, 2022.

[9] M. Alnæs, J. Blechta, J. Hake, A. Johansson, B. Kehlet, A. Logg, C. Richardson, J. Ring, M. Rognes, and G. Wells. The fenics project version 1.5. vol. 3, 2015.