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Implementation of a hybrid strategy for addressing mechanical structural models: AI and finite element analysis

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Abstract. FEM is one of the main numerical methods in engineering to solve boundary problems; however, the computational cost associated with this method is a challenge to be faced when using it in real cases. The objective of this paper is to evaluate the performance of Neural Networks (NN) in the approximation of results obtained by FEM while maintaining accuracy and reducing computational time. The results show an accurate model for the case of a flat plate subjected to tension, altering the elastic modulus (E), applied force (F), and plate thickness (h) in the trainig data. This work is a starting point for the optimization of computational time in the calculation of the approximate solution of engineering problems of greater complexity. In the future, hybrid strategies of FEM with neural networks could benefit mathematical modeling and computational simulation, making its use viable in critical areas such as medicine, where the presence of tissues with nonlinear characteristics is a common challenge to be solved or where real-time decision making is crucial.

Keywords: Computational Cost, Finite Element Method; Neural Networks.

1 Introduction

The Finite Element Method (FEM) is a widely employed numerical technique for approximating solutions to partial differential equations. This method works by discretizing the problem domain into a finite number of elements and estimating the solution values using prescribed boundary conditions. Through this approach, FEM enables the approximation of solutions to problems that would otherwise be intractable or yield less accurate results[1]. Despite its widespread adoption and proven effectiveness, FEM presents significant computational cost as a primary limitation, particularly in its application in time-critical scenarios or environments with limited computational resources [2]. Furthermore, this computational burden often requires substantial hardware investments and extended processing times, creating barriers to real-time applications and broader accessibility [3]. To address these limitations, this research proposes the development of a hybrid computational framework that integrates FEM with machine learning techniques. The objective is to optimize computational resource requirements while maintaining the accuracy of the solution to structural analysis problems. Moreover, this hybrid approach aims to leverage the strengths of both methodologies: the theoretical rigor and accuracy of FEM combined with the computational efficiency and pattern recognition capabilities of machine learning algorithms. In addition, the present investigation focuses on establishing a foundational framework by studying simple structural analysis scenarios. These geometrically simple cases will serve as the primary data source for training machine learning models, providing a controlled environment to validate the proposed hybrid methodology before extending it to more complex structural configurations.

2 State of art

Finite element method (FEM) has become the standard for solving mathematical models describing complex biomedical systems. Okereke and Keates [4], Otsuru et al. [5], and Sabat and Kundu [6] have documented FEM's evolution and applications. From biomechanical analysis of bone structures to soft tissue modeling, this method reliably solves biological model equations. Relevant examples include Vahdati and Rouhi's [7] trabecular bone adaptation models; Galbusera et al.'s [8] C5-C6 spinal unit analysis; and Grosland et al.'s [9] interactive multiblock approaches for patient-specific anatomic models.

However, traditional FEM faces significant medical application limitations. Anatomical complexity—irregular geometries, heterogeneous materials, and nonlinear behavior—dramatically increases computational time. Pellicer-Valero et al. [10], Phellan et al. [11], Morooka et al. [12], and Bro-Nielsen and Cotin [13] have documented these challenges. This computational burden severely limits FEM's practical use in real-time medical applications, particularly surgical planning and intraoperative guidance requiring immediate feedback.

Over the past decade, neural models for medical computational simulations have increased significantly. Suleimenov et al. [1] and Wang [2] established foundational AI work, while Muthukrishnan et al. [15] and Macukow [16] provided comprehensive neural network reviews, demonstrating machine learning as a valuable FEM complement in medical applications.

The universal approximation theorem enables neural networks to approximate complex FEM results for biological systems, providing instantaneous predictions without computational overhead once trained. Wang [2] and Bebis and Georgiopoulos [17] established this approach's theoretical foundation, while Pellicer-Valero et al. [10] and Morooka et al. [12] demonstrated practical implementations. Pellicer-Valero et al. [10] showed machine learning models trained on FEM simulations deliver immediate liver biomechanical modeling results. Morooka et al. [14] developed navigation systems with real-time finite element analysis for minimally invasive surgery, enabling immediate biomechanical feedback. Morooka et al. [12] implemented nonlinear real-time FEM with neural networks for soft organ deformation, supporting surgical simulation.

These developments represent significant computational surgery advancement. Bro-Nielsen and Cotin [13] showed increasingly sophisticated real-time volumetric deformable models using finite elements, and González et al. [3] demonstrated computational patient avatars as one of the most promising applications. These virtual patient representations enable personalized surgery planning, allowing surgeons to practice and optimize procedures beforehand.

Integrating artificial intelligence with finite element analysis in medicine represents a rapidly growing research field. Cueto and Chinesta [18] and Phellan et al. [11] have shown this combination continues evolving, emphasizing real-time simulation for computational surgery. As computational capabilities advance, the synergy between these methodologies promises to revolutionize medical practice through improved surgical planning, enhanced patient safety, and sophisticated virtual medical environments. The goal is creating comprehensive digital patient twins that accurately predict treatment outcomes and guide real-time clinical decision-making [3].

3 Development

3.1 Initial Model Architecture

The physical problem being addressed in this work corresponds to the structural analysis of a flat plate subjected to tension; with a total displacement restriction on the left side (A) and a tensile load on the right side (B), as shown in Figure 1. The first approach to solving this displacement prediction problem involved implementing a simple deep neural network trained on datasets with identical planar geometry and node structure, but varying elastic modulus (E), magnitude and direction of the applied force (F), and plate thickness (h) parameters. This initial architecture served as a baseline to establish the feasibility of neural network-based approaches for structural displacement prediction. in this case the architecture of the NN had a input layer of 5 neurons representing x,y and the 3 constants (F,E,H), 5 hidden layers (512,1024,1024,512), and an output layer of 2 neurons representing Δx and Δy.

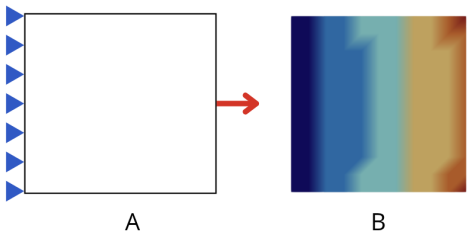


Figure 1. Flat plate model in traction. A. Model boundary conditions. B. Example of solution obtained by FEM

3.2 Training Performance and Learning Characteristics

For the training of the NN we use the results of a 100000 FEM simulations Changing the 3 constants and keeping the geometry, then we use the data point by point for training of the neural network.

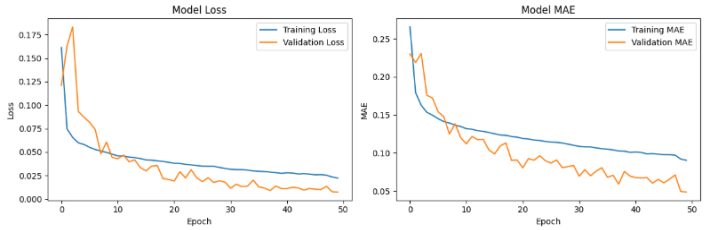


Figure 2. Training and validation performance curves showing model loss and Mean Absolute Error (MAE) over 50 epochs.

The simple deep neural network demonstrated promising learning capabilities, as evidenced by the training curves shown in Figure 2. The training process exhibited several key characteristics: **Convergence Behavior**: Both training and validation losses showed consistent decreasing trends over the 50-epoch training period, with the training loss stabilizing around 0.025 and validation loss converging to approximately 0.01. This convergence pattern indicates that the model successfully learned the underlying relationships between the input parameters and displacement fields. **Generalization Performance**: The close tracking between training and validation curves suggests good generalization capabilities, with no significant signs of overfitting. The Mean Absolute Error (MAE) metrics further support this observation, showing both training and validation MAE converging to similar values around 0.07-0.10.

3.3 Model Validation

The comparison between true and predicted displacement fields, as shown in Figure 3, reveals that the simple deep neural network approach successfully learned to approximate the structural response under varying loading conditions. The color-coded visualization shows that the model accurately reproduces the displacement magnitude distributions across the structural domain, with particularly good performance in predicting the smooth gradient transitions characteristic of elastic deformation patterns this is evident when you compare (A) with (B) and (C) with (D) . This is also confirmed with l2 metrics that are in the order $1e^{-7}$ that show an outstanding training for this case.

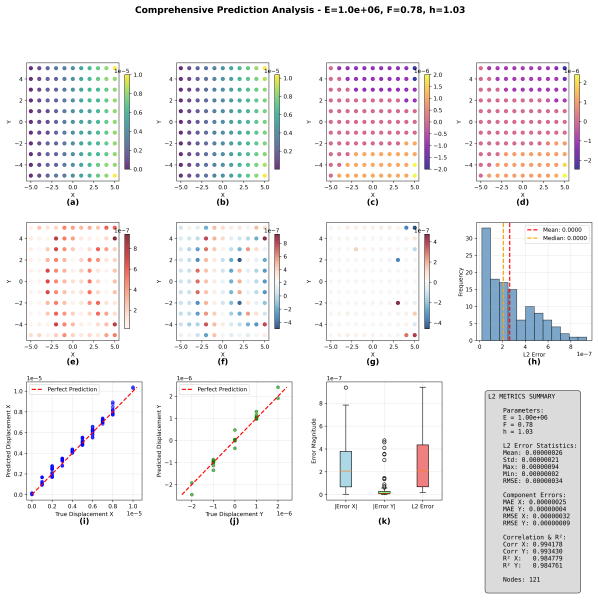


Figure 3. (a) True Displacement in X, (b) Predicted Displacement in X, (c) True Displacement in Y, (d) Predicted Displacement in Y, (e) L2 Error Distribution, (f) Error in X Direction, (g) Error in Y Direction, (h) L2 Error Distribution, (i) True vs Predicted (X), (j) True vs Predicted (Y), (k) Error Component Comparison.

This initial success with the simple neural network architecture provided strong motivation for exploring more sophisticated approaches, while establishing a baseline performance standard for subsequent model developments, while establishing a baseline performance standard for subsequent model developments.

4 Conclusions

This work represents a crucial first step in applying machine learning techniques to structural analysis problems. The implementation of a simple deep neural network for structural displacement prediction has demonstrated promising results, establishing a solid foundation for neural network-based approaches in computational mechanics. The model successfully learned the complex relationships between material properties (E), applied forces (F), plate thickness (h), and the resulting displacement fields, achieving good convergence and generalization performance as evidenced by the training curves and displacement field predictions. The ability of the neural network to accurately predict displacement patterns across varying loading conditions validates the fundamental approach and demonstrates the potential for data-driven methods in engineering applications.These findings also resonate with advances in medical simulation, where the integration of machine learning and FEM is enabling real-time, patient-specific modeling for applications such as surgical planning and intraoperative guidance. By demonstrating that neural networks can accurately predict displacement fields in simplified structural scenarios, this work lays foundational groundwork for future biomedical applications. In particular, the ability to replicate FEM outputs with minimal computational cost opens opportunities for developing fast and responsive biomechanical models of organs and tissues, an essential step toward real-time simulation in clinical environments. As such, this study contributes to the broader vision of creating digital twins of patients, where data-driven models enhance precision medicine by improving the speed, adaptability, and personalization of computational tools used in diagnosis and treatment planning.

4.1 Future Research Directions

The successful baseline established by this simple deep neural network architecture opens several promising avenues for future investigations. **Convolutional Neural Networks (CNNs)**: The spatial nature of displacement fields makes CNNs particularly well-suited for handling more complex geometries. Future work could explore CNN architectures to capture spatial correlations in displacement patterns, potentially improving prediction accuracy for irregular geometries and complex boundary conditions. **Physics-Informed Neural Networks (PiNNs)**: Enhanced PiNN architectures that incorporate physical laws and governing equations directly into the loss function could be investigated to handle more sophisticated material behaviors, including nonlinear material properties, anisotropic materials, and multi-phase composites while ensuring physical consistency. **Complex Geometries**: The methodology established here provides a framework for extending to more realistic engineering structures with irregular shapes, varying cross-sections, and complex boundary conditions that are commonly encountered in practical applications. **Advanced Material Models**: Future investigations could incorporate more sophisticated material constitutive models, including plasticity, viscoelasticity, and damage mechanics, expanding the applicability of neural network approaches to a broader range of engineering problems. The foundation laid by this initial investigation demonstrates that neural network-based approaches hold significant promise for revolutionizing computational structural analysis, offering potential advantages in computational efficiency and the ability to handle complex relationships that traditional finite element methods may struggle to address efficiently.

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