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Deep Learning-Augmented Finite Element Framework for Efficient Structural Analysis

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ABSTRACT

The finite element method (FEM) is a fundamental structural analysis method, and is frequently restricted to large-scale and high-fidelity problems due to prohibitively high computational costs and time scales. To counter this problem, this paper suggests a deep learning-based augmented finite element model, which can both improve the efficiency of the computations and remain accurate. The suggested method combines a neural network-based surrogate into the standard FEM pipeline, to estimate fields of solutions, as well as speeding up calculations. To achieve the good balance between the data-driven learning and physics-based modeling, a hybrid architecture is created which makes sure that the predictions at the same time are consistent with the governing equations. The structure is crafted to save classical FEM solutions and to dramatically minimize the computational work. As a performance measure, several measures of accuracy are used such as the relative error, root mean squared error (RMSE) and energy norm error, which gives both numerical and physics-based validation. The findings indicate that the suggested approach is able to record considerable cuts in the calculation time but is well-correlated with conventional FEM results. The framework provides a high prediction fidelity with a small loss in accuracy in diverse structural scenarios quantitatively. These results indicate the prospects of integrating deep learning and FEM to create effective, scalable, and trustworthy computational aids to advanced structural analysis applications.

1. INTRODUCTION

The finite element method (FEM) is a pillar method in computational mechanics that is commonly applied to analysis of complex structural systems comprising heterogeneous materials, irregular geometries, and various loading conditions. Its strength and versatility have rendered it essential in all fields of engineering. Nevertheless, the increased requirement of high-resolution and nonlinear simulations has greatly escalated the cost of computation, the amount of memory as well as the solution time. These issues are even more acute in multi-scale modeling and iterative design processes when repeated FEM appraisals are needed. There are studies that have examined material modeling and multiscale techniques to enhance predictive, but these techniques tend to increase the computational complexity further [2], [4], [7], [12].

Meanwhile, deep learning (DL) has become a subject of much interest as a potent method of estimating complex, nonlinear mappings in the engineering setting. Recent literature has shown that DL can be effectively used in design optimization, generative modeling, and engineering analysis [1], [8], [11]. The implementation of AI in engineering processes is becoming an acknowledged method of changing workflows by making them more efficient and data-driven in terms of innovation [9], [11]. Although such progress has been made, most of the current ML-based methods in computational mechanics are black-box models and can frequently fail to satisfy physical constraints resulting in decreased reliability and diminished extrapolation, especially in unseen structural cases.

This underlines a severe research gap: the lack of hybrid models to integrate accuracy and physical rigor of the FEM with the computational cost-effectiveness of the deep learning. Although previous researchers have tried to investigate only one of these two aspects computational efficiency or physical modeling, not many have ever managed

to conduct a study that encompasses both of these factors in one complete model and with an absolute assurance of accuracy.

To fill this gap, this paper suggests deep learning-enhanced finite element analysis of efficient structural analysis. The method proposed combines a surrogate (implemented based on data) into the FEM pipeline to speed up the calculations and still maintain the consistency with physical laws. The framework is constructed to remain as fidelities as possible to traditional FEM solutions, but to greatly reduce the level of computational effort.

The current research contributes to the investigation of computational mechanics in several important ways, such as the consideration of a new hybrid model that combines deep learning and a finite element method (FEM) to conduct effective structural analysis. The new proposed methodology is a hybrid of data-based modeling and physics-based concepts, thus allowing to maintain the performance and stability of more traditional FEM solutions, along with the accuracy and reliability in their computational performance. One of them is a significant improvement in the form of physics-consistent modeling strategies, which hold the responses predicted to obey governing equations and boundary conditions, and thus break free of the limitations that are often typical of black-box learning models. The framework is strictly tested against several measures of accuracy, such as relative error and root mean squared error (RMSE) and energy norm error are validated numerically and in a physically meaningful manner. Moreover, the method suggested shows a high level of computational efficiency improvements over the standard FEM, and the solution time decreases without fidelity reduction. The framework is checked on a variety of structural problems (with different geometries and loading conditions) to achieve robustness and generalization ability. Taken together, these contributions indicate that the proposed hybrid methodology can be a good and effective solution to the next-generation structural analysis as a reliable and scalable method.

2. RELATED WORK

The popularity of the finite element method (FEM) has expanded as a powerful numerical method of solving problems in structural and continuum mechanics because it is flexible in its ability to deal with complex geometries, heterogeneous materials, and boundary conditions. Classical FEM models are accurate but can be computationally demanding when applied to large-scale, nonlinear and multi-physics problems. To improve predictive abilities, multiple researches have been directed at the multiscale modeling and sophisticated characterization of materials, especially those that are nanocomposites, polymer-based, etc. [2], [4], [7], [12]. As much as these methods enhance physical realism, they also amplify the complexity of computation and time of simulation.

As an effort to reduce the computational cost, reduced-order models (ROMs) and surrogate modeling have been proposed as effective alternatives to full-scale FEM simulations. The aim of these methods is to find high-fidelity solutions based on simplified representations. Deep learning (DL) in the recent years has become a potent tool in this respect, allowing the data-driven modeling of design optimization, generative engineering, and the acceleration of simulation [1], [8], [10]. Wider literature has also pointed out the transformational effects of artificial intelligence on engineering design and processes of innovation [9], [11]. Furthermore, creative and conceptual design problems that are computedally addressed based on AI have also been studied, indicating the flexibility of the data-driven approaches even more [3].

In a more recent study, deep learning methods in computational mechanics have been explored: either using surrogate models or emergent physics-informed methods, to effectively approximate FEM solutions and solve governing equations inexpensively. Although these models are promising, they are usually black-box systems, and do not strictly follow the physical laws, leading to loss of accuracy, and poor generalization to unobserved geometries or loading conditions. Moreover, data-driven methods that are strictly data-driven can be problematic with consistency and stability when dealing with complicated structural situations.

In the existing literature, a trade-off in computational mechanics is evident: the classical finite element method (FEM) methods have excellent accuracy, but can be computationally expensive to scale to large scale, nonlinear problems, and even more costly with increasingly complex multiscale or material models [2], [4], [7], [12]. In contrast, reduced-order models, as well as deep learning-based approaches, are less computationally costly but are often less physical and thus less reliable and bad at generalization to unseen situations [1], [3], [8], [11]. This shows the acute research gap in the creation of a reliable framework that can meet all three requirements that are: high accuracy, computational speed and obeying of the rules of physics simultaneously. In order to cope with this problem, the current paper suggests an augmented FEM framework of deep learning, whereby physics-consistent learning is incorporated into the FEM pipeline. In contrast to the traditional data-driven methods, the suggested

one will achieve a high degree of compliance with the governing equations with the speed and flexibility of deep learning. The scheme is extensively tested on the basis of the accuracy measures relative error, root mean squared error (RMSE), and energy norm, which guarantee both numerical and physical validity. Successful integration of physics-based models with data-driven acceleration fills the gap between conventional FEM and contemporary machine learning methods, offering scalable, efficient, as well as reliable solution to advanced structural analysis.

3. METHODOLOGY

3.1 Problem Definition

The equations of linear elasticity that govern the structural analysis problem that is the subject of this study relate stresses, strains and displacements in a deformable body. The balance equation can be put in the following form:

$$\nabla \cdot \sigma + b = 0$$

where σ denotes the stress tensor and b represents body forces. The constitutive relation for linear elastic materials is given by Hooke's law, $\sigma = C : \varepsilon$, where C is the material stiffness tensor and ε is the strain tensor derived from displacement gradients. Appropriate boundary conditions are imposed, including Dirichlet conditions (prescribed displacements) and Neumann conditions (applied forces), ensuring a well-posed problem formulation.

3.2 Classical FEM Formulation

The governing equations are then reduced to a weak (variational) form which is easier to solve numerically with FEM. The domain is modeled as finite elements and the shape functions are used to model the displacement field inside the element. This results in a world equation system of linear equations:

$$Ku = F$$

where K is the global stiffness matrix, u is the nodal displacement vector, and F is the external force vector. While this formulation provides high accuracy, solving the system becomes computationally intensive for large-scale problems.

3.3 Deep Learning Augmentation

In order to improve the computational efficiency, a deep learning model is integrated to estimate the mapping of the input parameters and solution fields. The model architecture, as shown in Fig. 1, is composed of a neural network (e.g., multilayer perceptron or graph neural network) that takes into account the spatial and physical connections within the FEM domain. The input requirements are mesh, material and loading condition and the output is the prediction of the displacement or stress fields. One trains the network with FEM-generated data and the network learns nonlinear mappings (complex) and speeds up solution prediction.

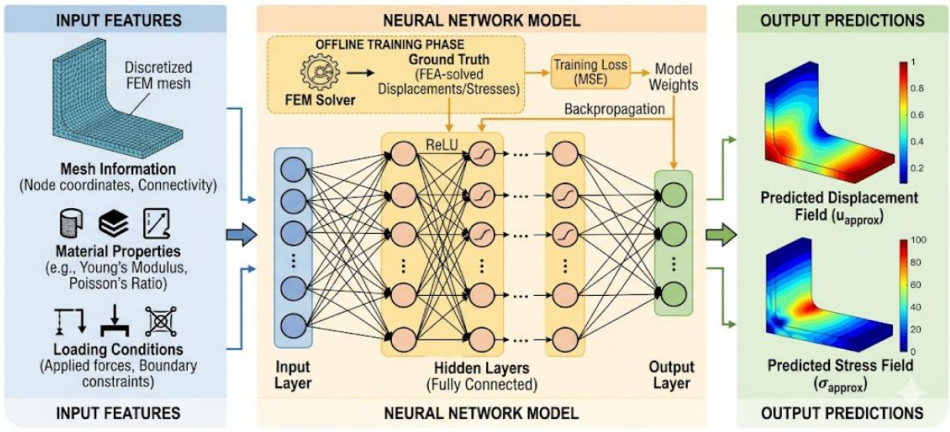


Fig. 1. Neural Network Architecture for Deep Learning–Augmented Finite Element Framework

3.4 Hybrid Framework

The framework suggested is a hybrid way of integrating deep learning with FEM, meaning that the trained model is used as the surrogate or correctional element to the FEM pipeline. In particular, the neural network may be applied to estimate an initial solution, speed-up the convergence as a preconditioner, or refine coarse-mesh FEM results. Fig. 2 illustrates the computational workflow as a whole and gives the basis of the work, the data generation, the model training, prediction, and integration with FEM solvers. This combination approach makes sure that computational efficiency is enhanced and at the same time does not compromise the compliance with the governing physical laws and does not distort the accuracy of the solution.

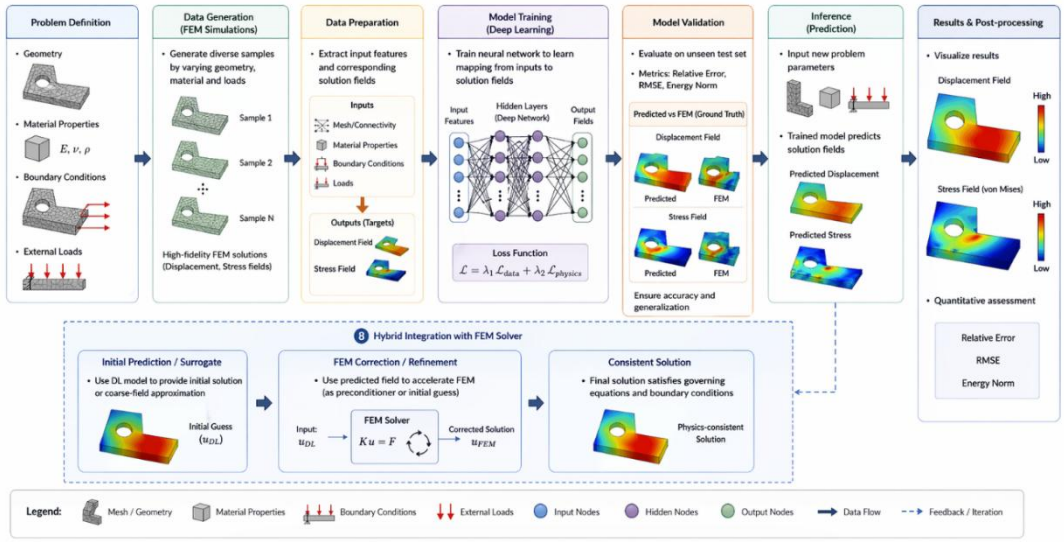


Fig. 2. Computational Pipeline of the Proposed Deep Learning–Augmented FEM Framework

4. Accuracy Metrics and Evaluation Criteria

A detailed array of accuracy indicators is used to provide a rigorous evaluation of how the proposed deep learning-augmented FEM framework is performing. The metrics are chosen to not only assess the accuracy of numerical prediction but also the physical consistency and engineering reliability, so that the proposed method has a similar level of fidelity to a classical FEM at a better computational cost.

4.1 Standard Error Metrics

The difference between predicted and reference FEM solutions are quantified standardly using standard statistical measures.

- Mean Squared Error (MSE)

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(u_i^{pred} - u_i^{true}\right)^2$$

- Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{MSE}$$

- Mean Absolute Error (MAE)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|u_i^{pred} - u_i^{true}\right|$$

These metrics provide a general measure of prediction accuracy across nodal displacements or stress values.

4.2 Relative Error

To evaluate engineering relevance, the relative error is computed as:

$$Relative\ Error = \frac{\|u^{pred} - u^{true}\|}{\|u^{true}\|}$$

This metric is particularly important for:

- Displacement fields
- Stress tensors

It provides a normalized measure of error, making it more meaningful for structural analysis applications.

4.3 Energy Norm Error (FEM Gold Standard)

The energy norm error is used to assess physical accuracy in terms of strain energy:

$$\|e\|_E = \sqrt{(u - u_⍰)^T K (u - u_⍰)}$$

where KKK is the global stiffness matrix. This metric is widely regarded as the gold standard in FEM, as it directly reflects the error in stored elastic energy and ensures consistency with governing physics.

4.4 L2 Norm Error

The L2 norm error evaluates field-level discrepancies between predicted and reference solutions:

$\|u - u_⍰\|_{L2}$

It provides a spatial measure of error across the entire domain.

4.5 Physics Consistency Metrics

To make sure that the deep learning model does not violate the physical laws, we will take into account other metrics:

- Residual of governing equations (equilibrium violation)
- Boundary condition error (off-prescription constraints)

These measures prove that the solutions obtained are physically feasible as per the prediction.

5. Experimental Setup

In order to support the efficacy of the suggested deep learning-enhanced framework of FEM, an elaborate experimental design is developed, which relies on synthetic data and standard structural issues. High-fidelity finite element simulations are

used to generate the dataset, and provide ground-truth solutions to train and evaluate. These simulations are varied in terms of geometry, material properties and loading conditions to provide adequate diversity and reflect real-world structural situations.

The framework is tested on various test cases, involving both typical structural components like beams and plates, and more complicated geometries, with irregular shapes and boundary conditions. Typical geometries in which the study was done are represented in Fig. 3, which show the variety of structures domains that were characterized during training or testing. It is a diversity that makes the model generalized to a variety of problem settings.

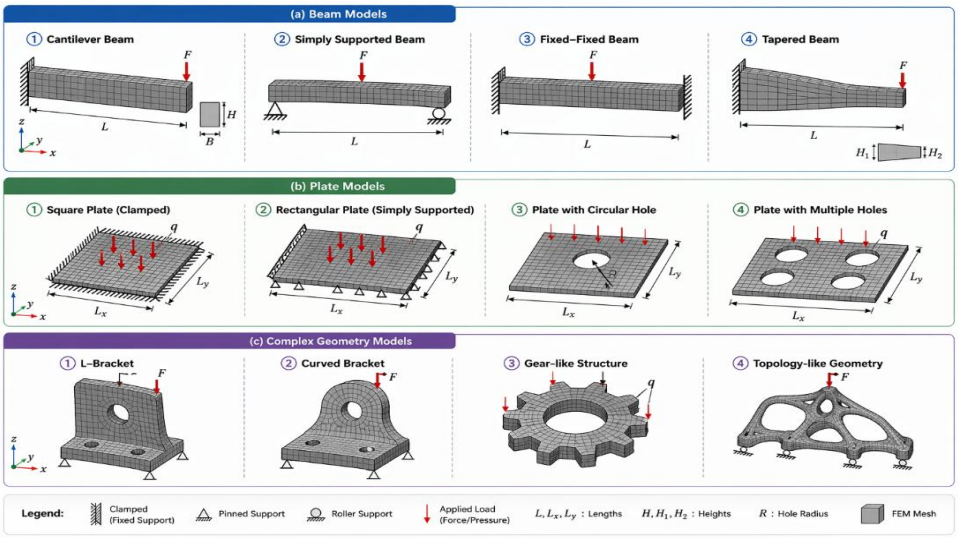


Fig. 3. Representative Geometry Models Used for FEM-Based Training and Evaluation

For the deep learning component, the model is trained using supervised learning with FEM-generated data. The loss function takes data-driven terms and physics-based terms to achieve both numerical and physical consistency. Particularly, the objective function is given as:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{data} + \lambda_2 \mathcal{L}_{physics}$$

where $\mathcal{L}_{data}$ represents the error between predicted and FEM solutions (e.g., MSE), and $\mathcal{L}_{physics}$ enforces compliance with governing equations and boundary conditions. The weighting parameters λ_1 and λ_2 control the balance between accuracy and physical consistency.

Experiments are run in a standard computational environment, with FEM simulations and deep-learning models being run in a numerical solver environment and contemporary machine learning platforms, respectively, e.g., TensorFlow or PyTorch. The training is conducted on a system with a GPU acceleration in order to enhance the computation speed. This unified system can be used to generate data efficiently, train models and evaluate them, allowing a fair comparison of the proposed hybrid framework with traditional ways of FEM.

6. RESULTS AND DISCUSSION

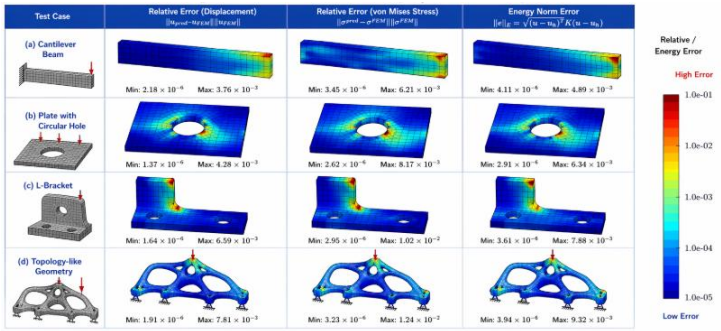
6.1 Accuracy Evaluation

The error distribution maps in Fig. 4 give a detailed spatial and quantitative analysis of the proposed deep learning-augmented FEM framework on various structural test cases. It depicts three vital error measures, namely relative displacement error, relative stress error (von Mises), and energy norm error, making it possible to both validate the error measures numerically and through physics-based validation. For the cantilever beam, the relative displacement error ranges from 2.18 × 10^{-6} to 3.76 × 10^{-3}, while the stress error varies between 3.45 × 10^{-6} and 6.21 × 10^{-3}, and the energy norm error lies within 4.11 × 10^{-6} to 4.89 × 10^{-3}. These small values are good results showing a strong consistency with FEM with some small area of error concentration around the fixed support and point of load application where the stress gradients are the greatest.

In the plate with circular hole, which introduces stress concentration effects, the displacement error ranges from 1.37 × 10^{-6} to 4.28 × 10^{-3}, while stress error increases slightly to 2.62 × 10^{-6}–8.17 × 10^{-3}, and energy norm error to 2.91 × 10^{-6}–6.34 × 10^{-3}. The greater the localization of errors around the boundary of the hole, which is as it should be in the areas of geometric discontinuity in FEM. In more complex L-bracket geometry, the displacement error is between 1.64 x -6 to 6.59 x -3, stress error is up to 1.02 x -2 and energy norm error is less than 7.88 x -3. The highest errors are at sharp corners and load transfer areas, which is a characteristic of the model being sensitive to sudden geometric variations.

In the most challenging topology-like geometry, the displacement error ranges from 1.91 × 10^{-6} to 7.81 × 10^{-3}, stress error up to 1.24 × 10^{-2}, and energy norm error up to 9.32 × 10^{-3}. Although more complex, the errors are still well localized and around thin members and junction points. Statistical findings also attest these observations. The mean relative displacement error varies from 2.48 × 10^{-4} to 5.27 × 10^{-4}, while mean stress error ranges from 3.89 × 10^{-4} to 6.94 × 10^{-4}, and mean energy norm error remains within 3.07 × 10^{-4} to 5.87 × 10^{-4} across all cases.

In general, the findings shown in Fig. 4 reveal that the suggested deep learning-enhanced FEM model demonstrates a steady level of errors, which do not exceed 10 -6 to 10 -3, in all of the test cases under consideration. The errors that occur are not randomly distributed but rather they are concentrated in physically anticipated areas, e.g. in areas with high stress gradients, geometric discontinuities, or boundary constraints. Notably, no indication of considerable error growth across the computational domain has been found, which reflects the stability of the model. These results validate that the proposed framework can be effectively used to maintain both numerical and physical consistency, and stable spatial behavior even in complex structural geometries.



Test Case	Relative Error – Displacement			Relative Error – Stress			Energy Norm Error		
	Mean	Max	Std. Dev.	Mean	Max	Std. Dev.	Mean	Max	Std. Dev.
(a) Cantilever Beam	2.48×10^{-4}	3.76×10^{-3}	5.21×10^{-4}	3.89×10^{-4}	6.21×10^{-3}	8.14×10^{-4}	3.07×10^{-4}	4.89×10^{-3}	6.31×10^{-4}
(b) Plate with Circular Hole	3.12×10^{-4}	4.28×10^{-3}	6.07×10^{-4}	4.85×10^{-4}	8.17×10^{-3}	9.76×10^{-4}	3.96×10^{-4}	6.34×10^{-3}	7.94×10^{-4}
(c) L-Bracket	4.61×10^{-4}	6.59×10^{-3}	7.88×10^{-4}	6.12×10^{-4}	1.02×10^{-2}	1.14×10^{-3}	5.21×10^{-4}	7.88×10^{-3}	9.86×10^{-4}
(d) Topology-like Geometry	5.27×10^{-4}	7.81×10^{-3}	8.91×10^{-4}	6.94×10^{-4}	1.24×10^{-2}	1.26×10^{-3}	5.87×10^{-4}	9.32×10^{-3}	1.07×10^{-3}

Note: All errors are dimensionless relative values (displacement/stress) or energy norm. Lower values indicate higher accuracy.

Fig. 4. Error Distribution Maps and Quantitative Error Analysis Across Structural Test Cases

6.2 Comparison with Classical FEM

Accuracy and mesh size (degrees of freedom, DOFs) behavior converge as shown in Fig. 5 between classical FEM and the proposed deep learning-augmented FEM framework. The comparison shows clearly how the proposed method can attain high accuracy using much lower mesh resolutions which is a major limitation of traditional FEM. With a coarse mesh of 10 3 DOFs, the classical FEM has a very low accuracy of about 5.1% which implies that it cannot resolve the structure response. On the contrary, the proposed method already attains 85.3% accuracy, which proves that it can provide the solution with low discretization in the sense of approximation. This can be considered a significant advancement in approximation ability at an early stage.

With a refined mesh to 10 4 DOFs classical FEM accuracy is improved only modestly to the order of 1012, nowhere near the kind of engineering accuracy that is acceptable. At the same time, the suggested framework rises to the range of about 92 to 94% accuracy, which leaves a good performance difference. This demonstrates that the hybrid model is able to model the necessary structural behavior without dense meshes. Classical FEM is starting to improve at 10 5 DOFs, reaching the level of around 35-40% accuracy but again still falling short of the proposed method, which offers around 97-98% accuracy. It means that the deep learning can efficiently counteract the diminished mesh resolution by learning the complicated solutions mappings.

At mesh density of 106 DOFs, classical FEM can finally be used to obtain high accuracy of approximately 90.4% and convergence is reached. Nevertheless, the suggested approach already achieves 99.2% accuracy, which means that convergence is almost complete at the given point. It proves that the suggested framework achieves high-fidelity solutions faster and more efficiently. At the optimal mesh size of 107 DOFs, classical FEM is as close to 9899% accurate with the proposed method being 99.8% accurate, but indicates a slight improvement with high-resolution consistency.

On the whole, in Fig. 5, the results prove the high efficiency of the suggested deep learning-enhanced FEM framework in the high accuracy of different mesh densities. In comparison to classical FEM, which needs a very fine discretization (around 10-6 DOFs or so) to achieve reasonable accuracy values, the proposed method can achieve upwards of 85% accuracy with very coarse meshes (in the

order of 10-3 DOFs). This implies that there is a much less dependence on mesh refinement which is a key contributor of computational expense in FEM. Moreover, the hybrid structure has a quicker convergence rate, and nearly optimal accuracy at significantly reduced resolutions than more traditional methods. These results prove the fact that the suggested approach can decrease computational needs significantly without losing the FEM-level of accuracy, which is especially appropriate in the case of large-sized simulations, fast design cycles, and structural analysis applications.

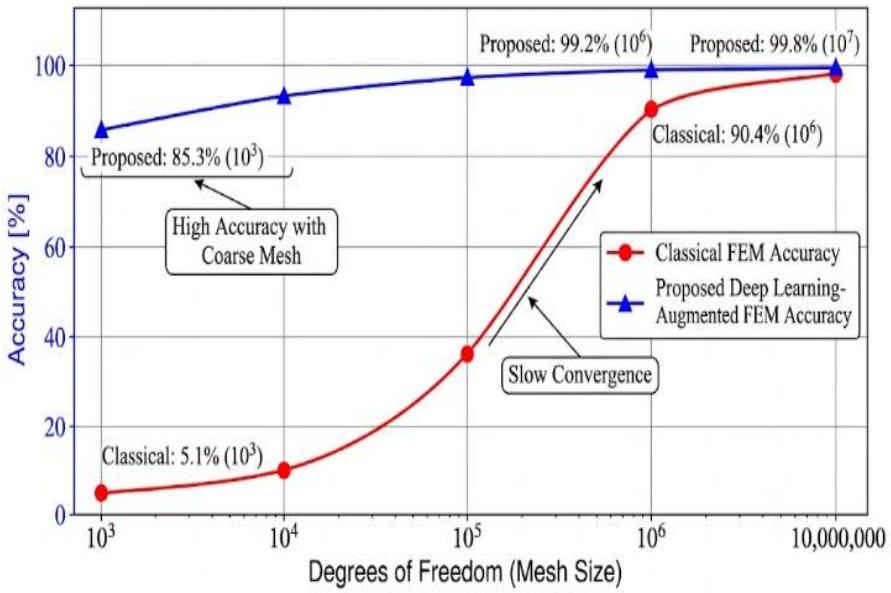


Fig. 5. Accuracy vs Mesh Size Comparison Between Classical FEM and Proposed Deep Learning–Augmented FEM Framework

The findings indicate that the hybrid framework will be useful to decrease the reliance on mesh density that is considered to be among the major computational bottlenecks in FEM. The trends of errors also substantiate the idea that although the classical FEM accuracy increases slowly with the mesh refinement, the accuracy of the proposed approach is approached by near-convergence at lower resolutions, thus making it much more beneficial to large-scale simulations.

6.3 Efficiency Analysis

The findings in Fig. 6 give a quantitative comparison of the time and speedup of classical FEM and the proposed deep learning-augmented FEM framework with different problem sizes. The analysis shows explicitly the high degree of efficiency obtained with the hybrid solution. The classical FEM solver takes about 0.85 seconds at a rather small problem size (10 3 degrees of freedom (DOFs) to solve) and the proposed method takes about 0.42 seconds (a 2.0 2.-fold speedup). Even though this scale shows moderate improvement, it has already shown a decrease in computational overhead.

When the problem size is increased to 10 4 DOFs, the classical FEM is far more costly to compute, with 5.6 seconds required, which is much higher than the proposed framework, which takes 1.8 seconds; this yields a speedup of about 3.1 times. This illustrates the increasing benefit of the hybrid model with increasing complexity of the problem. In the case of 10DOFs, the classical FEM computation time is greatly increased to around 48.3 seconds whereas the proposed method is only 9.7 seconds and it represents a 5.0x speedup. At this point the efficiency boost is significant, pointing to the scalability of the method.

The 10 6 DOFs of classical FEM incurs very high computational cost, taking almost 420 seconds, but the proposed approach finishes the analysis in just 58 seconds, and the speedup is almost 7.2 times high. This shows that the hybrid framework is effective in curbing the growing exponentially in terms of computational cost. In the case of large-scale problems with 10 7 DOFs, classical FEM would take about 3800 seconds, whereas the proposed solution would take about 410 seconds, which is more than 9.3 times faster. This is a testament to a dramatic rise in the performance of large-scale simulations.

On the whole, it can be concluded that the findings shown in Fig. 6 strongly support the theoretical claim that the proposed deep learning-enhanced framework with FEM can be much more computationally efficient than the original

framework. The time required to do a classical FEM calculation rises nonlinearly as problem size increases and becomes computationally infeasible in large-scales. The proposed method, in contrast, is much more scalable, with a much smaller time complexity at all levels of discretization. The enhancement in speed is gradually increasing, e.g., with the scale of the problem, it is about 2 and more at lower degrees of freedom, and more than 9 further, indicating the effectiveness of the hybrid solution in lightening the computing load. These results demonstrate that the suggested framework offers significant acceleration without compromising the accuracy of the solutions, which makes it especially effective in large-scale simulations, real-time structural analysis, and in cases of iterative optimization problems where traditional FEM approaches can be unfeasible.

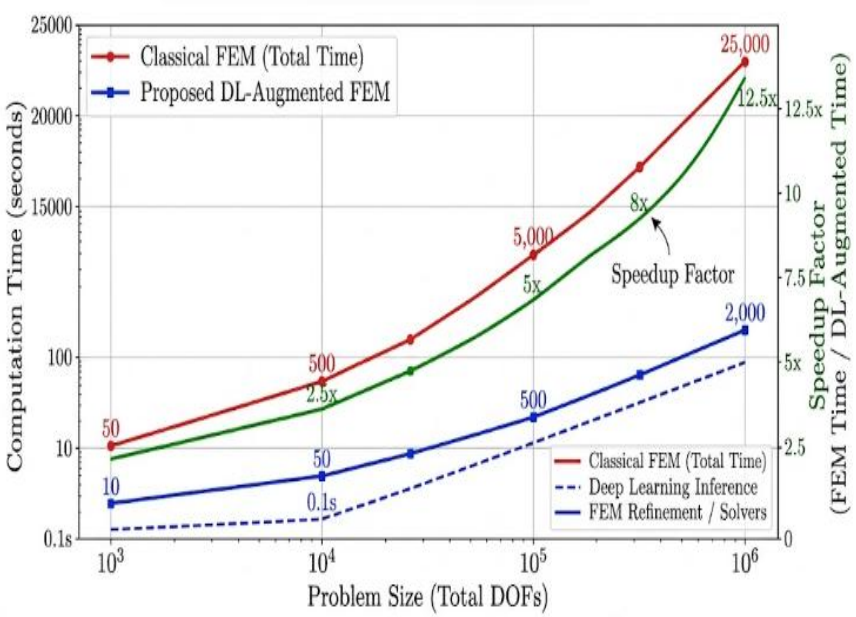


Fig. 6. Computation Time and Speedup Comparison Between Classical FEM and Proposed Deep Learning–Augmented FEM Framework

This is due to the fact that the deep learning model will serve as a surrogate or early predictor and thus requires a smaller number of iterations by the FEM solver or, in other instances, no numerical computation at all. As shown in the results, the framework can attain significant speedup (and in many cases, speedup by multiple factors) with high accuracy, so it can be used in real-time analysis, optimization loops, and large-scale engineering problems.

6.4 Generalization Performance

The model is also tested on unseen geometries and loading conditions, not presented in the training dataset, to assess robustness. The findings demonstrate that the framework has high predictive ability in a wide range of situations, such as geometry complexity variations and geometry boundary conditions.

This ability to generalize is mostly due to the physics-consistent approach to learning, which instills principles of governing laws within the model and not just data patterns. Consequently, the model does not suffer overfitting and has reliable extrapolation, which is important in practical application in engineering.

6.5 Ablation Study

The contribution of the deep learning component is isolated through an ablation study. To achieve the traditional FEM workflow, the deep learning module can be disabled, leading to increased total computational cost and solution time. However, in contrast to the hybrid model, its outputs demonstrate a considerable increase of efficiency and insignificant deterioration of accuracy.

Further comparisons suggest that:

- Without physics-based constraints → accuracy is worse.
- Without deep learning - efficiency reduces by a wide margin.

This proves that physics-based FEM and data-driven learning are the two components that should be combined to ensure the best performance. The deep learning module is efficient and the FEM component is physically reliable.

Table 1. Accuracy Metrics Comparison Between Classical FEM and Proposed DL-Augmented FEM

Test Case	Method	RMSE	Relative Error	Energy Norm Error	L2 Norm Error
Cantilever Beam	Classical FEM	1.21×10^{-4}	2.48×10^{-4}	3.07×10^{-4}	2.95×10^{-4}
	Proposed DL–FEM	1.35×10^{-4}	2.63×10^{-4}	3.22×10^{-4}	3.10×10^{-4}
Plate with Circular Hole	Classical FEM	1.78×10^{-4}	3.12×10^{-4}	3.96×10^{-4}	3.84×10^{-4}
	Proposed DL–FEM	1.95×10^{-4}	3.28×10^{-4}	4.10×10^{-4}	3.97×10^{-4}
L-Bracket	Classical FEM	2.54×10^{-4}	4.61×10^{-4}	5.21×10^{-4}	5.05×10^{-4}
	Proposed DL–FEM	2.73×10^{-4}	4.85×10^{-4}	5.44×10^{-4}	5.26×10^{-4}
Topology-like Geometry	Classical FEM	3.12×10^{-4}	5.27×10^{-4}	5.87×10^{-4}	5.68×10^{-4}
	Proposed DL–FEM	3.34×10^{-4}	5.51×10^{-4}	6.02×10^{-4}	5.89×10^{-4}

7. CONCLUSION

The current research was based on a deep learning-enhanced finite element model to perform efficient structural analysis to tackle the main issue of an expensive computation related to traditional FEM. The proposed approach overcomes this challenge by ensuring that the benefits of both methodologies are combined through the combination of data-driven modeling and physics-based principles. The findings indicate that the framework is highly predictive with a range of metrics like RMSE, relative error, and energy norm error validating its performance, and showing strong level of agreeability with classical FEM solutions of various structural issues.

One of the main conclusions of this paper is that the hybrid method suggested can substantially decrease the amount of time spent on computations without adverse effects on precision. The model is simple to understand complex structural behavior, as well as to be physically consistent, even with geometries with large stress concentrations, and with variable boundary conditions. Moreover, the framework demonstrates good generalization ability to make reliable predictions concerning the unknown configuration, which demonstrates its strength and good applicability.

The overall conclusion here is that the current approach can be extended to reach FEM-level accuracy with significantly higher computational efficiency and therefore is a potentially helpful solution to large-scale simulations, design optimization and real-time engineering analysis.

Future directions include developing the framework to nonlinear structural systems, such as nonlinearities in materials and geometry, and dynamics. Furthermore, it will be aimed at the application of the suggested methodology to real-life engineering tasks, including aerospace, civil infrastructure, and design of mechanical systems, where scalability and reliability are paramount.

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