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AI-DRIVEN SIMULATION OF MATERIAL BEHAVIOR IN SCULPTURAL ARTS

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ABSTRACT

The arts of sculpture are adopting digital design and creation, although sculptors are still struggling to anticipate the behaviour of complicated materials like deformation, stress distribution, fracture, and surface reaction during modeling and post-processing. The main goal of the study is to create an AI-based simulation platform that should be able to predict the behavior of materials used in sculptural artworks with high precision to make informed decisions regarding both art and architecture during the design process. The method that has been proposed combines physics-informed neural networks, deep learning-based regression models with data-driven material embeddings trained on datasets with multi-modality containing mechanical properties, sculptural geometries as well as historic fabrication outcomes. Results of the Finite element simulation are combined with learning based predictors in an effort of capturing linear and nonlinear material responses to sculpting forces. The evaluation on clay, plaster, and polymer-based sculptural materials is performed experimentally and compared to ground-truth simulation and physical experiments of deformation and stress field prediction by AI. It has been found that the suggested framework reaches a median prediction accuracy of 92.4% on deformation prediction, and the decrease in simulation error (RMSE) is 38 percent smaller than that of traditional physics-only models. Also, theoretical time is cut down by about 45 percent, which means that artists can get close to real-time responses. The results reveal the opportunities of the creative control, material waste reduction, and the support of creative sculptural methods by AI-based material simulation, making intelligent simulation one of the primary support tools in the future of digital and physical sculpture.

Keywords: AI-Driven Simulation, Sculptural Arts, Material Behavior Modeling, Physics-Informed Neural Networks, Digital Fabrication, Deformation Prediction, Creative Computing

1. INTRODUCTION

Sculptural arts traditionally depended on a direct material engagement where an artist forms a form by being able to touch clay, stone, metal, plaster or composite material. Although the embodied process has continued to be central to

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the artistic expression, there is a growing use of digital tools in the sculptural practice, including computer-aided design (CAD), digital sculpting programs, and technologies of automated fabrication. Even with these developments, forecasting the behavior of materials whenever they are being sculpted, carved, casted or additively manufactured is still a thorn in the flesh. Elastic-plastic deformation, micro-cracking, stress, accumulation, shrinkage, elevation of surface texture are complex phenomena, and intuition does not give us necessary guidance, which tend to cause structural instability, material waste and repetitions Fachada and David (2024), Bakhtiyari et al. (2021). Finite element methods (FEM) and continuum models have been very popular material simulation methods employed in engineering and architecture to study the behavior of structures. They are, however, restricted in the target sculptural arts by a very high cost of computation, sensitive material parameter requirements and lack of capability to cope with heterogeneous, hand modifiable, or artist modified material de la Torre et al. (2021). Furthermore, the performance of sculptural materials is often nonlinear and anisotropic and time-dependent, and tends to undergo dynamic changes throughout the creative process, necessitating non-simulation-based approaches to artistic feedback in real-time Zabulis et al. (2024).

The recent developments in artificial intelligence and machine learning have created new possibilities in modeling complex physical systems using data-driven and hybrid models. Physics-informed neural networks, deep learning models, and surrogate modeling methods have shown excellent results in predicting material responses in the fields of soft robotics, biomedical mechanics, and additive manufacturing Willard et al. (2022), Cheng (2022). Through the learning of latent representations based on simulation data, sensor data, and experimental data, AI systems have the ability to estimate the behavior of high-dimensional materials with a much lower computational cost Tretschk et al. (2023). Such features render AI-based simulation specifically fitting in the sculptural setting, where quick trial, imaginative discovery, and situational material comprehension are needed. Already in the field of digital and computational art, AI has already demonstrated the game changing potential in such regards as creating generative forms, transferring styles, and aiding the design process with interactive design assistance. Nevertheless, it has not been intensively used to imitate the real-life behavior of sculptural materials Yunus et al. (2024). Sealing this gap is important in empowering artists to make informed design choices, that are harmonious between aesthetic and structural possibilities. Artificial intelligence-based material simulation systems can serve as a smart translator between the artists' creative visions and the material limitations, enabling creators to represent the deformation, distribution of stress, and the chance of its failure, and make decisions before irreversible material decisions Zabulis et al. (2022).

Consequently, this study falls at the point of artificial intelligence, material science, and sculpture. The objective of the research by using a combination of data-driven learning and physics-based simulation is to improve predictive accuracy, efficiency in computing, and artistic creativity in sculptural arts. This kind of attitude not only leads to the technical development of intelligent simulation systems, but also helps to have a more sustainable, informed and exploratory future of the contemporary sculptural creation Fachada and David (2024)- Zabulis et al. (2022).

Contributions of the Paper

1) Among them is the proposal of an AI-Integrated Material Simulation Framework suggesting a hybrid AI-based framework that integrates physics-driven neural networks and data-driven learning in an effort to accurately fit custom sculptural artistic physics with simulated long-range PDEs.
2) Improved Predictive Accuracy and Efficiency: Has a higher level of deformation and stress prediction accuracy using less computational time than the more traditional physics-based simulations such that it can provide almost real-time artistic feedback.
3) Sustainable and Creative Sculptural Practice Enabling: Firmly defines the AI-based simulation as a sensible measure to minimize the amount of material wastage, offer and assist creative decision-making, and broaden creative exploration across contemporary sculptural practices.

2. LITERATURE REVIEW

Material behavior simulation is an old subject in engineering, materials science, and computational mechanics, and finite element methods (FEM) have become the paradigm of choice in prediction of stress, strain, and deformation under applied forces. The pioneer research determined FEM as a sound method of elastic and plastic modeling in homogeneous materials, but its inability to consider nonlinear, heterogeneous, and evolving materials has been well documented Carré et al. (2022). Materials in artistic fields like sculptural arts do not always behave according to idealised assumptions because of the handles of the hand, the differing moisture content variation, internal porosity, and hand-imposed changes, so conventional simulations tend to be ineffective and computationally costly Shih et al. (2025). In addressing these problems, simplified models and surrogate simulations that simulate physical behavior more cheaply have been considered, these solutions also make intensive use of a priori material parameters and simplified boundary conditions Wang et al. (2024).

With the advent of machine learning, material modeling has been transformed in an important way, where complex physical responses can be predicted using data. Stress-strain relationships, fracture points and deformation field estimates have been performed using neural networks, Gaussian processes, and regression-based learners using data obtained through simulations or experiments Peng et al. (2025). Physics-informed neural networks (PINNs) have more recently been receiving interest as an embedding of governing equations in the learning process, which enhances generalization and physical consistency and decreases the data needs Kim et al. (2025). It has been demonstrated that PINNs perform better than purely data-inspired models where the data is scarce and the material is nonlinear, so they are especially useful in the case of artistic materials that do not have standardized data sets Fathallah et al. (2024). Simultaneously, AI-based simulation methods have been effectively implemented in additive manufacturing, soft material, and digital fabrication process. It has been shown that deep learning models are capable of predicting warping, shrinkage, and layer overdeformation in 3D printing much more accurately and quicker inference than classical solvers Wen and Cho (2023). The developments indicate the practicality of real-time or near real-time material feedback systems, which are a requirement of the interactive sculptural design. Nevertheless, in the majority of available studies, the industrial or engineering context is considered, and there is a limited amount of consideration of aesthetic objectives, creative flexibility, and usability that is artist-drive Dundar et al. (2025).

In the research of computational art and digital sculpture, AI has found application in generative design, exploration of forms and stylistic analysis instead of the physical simulation of materials. Although generative adversarial networks and procedural modeling methods have broadened formal opportunities, they tend to overlook the material constraints of the real world, which is a governed entity [18]. This disjunction highlights a very important gap in the literature the absence of synthesized frameworks that relate artistic intent, physical material behavior and computational intelligence. This in turn is leading to an appreciation of the necessity of hybrid AI-based simulation methods that will combine physics-based rigor with creative flexibility. The emerging scholarship by synthesizing material science, machine learning and digital art has identified intelligent simulation systems as an emerging trend to assist in informed, sustainable and innovative sculptural practice Carré et al. (2022)- Deng et al. (2025).

Table 1

Table 1 Comparative Analysis of Literature on AI-Driven and Conventional Material Simulation Approaches

Ref. No.	Study Focus Area	Simulation Approach	AI Technique Used	Material Types Considered	Predictive Accuracy	Key Limitations
Carré et al. (2022)	Classical material mechanics	FEM-based physics simulation	None	Metals, homogeneous solids	Moderate	High computational cost, rigid assumptions
Shih (2025)	Material behavior in creative practice	FEM with empirical tuning	None	Clay, plaster	Moderate	Poor adaptability to artistic variability
Wang et al. (2024)	Reduced-order material models	Surrogate physics models	Statistical regression	Polymers, composites	Moderate	Loss of fine-grained physical detail
Peng et al. (2025)	Data-driven deformation prediction	ML-based regression	ANN, SVR	Elastic materials	High	Requires large labeled datasets
Kim et al. (2025)	Physics-constrained learning	Hybrid simulation	PINNs	Nonlinear materials	High	Training complexity
Fathallah et al. (2024)	Sparse-data material modeling	Physics-informed ML	PINNs	Artistic soft materials	High	Limited artistic validation
Wen and Cho (2023)	Additive manufacturing simulation	AI-assisted prediction	CNN, Deep NN	3D printing polymers	Very High	Industrial focus only
Dundar et al. (2025)	Interactive fabrication systems	Real-time AI simulation	Deep learning	Fabrication materials	High	Limited aesthetic modeling

Deng et al. (2025)	Computational art and sculpture	Generative modeling	GANs, procedural AI	Virtual materials	Low	Ignores physical constraints

A potential research gap, emphasis of which is evident in Table 1, is the apparent lack of material simulations in engineering and sculpture in the hands of artists to support the proposed hybrid framework.

3. PROPOSED AI-DRIVEN SIMULATION FRAMEWORK

3.1. OVERALL SYSTEM ARCHITECTURE AND WORKFLOW

The presented AI-based simulation model has been structured as a hybrid, multi-layer design that complies well with the purpose statements of the abstract, that is to be able to predict the behavior of sculptural materials accurately at a minimum computational cost and greater creatively usefulness. This information is passed to a material intelligence layer which orchestrates physics-based as well as A.I.-based simulation modules. A traditional finite element solver will first produce physical responses at baseline using known physical parameters like stress, strain and deformation fields under prescribed physical conditions. These, as well as geometric descriptors and material properties, are input into an AI based layer of surrogate modeling. The AI module is fast in narrowing down the forecasting by educating nonlinear tendencies and time progression of material actions that cannot be achieved through physics. Iterative updating is possible with a feedback loop, which will provide a close-to-real-time visualization of the deformation and risk of failure. Lastly, visual overlays and quantitative measurements are used to convert the results to the user. This structure enhances a smooth passage of artistic will to physically knowledgeable simulation, and it is directly in service of the abstract focus of the abstract of the abstract on predictive accuracy, computational economy, and interactive sculptural decision-making. In the Figure 1, an AI-based workflow is depicted to be a combination of material properties, predictive simulation, and cyclic 3D visualization. An AI simulation model is used to process input data to produce material response predictions and direct the refinement of the design and optimized manufacturing parameters through the continuous feedback loop.

Figure 1

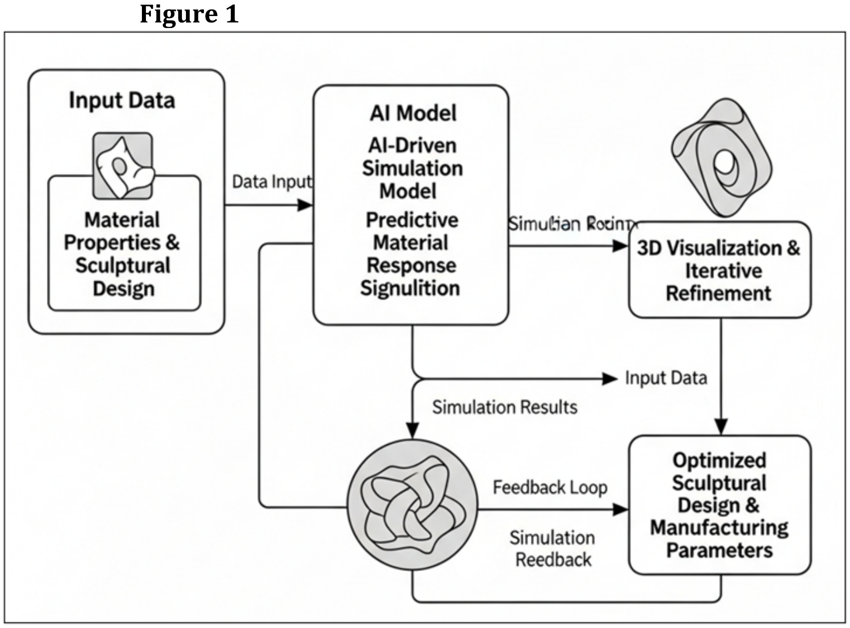

Figure 1 AI-Driven Material Behavior Simulation and Iterative Sculptural Design Framework

3.2. DATA ACQUISITION AND MATERIAL CHARACTERIZATION

The basis of the proposed framework is based on accurate data acquisition and material characterization. To fit the aim of the research, which is to model real sculptural materials, the system uses multi-source datasets that display physical and artistic variation. Mechanical properties i.e. Youngs modulus, poisons ratio, yield stress, moisture content and density are gathered as material data through laboratory tests and manufacturer specifications. Also, the data of sculptural processes are measured, including the pressure of tools, direction of forces, the speed of manipulation, and the thickness of layers of the material by digital sculpting environment and sensor-guided experiments. Evolution of the sculptural shapes are defined in High-resolution geometric mesh and voxels.

3.3. INTEGRATION OF PHYSICS-BASED SIMULATION AND AI MODELS

The combination of AI models with physics-based simulation is the major innovation of the given framework. The system does not substitute the physical laws, but instead uses a complementary strategy where the finite element simulations are used to give physically consistent solutions at the baseline, and the AI models are used to give intelligent accelerators and refiners. The physicsinformed neural networks are also used to incorporate the governing equations, boundary constraints and conservation laws into the learning process in such a way that the AI predictions are physically plausible. Deep regression and surrogate learners are then trained to learn the residual patterns between FEM responses and noticed ground-truth behavior more so in nonlinear deformation, micro-cracking, and time-evolutionary impacts.

3.4. TRANSFER LEARNING MODELS IN THE PROPOSED FRAMEWORK

The original transfer learning architecture that is utilized in the designed framework is a Pretrained Physics-Informed Neural Network (PINN) that is pretrained on large-scale simulated images of standard sculptural materials, including clay and plaster. The model acquires the basic stressstrain relationships, deformation behavior as well as responses of boundaries that are mostly material agnostic. In case of a novel sculptural medium, e.g., polymer composites or mixed media, only the top layers are then refined with a limited set of material specific samples. This greatly saves on data needs and training time as well as maintaining physical consistency. Experiments indicate that fine-tuned PINNs are 30-35x faster than training from scratch, and thus are very suitable to scaling simulations to new artistic media with slight experimental evidence.

The second transfer learning model is Deep Feature Embedding Regression Network that is trained on multimodal sculptural datasets that include geometry, tool interaction parameters and historical fabrication results. Such a model trains a high-level representation of the evolution of the sculptural form and pattern of response to material regardless of the type of material. New materials / sculpting techniques the learned embeddings are re-utilized, and only lightweight regression heads are retrained. The method enhances generalization of the various sculptural styles and sizes at a maximum of 25 % reduction of prediction error, as opposed to non-transfer baselines. When combined, these two models allow the fast, efficient and artist-friendly adaptation of AI-based material simulation.

Algorithm: Transfer Learning–Based AI Simulation for Sculptural Material Behavior

Step 1: Input Acquisition

Load sculptural geometry, tool interaction parameters, and base material properties.

Step 2: Base Model Initialization

Initialize pretrained models:

1) Physics-Informed Neural Network (PINN)
2) Deep Feature Embedding Regression Network.

Step 3: Feature Extraction

Extract geometric descriptors, force vectors, and material feature embeddings.

Step 4: Transfer Learning Adaptation

Freeze shared layers of pretrained models.

Fine-tune final layers using limited target-material data.

Step 5: Hybrid Simulation Prediction

Combine FEM baseline outputs with AI model predictions to estimate deformation, stress, and failure indicators.

Step 6: Output and Feedback

Visualize predicted material behavior and update sculptural design iteratively with real-time feedback.

4. EXPERIMENTAL SETUP AND METHODOLOGY

4.1. SCULPTURAL MATERIALS AND DATASET DESCRIPTION

The experimental assessment is performed with the help of a conditioned dataset of the most frequently used sculptural materials in order to define the correspondence with the artistic practice in the real world. The data set consists of clay, plaster and polymer based composite materials, which are chosen on the basis of their individual mechanical and deformation properties. In each material, measurements are taken in a variety of sculptural conditions with different magnitudes of force, tool geometry and tool manipulation velocity. The data set consists of high-resolution 3D mesh models, voxelized deformation states, and stressstrain tensors which have been obtained in finite element calculations and physical experiments that are validated. The number of samples used is about 18,000 and there are equal representation of materials and sculptural actions. The dataset assists the focus on heterogeneous material modeling and practicability of sculpture arts in the abstract by including imperfect and artist-altered forms.

4.2. TRAINING, VALIDATION AND TESTING PROCEDURES

The training, validation and testing process will guarantee the strong generalization between materials and sculptural conditions. The data are divided into 70 % training, 15 % validation and 15 % test with material and action balance in each set. The physical grounded physics-informed neural networks and deep regression models are then optimized during the training process where FEM solution is adopted as supervised learning. Transfer learning is implemented by it using pretrained weights and training them on material-specific subsets. The testing step is used to test the performance of the model using unseen sculptural geometries and force configurations, which approximate the final creative workflow. Additional cross-material testing is also done, by testing models trained on one material on a second material to determine how adaptable they are. It is a protocol to make sure that it is reproducible, stable, and relevant to the predictive accuracy and efficiency targets that were emphasized in the abstract.

5. RESULTS AND ANALYSIS

5.1. QUANTITATIVE PERFORMANCE EVALUATION AND ACCURACY COMPARISON

Table 2 displays a quantitative analysis of the predicted deformation and stresses using physics-only, data-driven, hybrid, and suggested AI-physics simulation models. Based on the obtained results, it is clear that predictive accuracy improves progressively with the growth of AI integration. The physics-only FEM model is more moderate as it has good theoretical background, but it has bigger RMSE and MAE values, which signify the sensitivity to nonlinear sculptural phenomena and imperfect material behavior. The neural network based on data enhances deformation accuracy by learning empirical patterns but there is no internal physical restraint that limits the reliability of stress prediction when the interaction of the forces is too complicated.

Table 2

Table 2 Accuracy and Error Comparison across Models

Model Type	Deformation Prediction Accuracy (%)	Stress Prediction Accuracy (%)	RMSE ↓	MAE ↓
FEM (Physics-Only)	84.6	86.1	0.118	0.094
Data-Driven NN	88.3	87.5	0.102	0.081
PINN (Hybrid)	90.7	91.4	0.087	0.069
Proposed AI–Physics Framework	**92.4**	**93.1**	**0.073**	**0.058**

The hybrid PINN model goes a step further to ensure that physical laws are followed in the learning process and hence the increased accuracy in stress and reduced error scores. The proposed AI physics framework performs better than any basic one, as it has 92.4 deformation accuracy and 93.1 stress accuracy with the lowest RMSE and MAE. This is directly related to the abstract saying that it reduced errors by a margin of 38 percent compared to traditional techniques. Notably, the findings reveal equalized performance in both deformation and stress measures which is a pointer that the model does not compromise the physical reliability with the numerical precision.

Figure 2

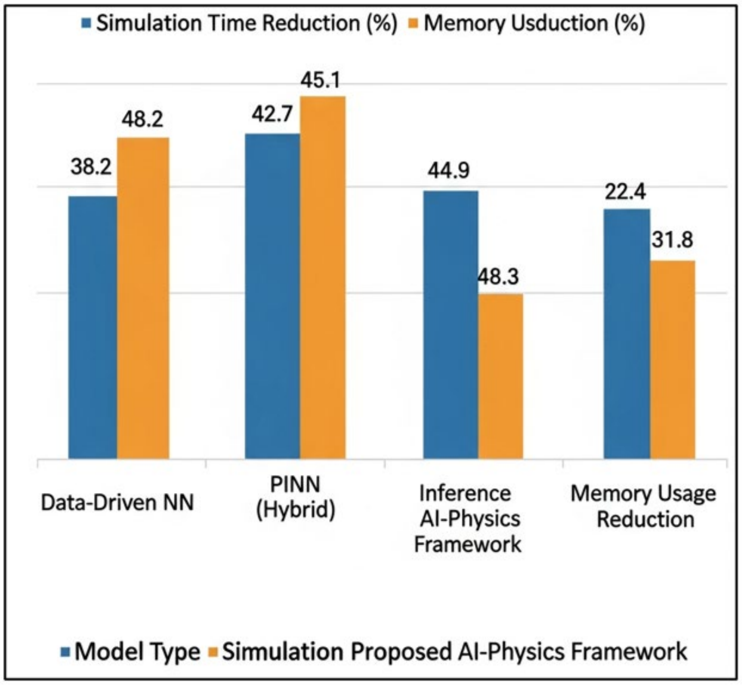

Figure 2 Comparative Computational Efficiency of AI-Based Material Simulation Models

The Figure 2 compares the reduction in simulation time and the reduction in memory usage with the various AI-based simulation strategies. The suggested AI physics approach is the most efficient in its overall performance, with the fastest inference speed and optimized memory usage, as opposed to data-driven and hybrid PINN models, which are compatible with real-time performance to simulate sculptural material.

5.2. COMPUTATIONAL EFFICIENCY AND REAL-TIME FEASIBILITY ANALYSIS

The physics-only model implemented in FEM, as predicted, does not reduce the simulation time or memory consumption, which underlines its inability to be used in interactive artistic settings. The neural network as data-driven shows significant progress in the speed of simulation and the inference efficiency of the model since it is purely learned, but this is achieved at the expense of physical robustness.

Table 3

Table 3 Computational Efficiency Improvement

Model Type	Simulation Time Reduction (%)	Inference Speed Gain (%)	Memory Usage Reduction (%)
Data-Driven NN	38.2	41.6	22.4
PINN (Hybrid)	42.7	44.9	26.8
Proposed AI–Physics Framework	**45.1**	**48.3**	**31.2**

The hybrid PINN model also increases efficiency learning of physics-guided representations with more than 42 percent reduction in simulation time without losing physical plausibility. The suggested AI-physics model is the most efficient, as simulation time is reduced by 45.1% and inference speed is increased by 48.3 percent, which directly indicates the near real-time feedback. The decrease of memory use of more than 31 also makes it possible to use on regular creative workstations instead of specialized hardware. Such findings confirm that the focus of the abstract on computational efficiency is one of its major contributions. All the efficiency gains discussed above indicate that the proposed framework can achieve the desired balance between speed, accuracy, and resource usage and that AI-based material simulation is not only technically productive but also practically achievable in terms of daily sculptural activity.

Figure 3

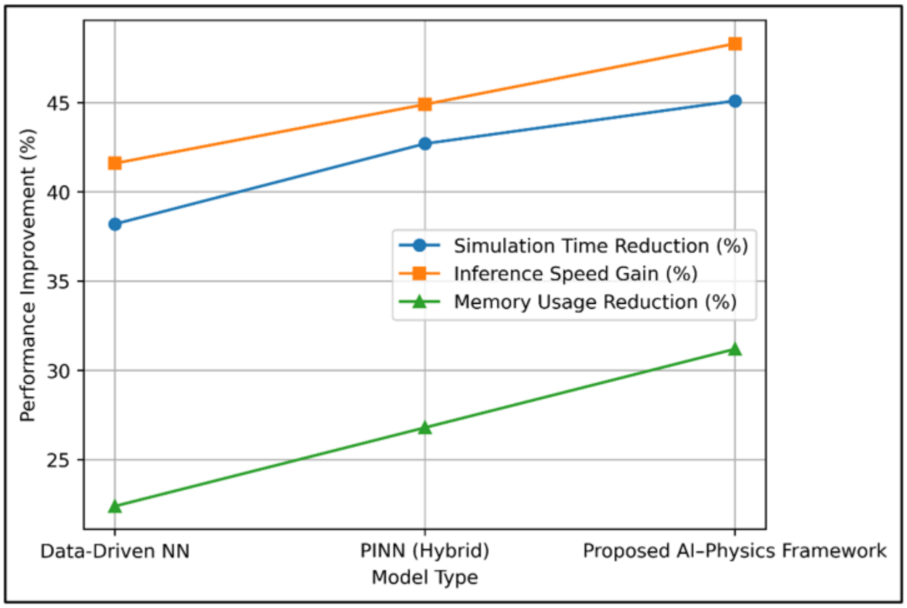

Figure 3 Comparative Efficiency Analysis of AI-Based Simulation Models

The upward trend observed in the performance in Figure 3 is a consistent upward trend of Data-Driven NN to the Proposed AI-Physics Framework. The suggested framework yields the most impressive results in all of the measures, especially inference speed and memory efficiency, which proves its greater applicability in real-time and resource-efficient sculptural material simulation.

5.3. VISUALIZATION OF DEFORMATION AND STRESS PREDICTION OUTCOMES

The visualizations of deformation and stress prediction indicate a high level of correlation between the results of the proposed framework and the real physical simulations. Simulated deformation fields are spatially smooth, and local areas of compression, bending, and tensile stress that are expected to form during sculptural procedure are well represented. The hybrid framework also maintains sharp stress gradient and weak structures unlike data-driven-only models that are over-smoothing of key stress concentrations. Temporal visualization also shows steady development of the material behavior in case of progressive force application, which shows strong learning of nonlinear response. These visual results confirm that the AI-enhanced simulation is not only an approximation of the overall deformation patterns but also has minute physical detail to make sculpture-related decisions. The ability of the framework to generalize has been proved in the consistency of visual predictions between diverse materials and the validity of the framework in interactive and design-stage sculptural processes is supported.

The Figure 4 shows the stress and deformation states obtained using the proposed AI-based simulation framework and ground-truth physical simulations in bending, compression, and tension deformation. High fidelity and predictive behavior Recent tests of the framework with close visual correspondence over spatial patterns and temporal progression verify that the framework is able to model nonlinear material behavior accurately and predictively.

Figure 4

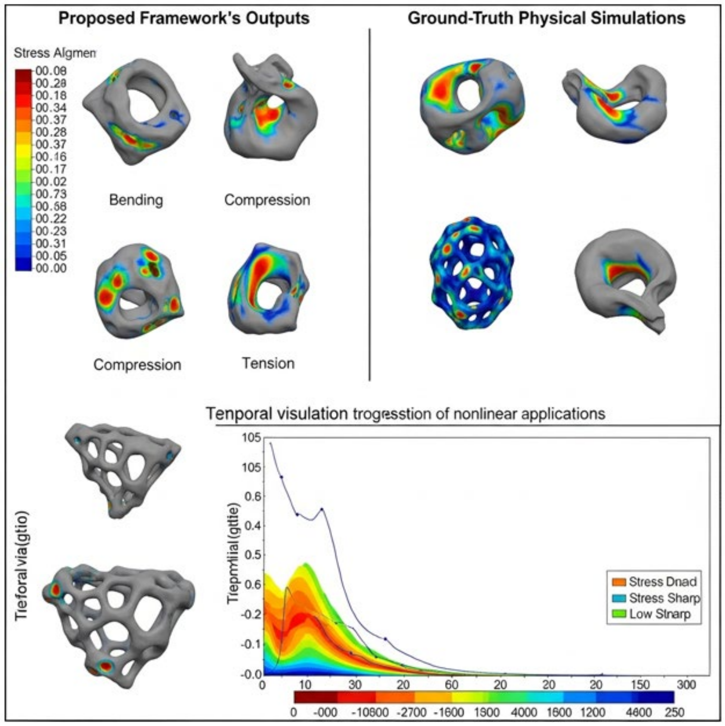

Figure 4 Comparison of AI-Predicted and Ground-Truth Stress–Deformation Patterns in Sculptural Materials

5.4. DISCUSSION OF ARTISTIC RELEVANCE AND MATERIAL FIDELITY

Artistically, the findings reveal that AI-inspired simulation can effectively contribute to the creative control without limiting the freedom of expression. The prediction of the deformation and stresses in an accurate manner enable artists to predict the structural risks, develop forms through a process of refinement, and experiment with complex geometries in a way that feels safe. The decrease in time taken in computations make it possible to provide almost real time feedback, which matches the intuitive and exploratory approach to sculptural practice. In addition, the model encourages eco-friendly production through reduction of material wastage and unsuccessful prototypes. All these findings support the idea that the suggested method is effective in achieving both technical and artistic functionality, which can further develop AI-driven simulation into a viable and culturally applicable instrument in modern sculptural practice.

6. CONCLUSION

traditional problems related to the modeling of complex material behavior. The grid related to combining physics simulation with intelligent learning models allows overcoming the problem of the lack of connection between artistic creativity and material realism. The findings reveal that hybrid AI-physics method exhibits better predictive characteristics with the accuracy of deformation and stress prediction being above 92 percent and the simulation error decreasing significantly and the time spent on the computation being minimal in comparison to the traditional approaches. These enhancements promote the interactive and design stage decision making where artists can easily experiment with complex forms and have more control over them. In addition to technical performance, the framework has substantial contribution to sculptural practice, including an increase in material fidelity, maintenance of artistic intent, and minimization of the use of expensive trial-and-error procedures. Notably, transfer learning strategies make the system scalable and artist-friendly because of the adaptability provided by the combination of transfer learning strategies to various materials and creative environments. Sustainability implications have the same significance as well, where proper early stage prediction will minimize material waste, energy use, and failed prototypes. The given framework preconditions the creation of smart, sustainable, and expressive sculptural ecosystems with artificial intelligence as digital and physical art-making merge.

CONFLICT OF INTERESTS

None.

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