

ALTAIR PHYSICS AI: REVOLUTIONIZING EXPLICIT DYNAMIC SIMULATIONS

Altair Physics AI is redefining explicit dynamic simulations by significantly reducing computational costs and manual effort. This paper explores its potential to improve predictive accuracy, accelerate design cycles, and overcome traditional limitations of simulation-led engineering.



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Abstract

With growing demands for efficiency, safety, and innovation, traditional simulation methods are struggling to keep pace. In sectors like aerospace, automotive, and manufacturing, explicit dynamic simulations are vital for analyzing high-impact scenarios. However, they are computationally expensive and operationally complex.

Artificial Intelligence (AI) and Machine Learning (ML) are now transforming simulation methodologies. Geometric Deep Learning (GDL), a subset of these technologies, offers the ability to predict key structural responses such as stress and deformation, without requiring time-intensive simulations. This approach facilitates faster design iterations, cost optimization, and earlier design exploration.

In this whitepaper, we demonstrate the use of PhysicsAI to streamline explicit dynamic simulations, reducing manual effort and computational time significantly. By training models on high-quality simulation data, the framework enables accurate predictions for new geometries within a defined design space. While initial investment in data generation is significant, the long-term gains include accelerated workflows, increased efficiency, and a scalable foundation for intelligent engineering.

Introduction

Explicit dynamic simulations are essential for analyzing highly nonlinear, transient events involving large deformations, material failure, and complex contact interactions. These simulations are crucial in domains like aerospace and automotive for tasks such as assessing vehicle crashworthiness, space debris impacts, and high-speed metal forming. By directly integrating the equations of motion using small time increments, these simulations capture the intricate dynamic behavior of systems subjected to extreme conditions.

In aerospace, they help validate component integrity during high-speed impacts and optimize safety-critical systems. In automotive, they are used for crash analysis, protective structure design, and regulatory compliance.

Despite their effectiveness, these simulations require extremely small-time steps for numerical stability, leading to high computational costs. The processing time for complex models can extend from several hours to weeks and often requires high-performance computing clusters. This computational burden limits the extent of design exploration and restricts real-time or interactive use cases. To address these challenges, AI-driven approaches are being explored to enhance speed, accuracy, and flexibility in simulation workflows.



AI and ML

AI and ML are redefining computational paradigms. AI mimics cognitive functions such as learning, problem-solving, and decision-making, while ML specifically focuses on developing algorithms that are capable of learning patterns from data without explicit programming. The principles of machine learning involve training models on large datasets, validating their accuracy, and continuously refining them to enhance their predictive capabilities.

Geometric Deep Learning

Geometric Deep Learning (GDL) is an emerging domain within AI that extends traditional deep learning methods to handle non-Euclidean data structures such as graphs, manifolds, and point clouds. Unlike conventional deep learning, which operates on grid-like data like images or sequences, GDL incorporates geometric principles to interpret complex and irregular structures. It leverages symmetries, invariances, and geometric priors to develop models capable of analyzing data with rich geometric and topological features. GDL has broad applications across computer vision, natural language processing, drug discovery, and social network analysis. By generalizing neural network architectures to non-Euclidean domains, GDL enables more nuanced and accurate modeling of real-world phenomena.

AI and ML significantly enhance the efficiency and accuracy of Finite Element Analysis (FEA) simulations across various fields. By integrating AI techniques, simulations can be executed faster and more effectively, reducing both computational time and cost. ML models trained on extensive datasets can predict simulation outcomes and optimize parameters, delivering more precise and reliable results. In Explicit dynamics, for example, machine learning algorithms can analyze data from crash, blast, metal forming; etc, traditionally time- and resource-intensive processes, and accelerate them through automated learning. Additionally, AI-powered reduced-order modeling (ROM) simplifies complex models, allowing engineers to assess system behavior with minimal computational overhead. This synergy between AI and simulation drives innovation by supporting rapid prototyping, more effective design cycles, and improved engineering decision-making.



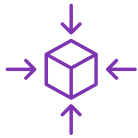
Objectives and Scope of the Work



Demonstrate the effectiveness of ML techniques in reducing computational costs of explicit dynamic analysis



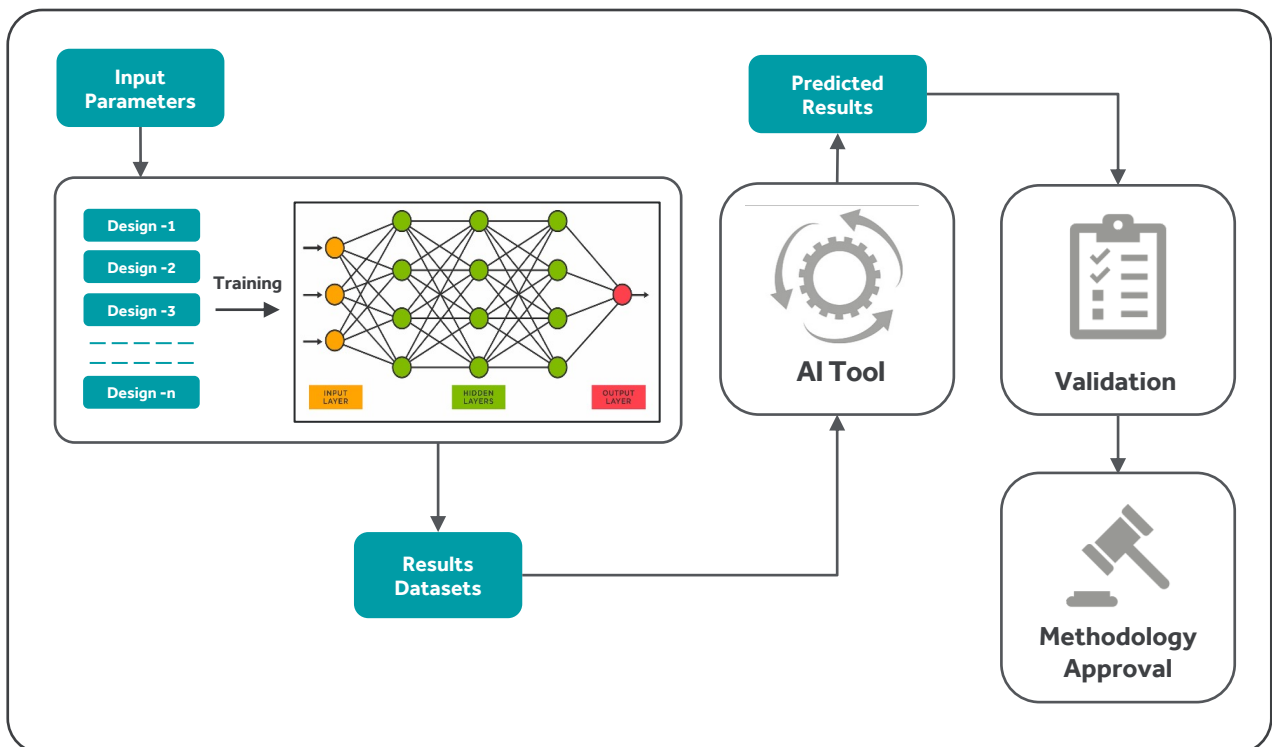
Present a real-world case study involving an automotive bumper crash



Evaluate the model's ability to predict structural behavior such as stress and deformation



Identify limitations in handling unseen geometries or topological changes



Key Terminologies

- **Geometric Deep Learning (GDL):** The core technology behind PhysicsAI. Unlike traditional machine learning which often relies on predefined parameters, GDL directly operates on the geometric data (3D meshes and CAD models) from CAE simulations. It learns relationships between the geometric shape and full contour results.
- **Dataset:** A collection of historical CAE simulation results used for training or testing a ML models. Typically includes input geometries and corresponding physics outputs (e.g., stress, strain, temperature, pressure fields).
- **Data Source:** PhysicsAI supports various CAE file formats (including .h3d and others compatible with HyperView), enabling organizations to leverage legacy simulation data.
 - **Inputs:** Model features used for predictions, such as cae.coord (spatial coordinates), cae.part_label (part names).
 - **Outputs:** Physical quantities that model is trained to predict, such as pressure, stress, displacement, etc.
- **Training Loss Curves:** Diagnostic tool that chart the value of the loss function over training epochs. They help detect underfitting or overfitting by comparing:
 - **Training Loss:** Error on the training dataset.
 - **Validation Loss:** Error on unseen validation data. Ideally, both curves should converge. Persistent gaps may indicate underfitting or overfitting.
- **Error Percentage Calculation:**
Used to quantify prediction accuracy:

$$\text{Error Percentage} = \left(\frac{|Max_{True} - Max_{pred}|}{Max_{True}} \right) \times 100$$

Where:

Max_{True} is the maximum fringe value from the ground truth simulation.

Max_{pred} is the maximum fringe value from the AI-predicted result.



Case Study

Automotive Bumper Crash Simulation

In the automotive industry, bumper crash tests are crucial for assessing vehicle safety and durability. These tests simulate real-world impacts to assess how effectively bumpers can absorb energy and protect occupants.

Methodology

A bumper impact analysis model was developed to study the influence of design parameters on performance. The following parameters were varied:

Fillet Radii

Bumper Thickness

Horizontal Height

Vertical Height

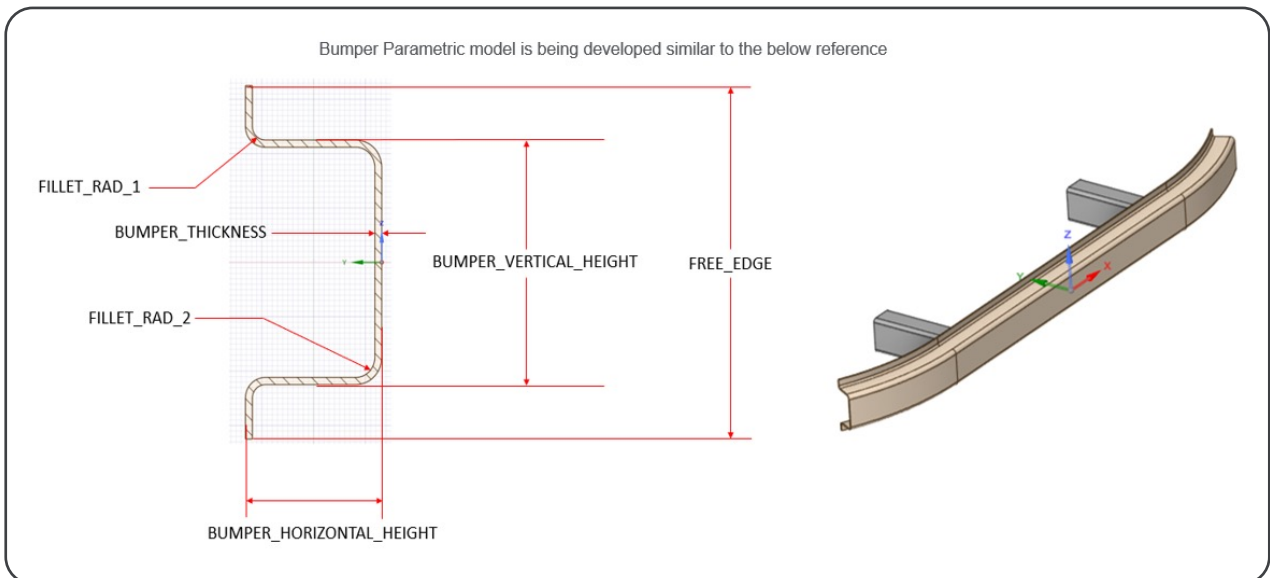


Fig: Picture showing the Parametric Model Used.

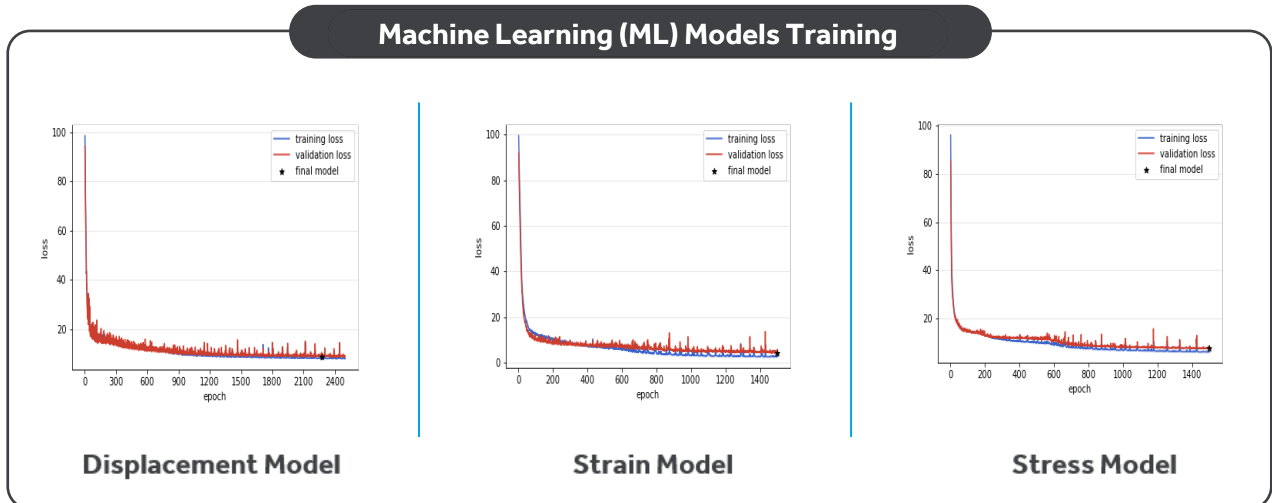
These variations resulted in 45 distinct models, forming the dataset used for ML training through a Design of Experiments (DOE) approach.



Model Development

Altair PhysicsAI, powered by GDL, was used to train machine learning models on the collected dataset. Separate models were developed to predict three mechanical outputs: displacement, stress, and strain. The dataset was split 80/20 for training and testing to ensure robust evaluation.

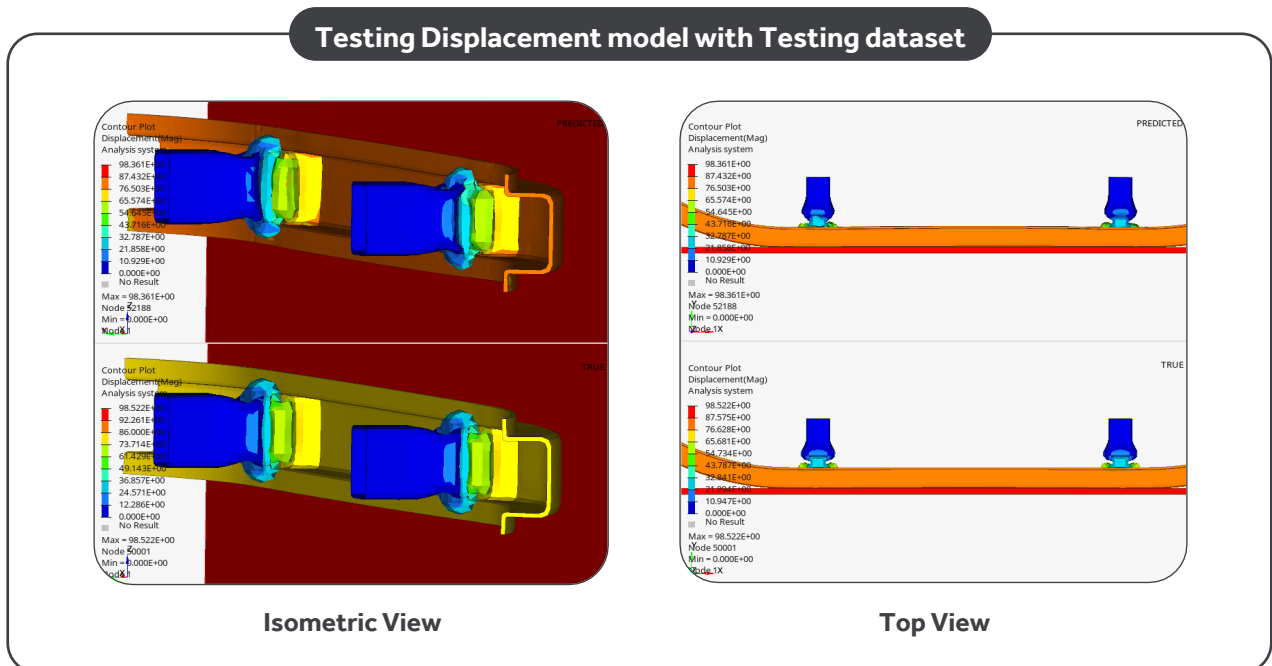
Loss curves for each output type were monitored during training to assess model performance and convergence. The resulting curves confirmed that the models generalize well to unseen geometries.



Validation and Testing

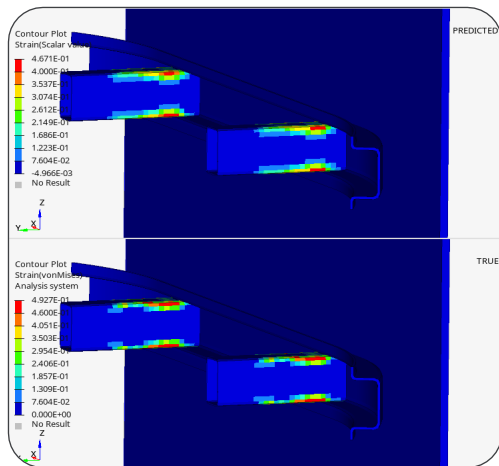
Model testing:

The trained ML models were then tested using test dataset. This step involved comparing the true results with the predicted results from the AI models to evaluate their accuracy and reliability.

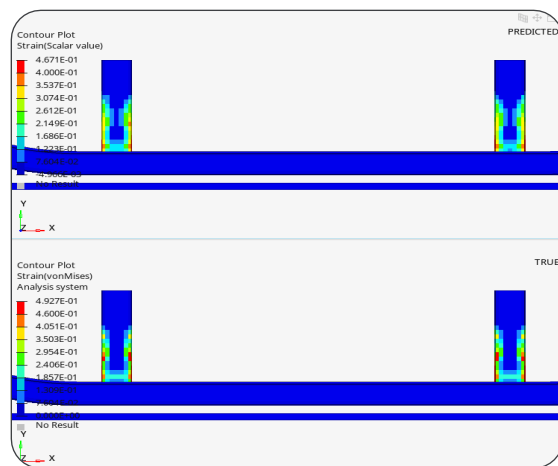


The Error Percentage is 0.163415278%

Testing Strain model with Testing dataset



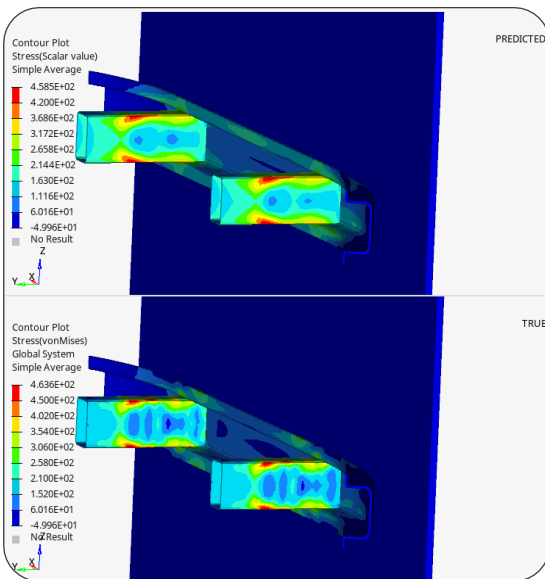
Isometric View



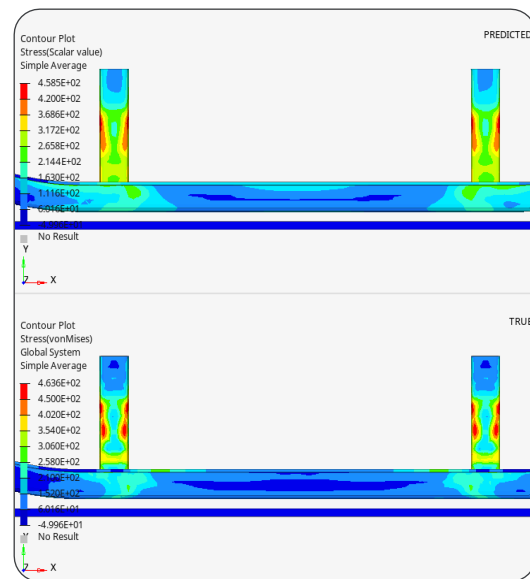
Top View

The Error Percentage is 2.1958%

Testing Stress model with Testing dataset



Isometric View

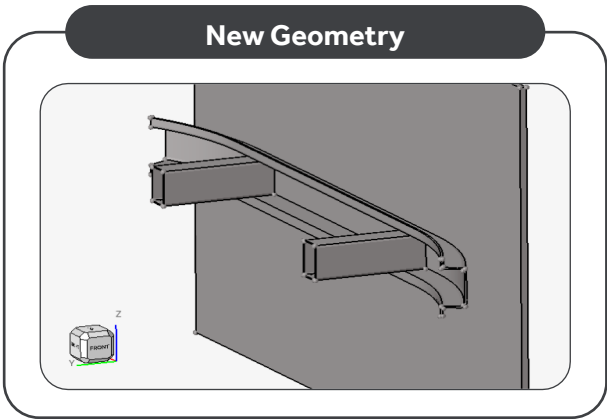


Top View

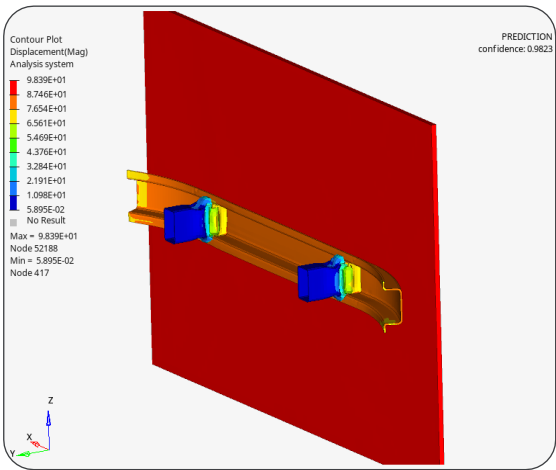
The Error Percentage is 1.1%

Model Prediction:

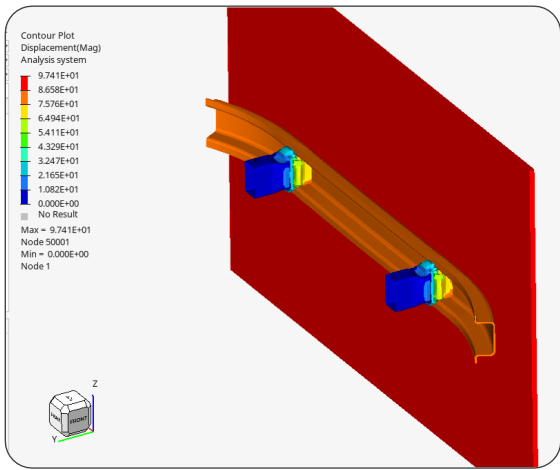
For the final step, predict results for a new geometry with the relevant ML models. Using the developed models, successfully predicted displacement, stress, and strain for the new geometry.



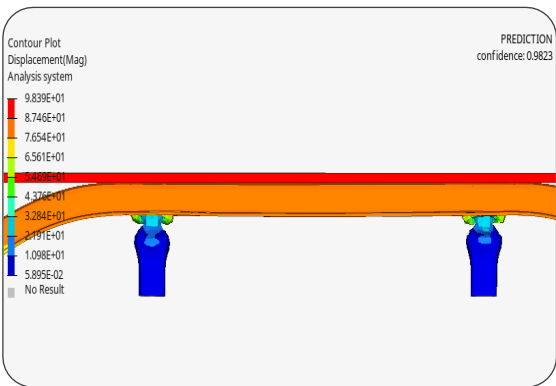
Displacement Prediction



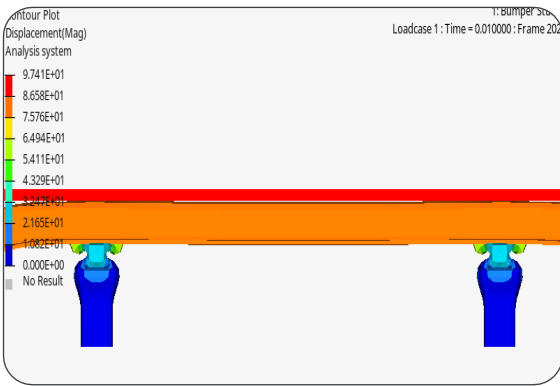
Predicted



True

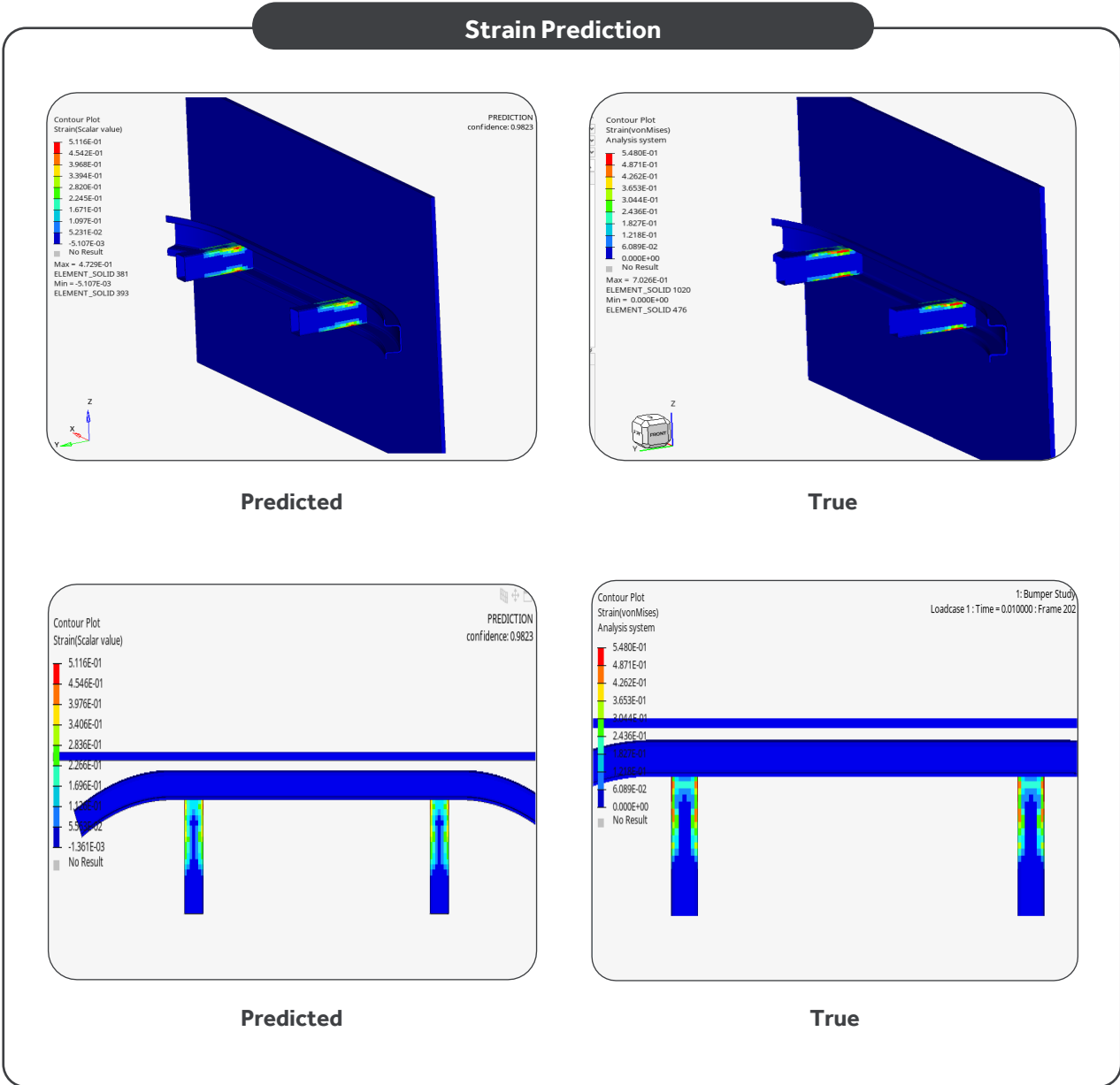


Predicted



True

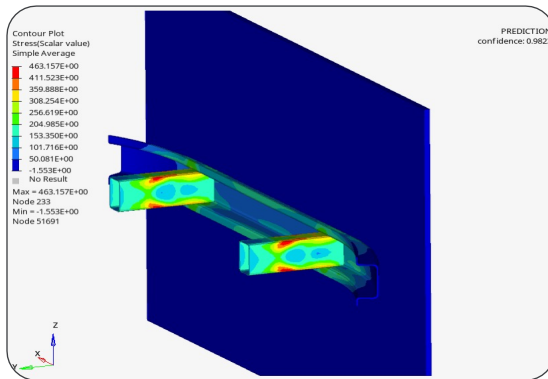
The Error Percentage is 1.006%



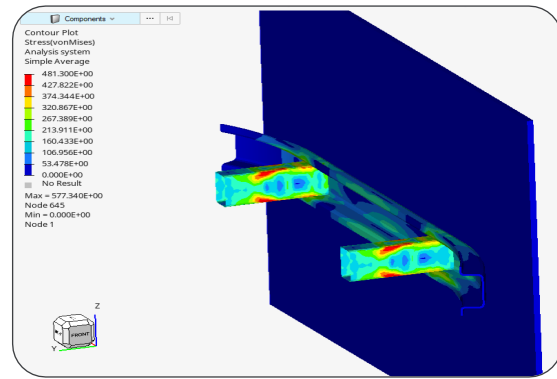
The Error Percentage is 6.6%



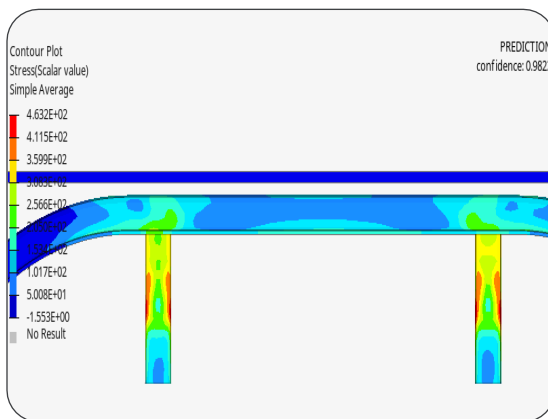
Stress Prediction



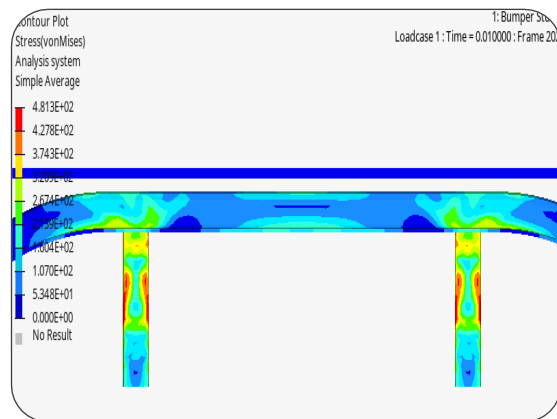
Predicted



True



Predicted



True

The Error Percentage is 3.76%

The Confidence score signifies that the new design approaches closer to the trained models. This will vary from 0-1.



Effectiveness of AI and ML

The case study illustrates how PhysicsAI drastically reduces simulation costs and time using geometric deep learning. Unlike conventional simulation methods that require extensive computational resources, PhysicsAI learns from previous simulations and directly applies insights to new designs. Predictions are generated within seconds or minutes, even for complex geometries..

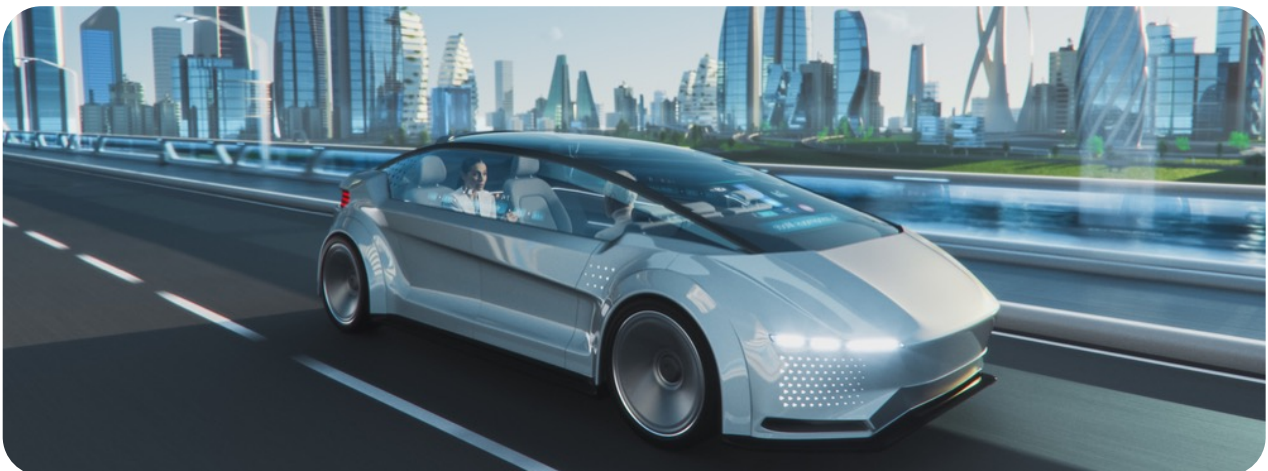
- **Manual effort is significantly reduced.** Traditional workflows often require extensive preprocessing, geometry cleanup, meshing, and setup. With PhysicsAI, much of this is automated, enabling engineers to focus on high-value tasks such as analysis and design optimization.
- **Rapid design exploration** becomes possible with the platform's cloud-connected burst compute capabilities, which allow hundreds of simulations to run simultaneously across GPUs. This is particularly impactful in crash scenarios, where multiple variants must be evaluated for compliance and safety. Engineers can quickly iterate and optimize designs, resulting in safer, higher-performing components.

Limitations of AI and ML

Despite their advantages, AI and ML present several limitations:

- **Training Data Quality:** The accuracy of ML models heavily depends on the quality and diversity of training data. Biased or insufficient datasets can lead to unreliable predictions.
- **Generalization to Unseen Geometries:** Models may not perform well when applied to geometries outside the scope of the training data, especially if there are significant topological changes.
- **Initial Investment:** Building comprehensive datasets and developing robust models requires significant time, expertise, and resources, which may pose a challenge for smaller organizations.
- **Tool Limitations:** In the case of PhysicsAI, predictions are reliable only within the dimensional variations of the training dataset. Major changes to topology may fall outside the model's predictive capability.

These constraints highlight the importance of ongoing research, data quality management, and thoughtful model development to fully leverage AI in simulation-driven design.



Conclusion

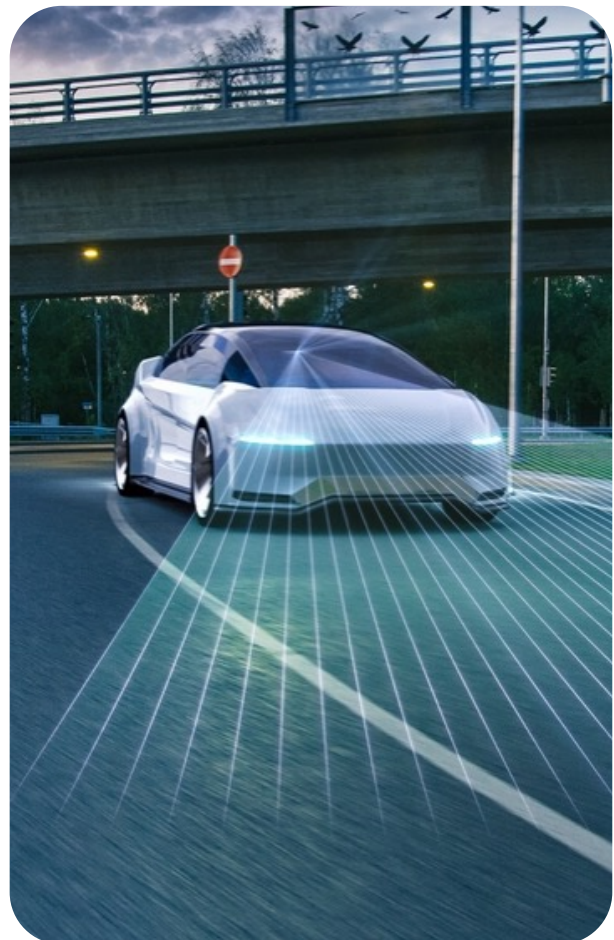
A machine learning model was successfully developed and validated using Altair PhysicsAI, leading to significant reduction in the time and resource requirements for explicit dynamic bumper impact analysis. This case study demonstrates the transformative potential of AI and ML in engineering simulations, enabling faster design exploration, reducing computational costs. And improving workflow efficiency in traditionally simulation environments.

Future Work

Future efforts will focus on expanding the dataset to encompass a broader range of impact scenarios and bumper geometries, thereby enhancing the model's generalization capabilities. The applicability of this methodology will also be explored across other explicit dynamic analysis domains. Additional work will aim to improve model accuracy and robustness, ensuring reliable performance under increasingly complex and varied conditions.

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About the Authors



Ayyappa Gadhi received his Bachelor's degree in Mechanical Engineering from Amrita Vishwa Vidyapeetham and has hands-on experience in the Finite Element Analysis (FEA) domain, in both static and dynamic analysis. He is proficient in leveraging AI tools in Computer Aided Engineering (CAE), notably utilizing PhysicsAI to simulate FEA analyses from the early stages of design. Currently working at Cyient, he supports Pratt & Whitney in advanced engineering initiatives. Prior to this, he played a pivotal role in developing machine learning models using PhysicsAI frameworks, contributing to their successful presentation at prominent industry events such as the GCC (Nov 2024) and Altair ATC (Apr 2025). His interests lie in integrating AI & ML with traditional engineering workflows to enhance simulation accuracy and efficiency across CAE applications.



Raviraj Shrivastava is a Mechanical Engineer with a Master's degree from BITS Pilani and has hands-on experience in the FEA domain, specializing in structural and modal analysis. He is currently working as a CAE Engineer at Cyient, where he supports John Deere and previously contributed to SME Automation for Pratt & Whitney engines. His expertise includes parametric modeling, DOE setup, fatigue analysis, and design automation using tools like ANSYS, HyperMesh. Raviraj is passionate about applying simulation-driven design approaches to enhance structural reliability in the automotive and aerospace sectors.



Sathish Kumar Garala received Master of Technology in Design Engineering from IIT Hyderabad and has over 10+ years of experience across IT & Engineering industries. He predominantly works in Crash/Impact Analysis using CAE tools to support the customers of Aero and Automotive domains. He carried out and led projects on functional evaluations of aero engine structures like bird strikes on Spinner cones, Fan blade-off events, blade out containments in compressor/turbine sections etc. On Automotive discipline, he extensively worked on sub-system and full vehicle crash evaluations for frontal and side impact load cases for passenger cars and vans. He also takes responsibility as one of the SMEs in LS-Dyna for crash studies at Cyient. His interest lies in exploring new designs, materials and technologies that can help in building much safer aero structures and automobiles.



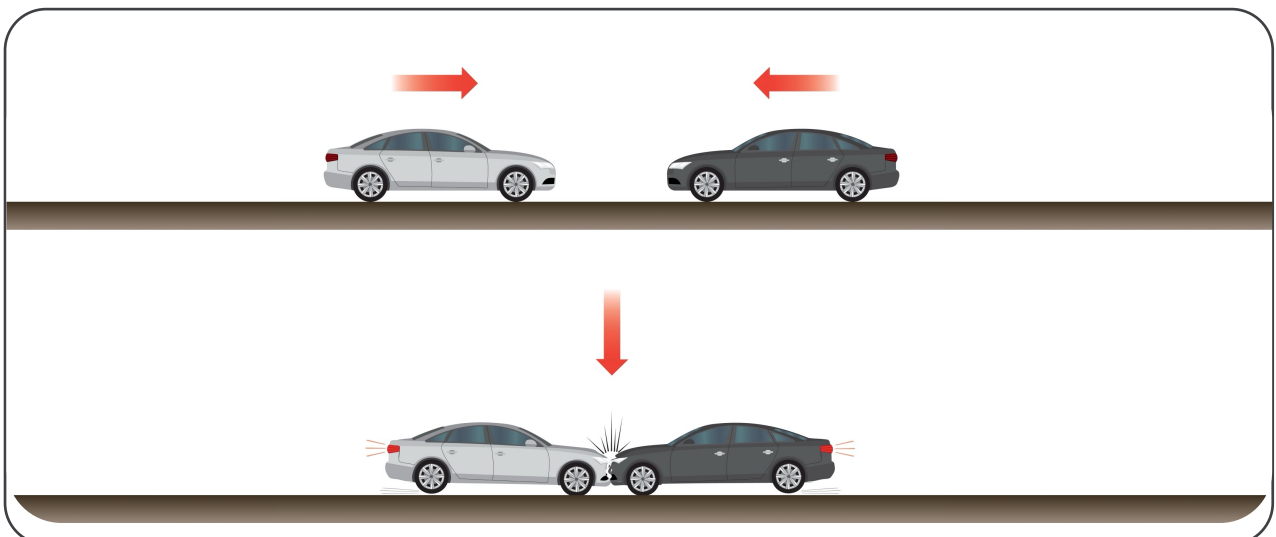
Leela Kishore Haresamudra holds an M.Tech degree from Bangalore University and brings over 19 years of experience in the Aerospace and Defense sector. He has extensive expertise in the design, analysis, and simulation of complex engineering systems. His core areas of specialization include Stress Analysis and Engineering Vibrations, with advanced proficiency in Low-Cycle Fatigue (LCF), High-Cycle Fatigue (HCF), and multidisciplinary optimization techniques.

Leela Kishore began his career at ADA-DRDO, where he contributed to the LCA Tejas project, supporting both military and naval variants. At Cyient, he has played a key role in supporting major aero engine programs for clients such as PWA, PWC, and IHI.

As a Subject Matter Expert (SME) within the Service Area, he collaborates across teams at Cyient to explore automation opportunities and develop innovative digital platforms. Currently, he performs multiple roles including Delivery Management, SME, and Innovation Champion for both the Service Line and Business Units.



Lakshman Kasina, an M.Tech graduate from IIT Madras, brings over 22 years of extensive experience in design, analysis, and simulation across various engineering domains. His expertise spans Stress Analysis, Impact Dynamics, Engineering Vibrations, and Composite Modeling. He is proficient in Low-Cycle Fatigue (LCF) and High-Cycle Fatigue (HCF), as well as advanced simulation techniques like multidisciplinary optimization. Lakshman has published over 10 papers in national and international conferences, demonstrating his significant contributions to the field.



About Cyient

Cyient (Estd: 1991, NSE: CYIENT) delivers intelligent engineering solutions across products, plants, and networks for over 300 global customers, including 30% of the top 100 global innovators. As a company, Cyient is committed to designing a culturally inclusive, socially responsible, and environmentally sustainable tomorrow together with our stakeholders.

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