

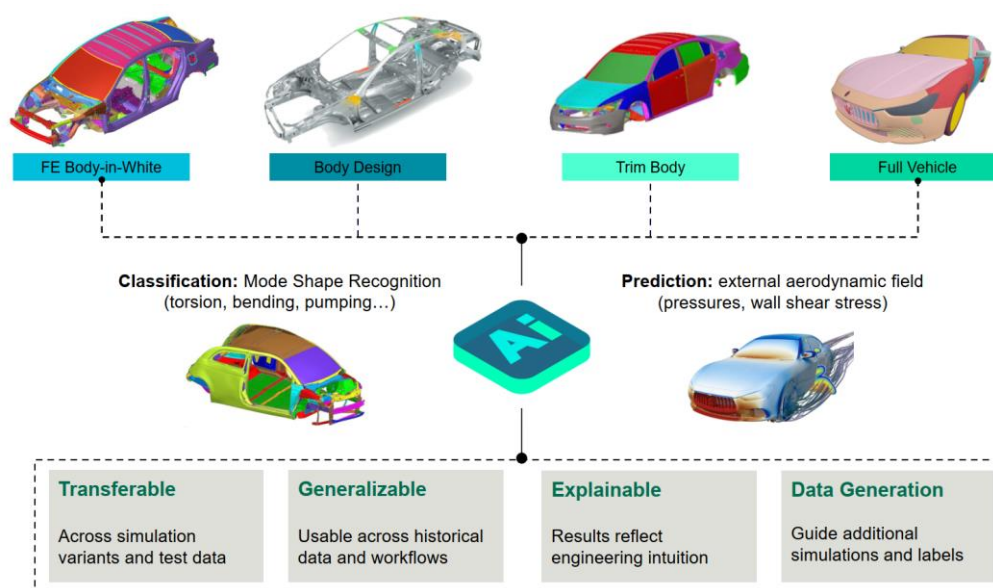
Toward Generalizable Graph Learning for 3D Engineering AI

Explainable Workflows for CAE Mode Shape Classification and CFD Field Prediction

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Automotive engineering development increasingly relies on heterogeneous 3D data, including finite element (FE) models, body-in-white (BiW) representations, CAD geometry, and CFD meshes. At the same time, engineering teams face growing pressure to shorten development cycles, improve performance and accelerate innovation. Although artificial intelligence (AI) is increasingly explored in this domain, many current methods remain task-specific, difficult to interpret, and hard to reuse across development stages. This paper presents a practical graph learning framework for 3D engineering AI, in which heterogeneous engineering assets are converted into physics-aware graph representations and processed by Graph Neural Networks (GNNs). The framework is designed to support both classification and prediction tasks. The framework is validated on two automotive applications: CAE vibration mode shape classification and CFD aerodynamic field prediction. For CAE vibration mode classification, a region-aware BiW graph supports explainable mode classification across vehicle and FE variants under label scarcity. For CFD aerodynamic field prediction, a physics-informed surrogate predicts pressure and wall shear stress (WSS) across aerodynamic body shape variants, while symmetry preserving downsampling retains accuracy with lower computational cost. The framework also outlines data generation guidance that can help engineers identify which additional simulations or labels are valuable to collect next. These results demonstrate a practical and reusable engineering AI workflow for more trustworthy CAE and CFD decision support.



For AI engineering deployment, four challenges remain especially important: data requirement, interpretability and explainability, reuse across variants, and industrial practicality. Despite rapid progress in industrial AI, current pipelines are still often node-specific, case-specific, or weakly connected to the engineering entities that engineers actually use in review. They also provide limited guidance on where new simulations, labels, or variant studies are most valuable once a surrogate or classifier is deployed. This gap is especially important in automotive development, where CAE, CFD models and test data are closely related in practice but remain difficult to reuse consistently across variant programs and workflow stages. This paper addresses that gap by formulating a graph-based framework. The key idea is to transform 3D engineering inputs into graph representations whose nodes, edges, and attributes retain physically meaningful structure while remaining flexible enough to support different downstream tasks. The proposed framework is physics-informed through engineering intuition embedded in graph construction, feature definition, pooling design, and task formulation. The main contributions of this work are as follows:

1. Graph-based engineering workflows for heterogeneous 3D assets, demonstrated on FE-derived BiW data and CFD surface data, and extensible to CAD and trimmed body assets.
2. Region-aware BiW graphs and a hierarchical graph attention classifier for explainable mode shape classification across BiW and FE variants under severe label scarcity.
3. Physics-informed aerodynamic surrogates based on surface graphs for accurate and efficient pressure and WSS field prediction, enabled by symmetry-aware graph preprocessing.
4. An integrated workflow perspective in which explainability and uncertainty analysis support data generation in practice.