Prediction of Pedestrian Head Protection Performance Using VisionGNN

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1 Abstract

Pedestrian safety assessment traditionally relies on computationally expensive Computer-Aided Engineering (CAE) simulations to predict the Head Injury Criterion (HIC) in vehicle–pedestrian collisions. In this study, we propose a novel approach that eliminates the need for CAE by leveraging a Vision Graph Neural Network (VGNN). The VGNN architecture integrates image-based geometric features of vehicle front-end structures with graph-based relational representations, enabling accurate prediction of HIC performance indicators. Experimental results demonstrate that the proposed method achieves comparable or superior predictive accuracy to conventional CAE-based workflows while drastically reducing computational cost. This research highlights the potential of VGNN to serve as an efficient surrogate model for early-stage pedestrian protection design, contributing to both rapid development cycles and enhanced safety performance evaluation.

2 Introduction

Pedestrian safety has emerged as a critical issue in the development of modern vehicles, driven by increasingly stringent regulations and consumer demand for advanced safety performance. Among the key evaluation metrics, the Head Injury Criterion serves as an essential indicator for assessing the severity of pedestrian head impacts during vehicle–pedestrian collisions. Conventional prediction of HIC heavily relies on Computer-Aided Engineering simulations, which, while accurate, require extensive computational resources and significant development time. These limitations make rapid iteration and early-stage design optimization challenging in industrial practice.

Recent advancements in machine learning, particularly deep learning, have enabled data-driven alternatives to traditional simulation-based methods. Vision-based neural networks have demonstrated high capability in extracting geometric features from images, while Graph Neural Networks excel at modeling structural and relational information [1]. However, few studies have attempted to integrate these two paradigms to directly predict pedestrian safety performance without the use of CAE.

In this study, we propose a VGNN framework that combines visual feature extraction with graph-based relational modeling to predict HIC values for pedestrian protection. By learning the relationship between vehicle front-end geometries and impact performance, our approach eliminates the dependency on time-consuming CAE simulations. Experimental validation demonstrates that the VGNN achieves comparable accuracy to conventional CAE-based approaches while significantly reducing computational cost. This contribution highlights the potential of VGNN as an efficient surrogate model, facilitating rapid safety evaluation and design iteration in pedestrian protection systems.

3 Model Architecture

The proposed model integrates visual feature extraction with GNN reasoning to predict pedestrian protection performance, particularly the HIC, without relying on CAE simulations. An overview of the workflow is illustrated in Figure 1.

3.1 Input Representation

The input data consist of three top-view rendered images of the hood (skin, frame, and other small components). These images capture structural differences that determine stiffness during pedestrian impact. To emphasize the functional regions related to head impacts, the images are combined, and each component is represented in a distinct color.

3.2 Grid-based Graph Construction

The combined segmentation image is discretized into a two-dimensional grid, where each cell corresponds to a localized region of the vehicle front-end. Each grid cell is treated as a node in the graph, and edges are defined between spatially adjacent cells (up, down, left, and right). This formulation preserves local geometric continuity while encoding the relational dependencies among neighboring regions.

3.3 Node Features

For each grid cell, visual features are extracted from the corresponding segmented region. These features reflect local geometric properties, which are essential for predicting the impact response. The extracted features are embedded into a latent vector space and assigned as the initial representation of each node.

3.4 Graph Neural Network Processing

The constructed graph is processed through multiple GNN layers. At each layer, node representations are updated by aggregating information from neighboring nodes, allowing structural and contextual information to propagate throughout the graph. This mechanism enables the model to capture interdependencies between adjacent regions and to represent deformation behavior and energy absorption patterns of the hood structure.

3.5 Output Prediction

The final node representations are mapped to HIC values corresponding to their spatial positions, resulting in a predicted HIC distribution map. During training, the predicted map is compared with CAE-derived ground truth, and the network is optimized using a regression loss function to minimize prediction error.

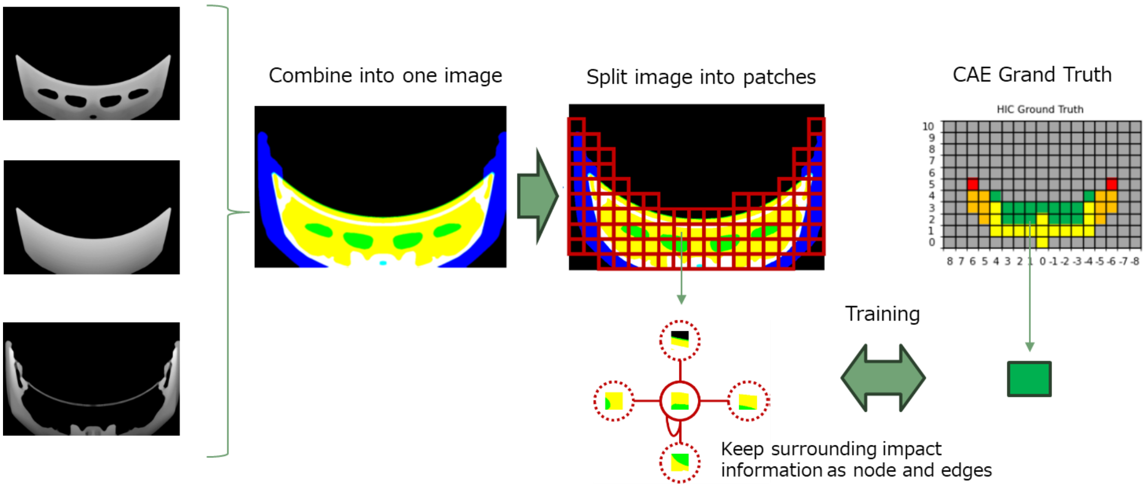

Fig.1: Overview of the proposed model workflow

4 Validation Result

To validate the effectiveness of the proposed framework, cross-validation was performed using data from 18 vehicle models. Each model was used as the validation set in turn, while the remaining models served as the training set, thereby evaluating the generalization capability of the network.

The proposed method demonstrated approximately 6% improvement in prediction accuracy compared to the conventional model [2]. It showed a stronger ability to capture local structural variations, achieving higher accuracy even in regions where the previous method tended to leave residual errors.
Table 1 summarizes the comparison results between the conventional and the proposed models.

	LeNet-5(Conventional)	**VGNN(Our method)**
Car No	Accuracy	Accuracy
1	0.714	0.833
2	0.593	0.815
3	0.613	0.738
4	0.712	0.864
5	0.758	0.833
6	0.825	0.825
7	0.670	0.792
8	0.691	0.782
9	0.800	0.909
10	0.755	0.643
11	0.683	0.651
12	0.625	0.833
13	0.755	0.786
14	0.837	0.769
15	0.689	0.709
16	0.542	0.687
17	0.695	0.661
18	0.816	0.757
Average	**0.709**	**0.772**

5 Summary

In this study, we proposed a novel method for predicting pedestrian protection performance, specifically the Head Injury Criterion, without relying on CAE simulations, by employing a Vision Graph Neural Network. Using top-view rendered images of the hood components (skin, frame, and small parts), the inputs were converted into color-coded segmentation maps, discretized into a two-dimensional grid, and modelled as graphs. This approach enabled the model to capture local structural variations and achieve accurate performance prediction.

Cross-validation with 18 vehicle models demonstrated that the proposed method achieved approximately a 6% improvement in accuracy compared to the conventional approach [2]. The framework significantly reduces dependency on CAE simulations while enabling reliable and rapid evaluation of pedestrian protection performance in the early design stage.

Future work will focus on extending the methodology to a wider variety of vehicle architectures and to additional injury criteria (e.g., lower extremity indices), aiming toward a comprehensive predictive framework for pedestrian safety assessment.

6 Literature

[1] Kai H:Vision GNN: An Image is Worth Graph of Nodes, arXiv:2206.00272v3 [cs.CV], 2022
[2] Osamu I: PREDICTION OF PEDESTRIAN PROTECTION PERFORMANCE USING MACHINE LEARNING, 26th ESV, 2019