Automated Vehicle Damage Detection and Severity Estimation using Deep Learning

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Abstract. Vehicle damage assessment after an accident is a critical yet traditionally slow process, often requiring over a week for physical inspections and reports. This paper proposes an end-to-end automated solution, AIDentify, which utilizes deep learning—specifically the YOLOv8 architecture—to detect and localize vehicle damage from user-submitted images, videos, or webcam feeds. The system segments vehicle parts, classifies the type and severity of damage, and provides a real-time confidence score. Using a dataset of 778 labeled images across eight damage types, AIDentify achieves over 91 percentage accuracy, reducing assessment turnaround time, and minimizing human bias. This model enhances efficiency in insurance claims and post-accident services

Keywords: Vehicle Damage Detection · Deep Learning · YOLOv8 · Computer Vision · Semantic Segmentation · Insurance Automation

1 Introduction

Road traffic accidents are a major concern globally, with India alone reporting over 460,000 cases in 2022, leading to substantial vehicle damage and financial implications. The aftermath of such incidents involves a crucial step: vehicle damage assessment. Traditionally, this process is time-consuming, labor-intensive, and reliant on human evaluators. The workflow includes image collection, submission of a First Notice of Loss (FNOL), inspection by appraisers, and final report generation—taking an average of seven days. However, this method suffers from inefficiencies, inconsistent evaluations, and potential human bias. In the era of digital transformation, there is an urgent need for a system that automates and standardizes the process to deliver accurate, fast, and fair damage assessments. The integration of artificial intelligence, particularly deep learning, has shown promise in automating visual tasks with precision and scalability.Recent studies have explored semantic segmentation and object detection models to identify and quantify vehicle damage. However, many are limited to static image inputs, lack real-time processing, or fail to integrate seamlessly into web-based ecosystems.

To address these gaps, this study presents AIDentify—an end-to-end deep learning-powered system that uses the YOLOv8 architecture for real-time vehicle damage detection from images, videos, and webcam feeds. The system classifies damage into multiple categories and localizes affected areas, significantly reducing turnaround time and improving insurance claim workflows. This research builds upon and extends the modular deep learning approach proposed in leading IEEE works, aiming for practical deployment and high accuracy in real-world Indian scenarios.

2 Literature Review

2.1 Paper 1 – Ma et al. (2024))

Introduced a multi-stage deep learning system using semantic segmentation (DeepLabV3+ with EfficientNet-b5) for vehicle damage localization, achieving mean Intersection over Union (mIoU) scores of 0.804 for part segmentation and 0.463 for damage segmentation. While effective, this method is computationally intensive and lacks real-time capabilities.

2.2 Paper 1 Shirode et al.

Developed a CNN-based system for car damage detection and classification, focusing on common types such as dents and scratches. While the model achieved satisfactory classification accuracy, it lacked capabilities for damage localization and severity estimation. Moreover, the approach was limited to static image classification, contrasting with AIDentify's real-time localization and severity analysis framework.

2.3 Paper 3 – Bandi et al. (2021)

Applied transfer learning with VGG16 and CNN ensembles to classify vehicle damage and severity levels, attaining up to 87.9 percentage accuracy. However, their model required highquality images and was limited by dataset size.

2.4 Paper 3 Sruthy et al.

Proposed a transfer learning-based approach for car damage identification and categorization using pre-trained CNN models. Their system effectively classified damage types such as dents, scratches, and cracks on vehicle surfaces, achieving good accuracy with limited training data. However, the work primarily focused on classification without incorporating damage localization or severity estimation, which are addressed in the AIDentify framework.

2.5 Paper 5 – Dhieb et al. (2019))

Proposed a very deep transfer learning model for vehicle damage detection and localization using convolutional neural networks pretrained on ImageNet. Their approach leveraged the ResNet50 architecture, achieving high classification accuracy on a limited dataset by finetuning only the top layers. The study demonstrated that transfer learning can significantly improve the generalization of models trained on small automotive datasets. Notably, the model achieved over 96 percentage classification accuracy and 77.78 percentage mAP in detecting various types of vehicle damage, validating the effectiveness of pretrained networks in realworld applications. However, the method relied on high-quality static images and lacked realtime performance, which AIDentify addresses through lightweight YOLOv8 deployment and real-time webcam integration.

3 Comparative Analysis

This section provides a comparative analysis of the reviewed studies, highlighting their methodologies, contributions, and limitations in the context of automated vehicle damage detection. As summarized in Table 1, these works collectively demonstrate the evolution from traditional CNN-based classifiers to advanced real-time object detection models like YOLOv8, which underpin AIDentify's framework.

Early works such as Shirode et al. and Sruthy et al. adopted traditional CNNs and transfer learning for static image-based classification of damage types. While they achieved satisfactory accuracy, they lacked real-time processing, localization, and severity estimation—features that are crucial for practical deployment in insurance and service applications.

Dhieb et al. further enhanced classification accuracy using deep transfer learning with ResNet50, achieving high mAP and over 96% accuracy. However, like earlier methods, the reliance on static, high-quality images restricted real-time applicability.

In contrast, Ma et al. introduced semantic segmentation models capable of part-level localization using DeepLabV3+ and EfficientNet-b5. Despite high mIoU scores, their system was computationally intensive and unsuitable for real-time use.

Parihar et al. provided a direct comparison of YOLO variants, demonstrating YOLOv8's superior performance (72% mAP50) with real-time capabilities. This aligns closely with the goals of AIDentify, which builds upon

YOLOv8's lightweight yet accurate architecture to support webcam/video input, multi-class damage classification, localization, and severity scoring—all in real-time.

Table 1. Comparative Summary of Reviewed Studies

Study	Methodology	Strengths	Limitations
Shirode et al. (2022)	CNN-based classification	Goodaccuracyfor static images	No localization or severity estimation
Sruthy et al. (2021)	Transferlearning with CNNs	Effective with limited data	Lacks localization and real-time use
Bandi et al. (2021)	VGG16 and CNN ensemble	87.9% accuracy, sever-ity classification	Needs high-quality input, small dataset
Dhieb et al. (2019)	ResNet50-based transfer learning	96% accuracy, 77.78% mAP	Static images only, no real-time processing
Ma et al. (2024)	DeepLabV3+ with EfficientNet-b5	High mIoU for part segmentation	Computationally intensive, not real-time
Parihar et al. (2023)	YOLOv3/5/8 with SGD	YOLOv8 reached 72% mAP50, real-time	Limited to classification, no severity scoring
AIDentify (Propos ed)	YOLOv8with real-time video/image input	Real-time damage localization, classification, severity estimation	Minor limitations due to dataset size

3.1 Analysis of Key Findings:

The literature demonstrates a clear trajectory in vehicle damage assessment from static image classification to real-time deep learning-based systems. Early approaches by Shirode et al. and Sruthy et al. used CNNs and transfer learning for damage type classification, offering good accuracy but lacking spatial localization and real-time utility. Bandi et al. and Dhieb et al. showed that transfer learning with deeper architectures like VGG16 and ResNet50 enhances classification performance, yet their reliance on high-quality static images limits deployment in dynamic environments.

Ma et al. (2024) advanced the field with semantic segmentation using DeepLabV3+ and EfficientNet-b5, introducing part-level localization. However, the computational cost restricts real-time application, a critical requirement in insurance workflows. Parihar et al. (2023) contributed a performance comparison among YOLO variants, validating YOLOv8 as a lightweight yet accurate model suitable for real-time use.

These findings underscore a growing consensus on the need for fast, accurate, and scalable systems. The AIDentify framework builds on this trajectory, integrating YOLOv8 for real-time video/image input, damage classification, localization, and severity estimation—all within a deployable architecture. It bridges the gap between high-accuracy static models and real-world, real-time assessment needs, particularly in the context of Indian road conditions and insurance practices. The model's end-to-end functionality marks a significant advancement toward fully automated, bias-minimized vehicle damage evaluation.

3.2 Overall Summary of Findings:

The domain of automated vehicle damage detection using deep learning has evolved from simple image classification techniques to highly efficient real-time models capable of damage localization and severity estimation. Earlier works primarily focused on using CNNs and transfer learning on static images, achieving good classification accuracy but lacking spatial context and real-time responsiveness. The introduction of semantic segmentation and object detection frameworks, especially YOLO variants, marked a pivotal shift toward real-time, deployable solutions.

Despite significant progress, challenges such as dataset limitations, variability in vehicle types and damage patterns, and the need for scalable deployment persist. Studies have increasingly emphasized the integration of detection and classification in a unified pipeline. The YOLOv8-based AIDentify framework addresses these gaps by offering a lightweight, accurate, and real-time system tailored for real-world applications such as insurance claims and automated assessments. Its end-to-end architecture ensures fast processing, accurate localization, and severity estimation even in diverse road and lighting conditions.

Table 2. Summary of Key Research Papers on Vehicle Damage Detection using Deep Learning

Paper (Year)	Core Approach	Input Type	Key Contribution / Focus
Shirode et al. (2019)	CNNs for classification	Static images	Damage classification by type; limited to image input, no localization
Sruthy et al. (2020)	Transfer Learning with MobileNet	Car images	Lightweight model for insurance claim applications
Bandi et al. (2021)	VGG16 and ResNet50	Car crash datasets	Compareddeepmodels for damage classification
Dhieb et al. (2022)	CNN + Grad-CAM	Static images	Added interpretability to damage classification with visual explanations
Ma et al. (2024)	DeepLabV3+ and EfficientNet-b5	Vehicle images	Semantic segmentation with part-level classification; high computational cost
Parihar et al. (2023)	YOLOv3-v8 comparison	Real-time video frames	Performance benchmarking; YOLOv8 proven best for realtime detection
Our Work (2025)	YOLOv8 + Severity Estimation Pipeline	Real-time images/videos	End-to-end real-time system with localization, classification, and severity analysis

4 Results/Discussion

Our system demonstrates that YOLOv8 can provide comparable accuracy to segmentationbased models while offering real-time inference. The simplified architecture improves speed and usability in practical settings, such as mobile apps and web portals. However, while our bounding box predictions are sufficient for surface-

level damage categorization, fine-grained severity estimation remains a challenge without pixel-wise masks. Another limitation is the model's reduced accuracy on low-resolution or poorly angled inputs, suggesting the need for better pre-filtering or user guidance.

4.1 Interpreting the Findings:

The results confirm the effectiveness of the AIDentify system for real-time vehicle damage detection using YOLOv8. The model achieved high accuracy, especially for clearly defined damage types like glass shatter, dents, and flat tires, with F1-scores above 90 percentage, consistent with findings by Parihar et al. [27]. However, performance decreased for subtle damages such as scratches and cracks, which aligns with limitations noted in prior CNN-based models (e.g., Bandi et al. [26]). This suggests a need for more granular annotations and data augmentation.

Compared to segmentation models like that of Ma et al. [1], AIDentify offers a more efficient inference process with minimal accuracy trade-off, making it better suited for real-time applications.The system's web-based interface and support for images, video, and webcam input enhance its deployment readiness, while the integration of a refined confidence scoring mechanism improves the trustworthiness of predictions in practical use cases like insurance assessment.

4.2 Implications:

The AIDentify system presents significant implications across several key sectors, offering a range of benefits. In Insurance and Claims, it streamlines operations by automating vehicle damage detection, thereby drastically cutting claim processing times from days to minutes, enhancing assessment consistency, and reducing the likelihood of fraud. For Road Safety and Enforcement, integrating AIDentify with existing infrastructure like roadside kiosks or surveillance systems allows for real-time estimation of accident severity, which in turn facilitates quicker emergency responses and more efficient accident documentation. Workshop and Service Centers can leverage the system to pre-estimate necessary spare parts and repair durations, leading to improved logistical efficiency and better customer service. Furthermore, AIDentify's applicability extends to Smart City Applications, where its integration into urban monitoring systems can yield valuable insights for infrastructure planning and the analysis of accident patterns. Finally, the system boasts Scalable AI Deployment capabilities, supporting edge computing on mobile and web platforms. This significantly reduces reliance on cloud infrastructure, making AIDentify viable for deployment in remote or areas with limited connectivity.

4.3 Limitations:

Despite progress, key limitations remain:

- Fine-Grained Damage Accuracy: It struggles with subtle or low-contrast damages such as light scratches or minor dents due to bounding box-level detection.
- Environmental Constraints: Performance degrades under poor lighting, low resolution, or motion blur, requiring future improvements in robustness.
- Limitations: The model is trained on a moderately sized dataset (778 images), which may not fully represent all vehicle types, damage variations, and real-world conditions.
- No Internal Damage Estimation: It cannot detect mechanical or structural damages that are not visually apparent.
- Prediction Absent: The system classifies severity but does not estimate repair costs or generate damage reports, which are essential for insurers and workshops.

4.4 Future Research Directions:

Future efforts should focus on:

– Level Segmentation Integration: Combine YOLOv8 with segmentation models (e.g., Mask R-CNN) for better localization accuracy.

– Cost Estimation Module: Use regression models or expert systems to convert visual damage severity into estimated repair costs.

– 3D Reconstruction and Multi-View Analysis: Use NeRF or stereo imaging to capture hidden or occluded damages.

– Dataset Expansion: Curate larger and more diverse datasets that include multiple vehicle types, lighting conditions, and damage scenarios.

– Edge-Ready Optimizations: Convert the model to run efficiently on smartphones or embedded devices for offline use.

– Behavioral Data Fusion: Integrate telematics or accelerometer data to enhance damage context and predict accident severity with more precision.

5 Conclusion

This paper presents a novel automated system for vehicle damage detection and severity estimation using YOLOv8 and a web-based interface, targeting applications in insurance, vehicle servicing, and post-accident analytics. The AIDentify system achieves a high accuracy of 91 percentage in identifying and classifying vehicle damage across eight categories and demonstrates robust performance on various input formats including images, videos, and live webcam feeds.By streamlining the traditional damage assessment process, our system reduces dependency on manual inspection, minimizes human error, and enhances customer satisfaction. Furthermore, the lightweight architecture and real-time inference make it suitable for both desktop and mobile environments.While the current implementation focuses on exterior damage visible from images, future work will expand to include interior damage, repair cost estimation, and integration with 3D reconstruction technologies for enhanced severity analysis. We also plan to incorporate more granular damage categories and improve model robustness across diverse lighting and weather conditions.

Overall, AIDentify represents a significant step toward intelligent and automated vehicle damage assessment, offering a scalable solution for the next generation of automotive support systems.

References

1. Ma, Y., et al.: A system for automated vehicle damage localization and severity estimation using deep learning. IEEE Trans. Intell. Transp. Syst. (2024)
2. Lin, T.Y., et al.: Focal loss for dense object detection. In: Proc. IEEE Int. Conf. on Computer Vision (ICCV), pp. 2980– 2988 (2017)
3. Sandler, M., et al.: MobileNetV2: Inverted residuals and linear bottlenecks. In: Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), pp. 4510–4520 (2018)
4. Redmon, J., et al.: You only look once: Unified, real-time object detection. In: Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), pp. 779–788 (2016)
5. Pasupa, K., Sunhem, W.: Evaluation of deep learning algorithms for semantic segmentation of car parts. Complex Intell. Syst. 18(2), 455–470 (2022)
6. Shirode, A., et al.: 2D-to-3D: Car damage detection and assessment using CNN. In: IEEE DELCON, pp. 142–146 (2022) 7. Waqas, U., et al.: Vehicle damage classification and fraud detection. In: IEEE CCECE, pp. 1–6 (2020)
8. Dhieb, N., et al.: A deep transfer learning model for vehicle damage detection and localization. In: IEEE ICM, pp. 88–91 (2019)

9. Li, L., et al.: A deep learning and transfer learning approach for vehicle damage detection. In: FLAIRS Conf. (2021)
10. Buslaev, A., et al.: Albumentations: Fast and flexible image augmentations. Information 11(2), 125 (2020)
11. Dhieb, N., et al.: A very deep transfer learning model for vehicle damage detection and localization. In: IEEE Int. Conf.
on Microelectronics (ICM), pp. 158–161 (2019)
12. Patil, K., et al.: Deep learning based car damage classification. In: 16th IEEE Int. Conf. on Machine Learning and Applications (ICMLA), pp. 50–54 (2017)
13. Rakshata, P., et al.: Car damage detection and analysis using deep learning algorithm for automotive. Int. J. Sci. Res. Eng. Trends 5(6), 34–38 (2019)
14. Zhu, X., et al.: Improved Mask R-CNN for vehicle damage detection. IEEE Trans. Intell. Veh. 5(3), 568–576 (2020)
15. de Deijn, J., et al.: ConvNet-based car damage estimation using transfer learning. Preprint (2021)
16. Bandi, H., et al.: Assessing car damage with convolutional neural networks. In: IEEE Int. Conf. on Communication Information and Computing Technology (ICCICT), pp. 89–94 (2021)

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