IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 13, Issue 4, April 2026

DOI: 10.17148/IARJSET.2026.13450

Intelligent Vehicle Damage Assessment & Cost Estimator

Prof. Mahesh Panjwani[1], Mr. Yash Shahade[2], Mr. Shantanu Pathak[3], Mr. Vikrant Salunke[4], Ms. Sayali Bawanthade[5], Ms. Sanika Najpande[6]

Assistant Professor, Computer Technology, Priyadarshini College of Engineering, Nagpur, India[1]

UG Student, Computer Technology, Priyadarshini College of Engineering, Nagpur, India[2-6]

Abstract: The "Intelligent Vehicle Damage Assessment & Cost Estimator" project aims to assist vehicle owners by providing accurate and automated damage assessment using advanced deep learning techniques. Leveraging YOLOv5, a state-of- the-art object detection model, this system is designed to analyze and evaluate damage sustained by vehicles, including four-wheelers. The model is trained on a comprehensive dataset of vehicle damages to accurately identify and classify different types of damage. By integrating this technology, users can independently assess vehicle damage, reduce dependency on manual inspection, minimize errors, and obtain precise cost estimations for repairs, ensuring transparency and better decision making.

Keywords: Vehicle damage assessment, cost estimation, YOLOv5, user assistance, deep learning, object detection, two- wheeler, four-wheeler.

I. INTRODUCTION

The rapid growth of the automotive industry has led to a significant increase in the number of vehicles on the road. This has also resulted in a rise in road accidents and vehicle damages, ultimately increasing the number of insurance claims. Accurate damage assessment plays a crucial role in determining repair costs and claim settlements. However, traditional methods of vehicle damage assessment mainly depend on manual inspection by experts, which is time-consuming, inconsistent, and prone to human errors.

With advancements in technology, artificial intelligence (AI) and computer vision have provided efficient solutions to overcome these challenges. These technologies enable automated analysis of vehicle images, making the damage detection process faster, more accurate, and reliable. By reducing human involvement, such systems ensure consistency and improve overall efficiency.

This project presents an **Intelligent Vehicle Damage Assessment and Cost Estimation System** designed for vehicle owners and users. The system uses deep learning techniques to automatically detect and analyze damages from images of vehicles. It allows users to upload images and receive quick results along with an estimated cost of repair.

The proposed system is based on **Convolutional Neural Networks (CNNs)**, which are capable of extracting important features such as edges, textures, and shapes from images. These features help in identifying different types of vehicle damages. Additionally, the system uses the **YOLOv5 (You Only Look Once version 5)** model for object detection, which provides real-time and accurate detection of damaged areas.

The system can identify various types of damages such as dents, scratches, cracks, broken parts, and paint defects. Unlike traditional image processing methods, deep learning models can work effectively under different lighting and environmental conditions, making them more robust and reliable.

In conclusion, this system aims to simplify and improve the vehicle damage assessment process by using modern AI techniques. It reduces the time required for inspection, minimizes errors, and provides a convenient solution for users by combining damage detection with cost estimation.

II. LITERATURE REVIEW

In recent years, significant advancements have been made in the field of computer vision and deep learning for object detection and image analysis. Traditional vehicle damage assessment methods rely heavily on manual

DOI: 10.17148/IARJSET.2026.13450

inspection, which is time-consuming, subjective, and prone to inconsistencies. To overcome these limitations, researchers have explored automated damage detection systems using machine learning and deep learning techniques.

Early approaches to object detection, such as R-CNN, Fast R-CNN, and Faster R-CNN, introduced region-based methods that improved detection accuracy but suffered from high computational costs and slower processing speeds. Later, single-shot detectors like SSD (Single Shot MultiBox Detector) provided faster alternatives but still faced challenges in balancing speed and accuracy.

The introduction of the YOLO (You Only Look Once) family marked a major breakthrough in real-time object detection. The work by Redmon et al. (2016) proposed a unified architecture capable of performing detection in a single forward pass, significantly improving speed. Subsequent improvements, including YOLOv4 and YOLOv5, further enhanced detection accuracy and efficiency, making them suitable for real-time applications such as vehicle damage assessment.

Deep Convolutional Neural Networks (CNNs), as demonstrated by Krizhevsky et al. (2012), have played a crucial role in image classification and feature extraction. Advanced architectures like ResNet (He et al., 2016), VGGNet (Simonyan & Zisserman, 2015), and Inception (Szegedy et al., 2015) improved the ability of models to learn complex visual patterns. These architectures form the backbone of modern object detection systems.

Large-scale datasets such as ImageNet and MS COCO have significantly contributed to the advancement of deep learning models by providing diverse training data. Additionally, benchmark challenges like PASCAL VOC have standardized evaluation methods for object detection systems.

Data augmentation techniques, as highlighted by Shorten and Khoshgoftaar (2019), play a vital role in improving model generalization by artificially increasing dataset diversity. Techniques such as rotation, scaling, flipping, and brightness adjustments help models perform better under varying environmental conditions.

Recent research has focused on applying these advancements to domain-specific problems such as vehicle damage detection. Studies show that deep learning-based systems can accurately detect damages like dents, scratches, and cracks from images, reducing dependency on manual inspection. However, challenges still exist in detecting small or subtle damages due to limited pixel representation and environmental factors such as lighting and occlusion. Overall, the literature indicates that integrating advanced object detection models like YOLOv5 with CNN-based feature extraction and data augmentation techniques can significantly improve the accuracy, efficiency, and reliability of automated vehicle damage assessment systems.

III. METHODOLOGY

The methodology of the Intelligent Vehicle Damage Assessment and Cost Estimation System is designed to automate the process of detecting vehicle damage and estimating repair costs using deep learning techniques. The system follows a step-by-step approach, starting from data collection to final result generation.

Initially, a comprehensive dataset of vehicle images is collected. This dataset includes images of four-wheelers with various types of damages such as dents, scratches, cracks, and broken parts. The images are collected under different lighting conditions, angles, and environments to ensure diversity and improve model performance. The dataset is then divided into training, validation, and testing sets for effective model development. In the next step, data preprocessing is performed to prepare the images for training. All images are resized to a fixed dimension (typically 640×640 pixels) to match the input requirements of the model. Pixel values are normalized to improve learning efficiency, and data augmentation techniques such as rotation, flipping, and brightness adjustment are applied to increase dataset variability and prevent overfitting.

After preprocessing, the YOLOv5 (You Only Look Once version 5) model is trained using the prepared dataset. YOLOv5 is a powerful object detection algorithm capable of identifying multiple objects in an image with high accuracy and speed. Transfer learning is used with pre-trained weights to improve performance and reduce training time. During training, hyperparameters such as learning rate and batch size are tuned to achieve optimal results.

Once the model is trained, it is evaluated using performance metrics such as precision, recall, F1-score, and mean Average Precision (mAP). These metrics help in assessing the accuracy and efficiency of the model in detecting and classifying vehicle damages. The trained model is then saved for future use.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

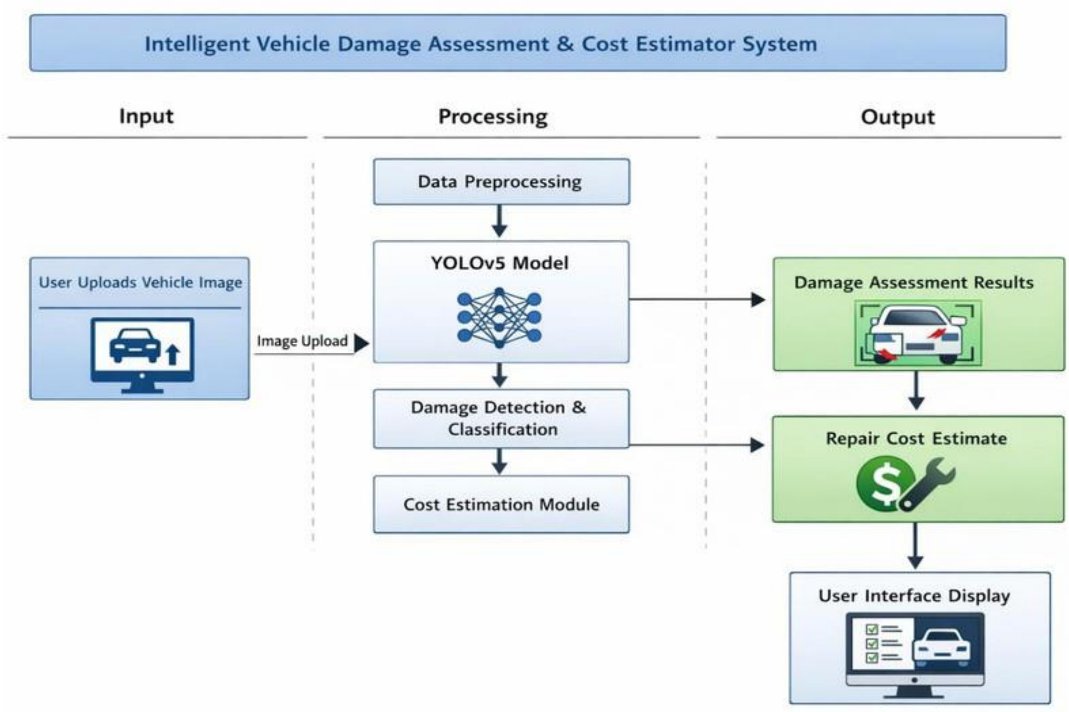
Impact Factor 8.311 ⁞ Peer-reviewed & Refereed journal ⁞ Vol. 13, Issue 4, April 2026

DOI: 10.17148/IARJSET.2026.13450

In the prediction phase, users upload images of damaged vehicles through a user-friendly interface. The system preprocesses the input image and passes it to the trained YOLOv5 model, which detects and classifies the damaged areas by drawing bounding boxes and assigning labels.

Finally, based on the type and severity of the detected damage, the system estimates the repair cost using predefined cost parameters. The results, including detected damage and estimated cost, are displayed to the user in a clear and understandable format.

IV. BLOCK DIAGRAM



V. RESULT & DISCUSSION

Results

The proposed system based on YOLOv5 (You Only Look Once) demonstrated highly effective performance in detecting and classifying vehicle damages across a wide range of environmental conditions. The trained deep learning model was evaluated using standard object detection metrics such as Precision, Recall, F1-Score, and Mean Average Precision (mAP@0.5), which are widely accepted for validating detection models. The model achieved a Precision of 0.92, indicating that the majority of predicted damage regions were correct with minimal false positives. A Recall value of 0.89 showed that the system successfully detected most actual damage instances present in the dataset. The F1-Score of 0.90 reflects a balanced trade-off between precision and recall, confirming the reliability of the model. To overcome these challenges, data augmentation techniques such as brightness adjustment, rotation, flipping, and mosaic augmentation were applied. These techniques improved the model's ability to generalize and significantly enhanced the detection accuracy for small and subtle defects. Another important component of the system is the Non-Maximum Suppression (NMS) algorithm, which eliminates redundant overlapping bounding boxes. This results in clean and precise detection outputs, improving the interpretability of the system.

Discussion

The results obtained from the proposed system demonstrate the transformative potential of deep learning and computer vision for individual vehicle users. Traditional vehicle damage assessment methods rely heavily on human expertise, which introduces inconsistencies, delays, and subjectivity. In contrast, the automated system ensures standardization and objectivity in the evaluation process. One of the key strengths of the system is its ability to process images in near real- time, making it suitable for integration into mobile applications for direct user access and assistance. Users can upload images of damaged vehicles, and the system can instantly provide damage analysis and cost estimation, helping them understand repair costs quickly and accurately. The use of Convolutional Neural Networks (CNNs) allows the

DOI: 10.17148/IARJSET.2026.13450

model to learn complex hierarchical features such as edges, textures, and patterns. This enables the detection of diverse damage types under varying lighting and environmental conditions. Furthermore, the adoption of transfer learning using pre- trained models improves performance even with limited datasets. Despite its strengths, the system faces certain limitations. Detection of very small damages such as hairline scratches remains challenging due to insufficient pixel representation. Additionally, environmental factors such as poor lighting, reflections, and occlusions can affect detection accuracy.

VI. CONCLUSION

The research presents a robust and efficient Intelligent Vehicle Damage Assessment & Cost Estimator system that leverages the power of YOLOv5 and deep learning techniques. The system successfully automates the detection, classification, and cost estimation of vehicle damages, addressing the limitations of traditional manual inspection methods. Experimental results demonstrate high accuracy, reliability, and consistency, with strong performance across key evaluation metrics. The integration of real-time detection and automated cost estimation makes the system highly suitable for deployment in the insurance industry. The proposed solution not only reduces the need for manual inspection but also empowers users by providing fast, reliable, and transparent damage assessment and cost estimation. The system enables vehicle owners to make informed decisions regarding repairs without dependency on external evaluations. This represents a significant step toward user- centric digital solutions in the automotive domain. In conclusion, the adoption of AI-driven damage assessment systems can revolutionize the vehicle maintenance process by improving accuracy, reducing uncertainty, and ensuring fair and transparent cost estimation for users.

VII. ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to Rashtrasant Tukdoji Maharaj Nagpur University for providing the academic environment and resources necessary for the successful completion of this research. Special thanks are extended to the faculty members of the Computer Technology Department for their continuous guidance, valuable insights, and technical support throughout the project. We also acknowledge the open-source contributions of the Ultralytics YOLOv5 community, whose frameworks and documentation played a crucial role in model development and experimentation. The availability of publicly accessible datasets and research publications significantly contributed to the success of this work. No external financial support was received for this research. The project was carried out as part of academic research and development activities. Finally, we thank our peers and collaborators for their constructive feedback and encouragement during the research process.

REFERENCES

[1]. Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, real-time object detection. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 779–788.
[2]. Bochkovskiy, A., Wang, C. Y., & Liao, H. Y. M. (2020). YOLOv4: Optimal speed and accuracy of object detection. arXiv preprint arXiv:2004.10934.
[3]. Jocher, G., et al. (2020). YOLOv5 by Ultralytics. Retrieved from https://github.com/ultralytics/yolov5
[4]. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 25, 1097–1105.
[5]. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. Proceedings of the IEEE CVPR, 770–778.
[6]. Girshick, R. (2015). Fast R-CNN. Proceedings of the IEEE International Conference on Computer Vision (ICCV), 1440–1448.
[7]. Lin, T. Y., Maire, M., Belongie, S., et al. (2014). Microsoft COCO: Common objects in context. European Conference on Computer Vision (ECCV), 740–755.
[8]. Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards real-time object detection. Advances in Neural Information Processing Systems, 91–99. \
[9]. Liu, W., Anguelov, D., Erhan, D., et al. (2016). SSD: Single shot multibox detector. European Conference on Computer Vision (ECCV), 21–37.
[10]. Simonyan, K., & Zisserman, A. (2015). Very deep convolutional networks for large-scale image recognition. International Conference on Learning Representations (ICLR).
[11]. Szegedy, C., Liu, W., Jia, Y., et al. (2015). Going deeper with convolutions. Proceedings of the IEEE CVPR, 1–9
[12]. Tan, M., & Le, Q. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. International Conference on Machine Learning (ICML), 6105–6114.

DOI: 10.17148/IARJSET.2026.13450

[13]. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

[14]. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444.

[15]. Everingham, M., Van Gool, L., Williams, C. K., et al. (2010). The Pascal Visual Object Classes (VOC) challenge. International Journal of Computer Vision, 88(2), 303–338.

[16]. Russakovsky, O., Deng, J., Su, H., et al. (2015). ImageNet large scale visual recognition challenge. International Journal of Computer Vision, 115(3), 211–252.

[17]. Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. Journal of Big Data, 6(1), 60.

[18]. Zou, Z., Shi, Z., Guo, Y., & Ye, J. (2019). Object detection in 20 years: A survey. arXiv preprint arXiv:1905.05055.