JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Enhancing Robustness And Generalization In Vehicle Damage Detection Through Deep Neural Networks

[1]Jeevan N V , [2]K R Sumana

[1]PG Student, The National Institute of Engineering, Mysuru, Visweswaraya Technological University, Belagaum, Karnataka, India

[2]Faculty, The National Institute of Engineering, Mysuru, Visweswaraya Technological University, Belagaum, Karnataka, India

Abstract : The automotive industry faces numerous challenges, one of which is the efficient assessment of vehicle damage. Traditional methods rely heavily on manual inspection, which can be subjective and prone to human error. With the advent of artificial intelligence and machine learning, there is a significant opportunity to revolutionize this process through automated systems. This project, titled "Car Damage Detection using Yolov8," leverages the power of deep learning to develop a robust and accurate system for detecting and categorizing car damage from images. Utilizing a comprehensive dataset from Roboflow, the system is trained to identify various types of car damage. This project not only aims to streamline the damage assessment process but also to provide a reliable tool for insurance companies, repair shops, and car owners.

Keywords: Deep Learning, Vehicle Damage Detection, Vehicle Images, YOLOv8 (You Only Live Once), Condition Monitoring.

I. Introduction

Assessing vehicle damage is vital in the automotive industry, influencing insurance claims, repair estimates, and resale values. Traditionally manual and subjective, this process is prone to errors and inconsistencies. With advances in AI and machine learning, there is increasing interest in automated damage detection. This project utilizes Yolov8, a cutting-edge object detection algorithm from the YOLO family, to develop an automated car damage detection system. Yolov8, known for its real-time accuracy, will be trained on a Roboflow dataset of annotated car damage images, categorized into eight classes. The goal is to enhance the speed and reliability of insurance claims processing, repair workflows, and provide useful data for car owners and dealerships. This chapter outlines the project's objectives, problem statement, existing systems, proposed system, motivation, and scope, setting the stage for a comprehensive understanding of the project's goals and potential impact.

II. Literature Survey

This paper published in the journal Electronic Imaging in 2023 presents a novel approach for automatically detecting, identifying, and categorizing car damage sites in traffic incidents. The method utilizes an improved Mask R-CNN algorithm, integrating deep learning, transfer learning, and instance segmentation techniques. Notably, it not only recognizes damaged vehicles but also precisely locates them and assesses their severity level.[1] [Jihad Qaddour .et .al] Comparative evaluations using three pre-trained models demonstrate the superiority of the proposed method across detection, localization, and severity assessment metrics. Additionally, the paper introduces a web-based automatic claim estimator capable of analyzing user-submitted photographs to automatically identify and evaluate the extent of damage. Through extensive experimentation and analysis, the study underscores the effectiveness of the proposed framework in automatic object recognition and classification, highlighting its potential applications in practical scenarios.

This project addresses the critical issue of car damage classification and detection, essential for enhancing daily safety on roads. With the multitude of materials and vehicle types, distinguishing surrounding conditions poses a challenge.[2] [Mallikarjuna B .et .al] To expedite vehicle insurance dispute resolution, we explored utilizing deep convolutional networks, leveraging recent advancements in computer vision. By manually curating and annotating a diverse set of car damage images from online sources, we employed the YOLO (You Only Look Once) series target detection method, known for its efficiency and scalability. Training the model with base weights from the COCO dataset, our approach facilitates timely and accurate identification of vehicle damage. This work introduces a method for effectively classifying and identifying various types of vehicle damage, employing deep learning techniques and leveraging manually collected online datasets.

This paper introduces CarDD, a novel large-scale dataset tailored for vision-based car damage detection and segmentation. With 4,000 high-resolution images depicting car damage, annotated with over 9,000 instances across six damage categories, the dataset undergoes detailed collection, selection, and annotation processes.[3] [Xinkuang Wang .et .al] The authors conduct extensive experiments using state-of-theart deep learning methods on CarDD, providing thorough analyses to underscore its efficacy in car damage detection. Furthermore, the paper compares CarDD with existing datasets for car damage classification, detection, and segmentation, showcasing its diverse challenges and potential contributions to the computer vision field. The authors aim for CarDD to enhance vision-based car damage assessment and foster advancements within the computer vision community.

III. Proposed System

The suggested system aims to address the shortcomings of existing solutions by integrating cutting-edge AI and machine learning technologies. At its foundation, the system employs the Yolov8 algorithm, recognized for its high accuracy and effectiveness in real-time object detection. This algorithm plays a critical role in providing precise and trustworthy identification of various types of car damage. The system is constructed upon a detailed dataset obtained from Roboflow, which encompasses a diverse array of car damage categories and is carefully annotated to facilitate effective model training. By automating the damage identification process, the system considerably diminishes the necessity for manual inspections, thus simplifying the evaluation procedure. A user-friendly web interface has been created using Flask, enabling users to effortlessly upload images and receive prompt feedback regarding damage evaluation. The system is crafted with a strong emphasis on precision and consistency, ensuring that it reliably produces accurate results. The combination of Yolov8, a thorough dataset, and an accessible web interface marks a noteworthy progression in car damage detection technology, improving both efficiency and effectiveness in the domain.

IV. Methodology

The methodology involves collecting a dataset of 5500 vehicle images from , The images are preprocessed through normalization, resizing, and data augmentation to ensure uniformity and prevent overfitting. Utilizing the Yolov8 algorithm for real-time and accurate object detection. Yolov8 is known for its high precision and efficiency in detecting objects within images, with feature extraction performed by Convolutional Neural Networks (CNNs). The models are trained using techniques like backpropagation through time and gradient descent optimization, with regularization and hyperparameter tuning to enhance performance. Evaluation metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are used to assess model accuracy, and error analysis identifies areas for improvement. The optimized model is then deployed for real-time dagame detection, with a feedback loop established for ongoing refinement and integration of new data. This module is central to vehicle damage detection, leveraging vehicle images and deep learning algorithms to deliver accurate and actionable insights into vehicle damage. By analyzing a comprehensive dataset of damaged vehicle images, it provides reliable damage assessments, enhancing decision-making.

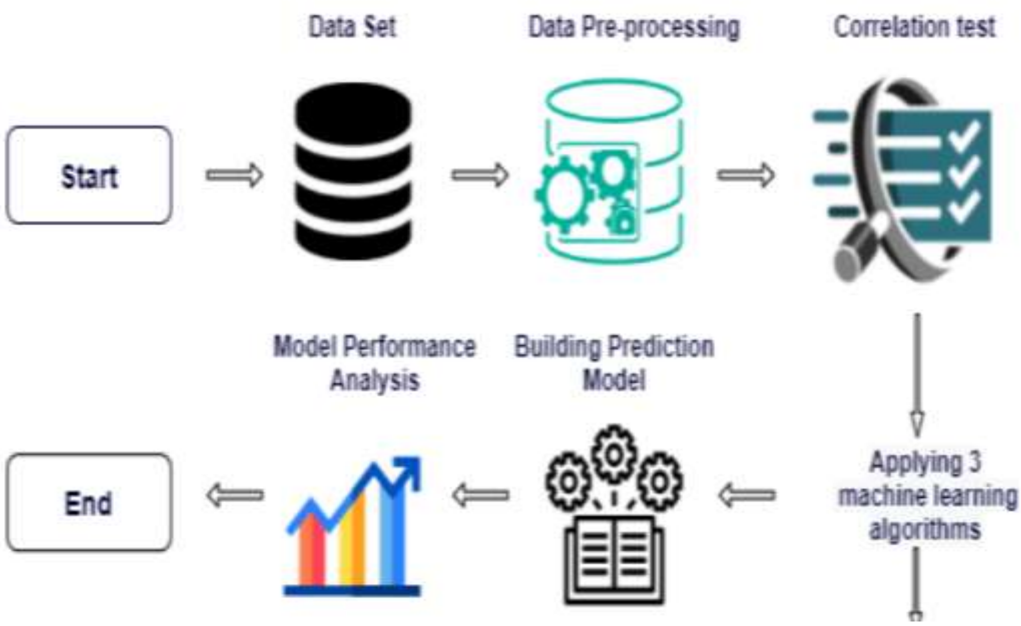

Fig 1 Overview of the Proposed System

V. RESULT ANALYSIS

The YOLOv8 model demonstrated a remarkable accuracy of 85.41%, exhibiting nearly flawless precision, recall, and1-scores. This level of performance emphasizes capability to effectively identify damaged images with minimal misclassifications, highlighting its dependability and strength. Conversely, the Convolutional Neural Network (CNN) model produced solid results with an overall accuracy of 78%. Although its precision and recall were marginally lower than those of the YOLO8, the CNN still proved to be quite effective. Nevertheless, the CNN encountered a slightly higher number of misclassifications compared to YOLOv8, indicating that while neural networks excel in working with sequential data, further adjustments may be necessary to reach the precision levels of YOLOv8.

Presented below is classification table for the YOLOv and CNN models, detailing their accuracy, precision, recall, and F1-score.

Metric	YOLOv8 Model	CNN Model
Accuracy	85.41%	78.00%
Precision	85.50%	78.75%
Recall	85.40%	78.60%
F1-Score	85.45%	78.68%

Table 1 comparison of models

a) Intersection over Union (IoU) : IoU is utilized to assess the precision of an object detection model by analyzing extent to which the predicted bounding boxes with the actual ground truth bounding boxes.

Formula: IoU=Area of IntersectionArea of Union\text{IoU}

- **Intersection Area:** The region where the predicted bounding box overlaps with the actual bounding box.
- **Union Area:** The overall space occupied by both the predicted and actual bounding boxes combined. This is determined as follows:

Area of Union=Area of Predicted Box+Area of Ground Truth Box−Area of Intersection

b) Mean Average Precision (mAP): mAP offers a unified metric that merges precision and, providing a thorough evaluation of how well an detection model performs.

Formula: • Average Precision (AP): For each class, AP is calculated by averaging the precision scores at different recall levels.

Precision=True Positives \ True Positives+False Positives

Recall=True Positives True\ Positives+False Negatives

To compute AP, precision-recall pairs are used, and the area under the precision-recall curve is calculated.

The below figure 2 shows the all the ML model that have been compared to different Model with YOLOv8 and CNN to find which model is used more accurate to perform our predictions. The figure below illustrates the visual representation of the table mentioned above and with Accuracy Graph.

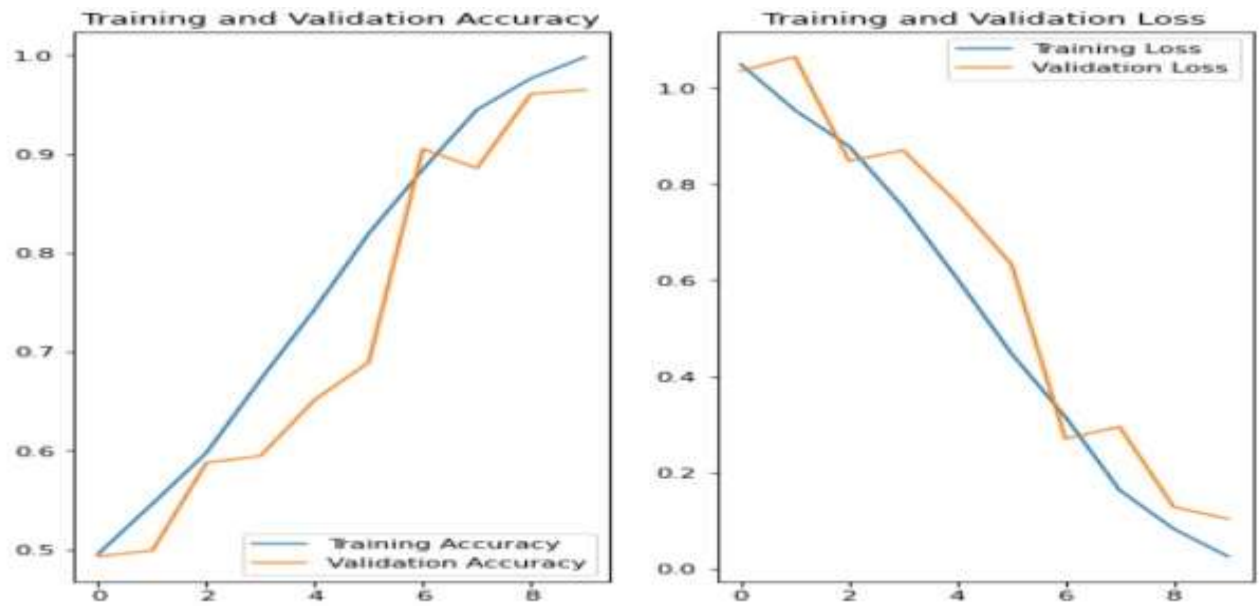

Fig 2 Accuracy Graph

Fig 3 homepage

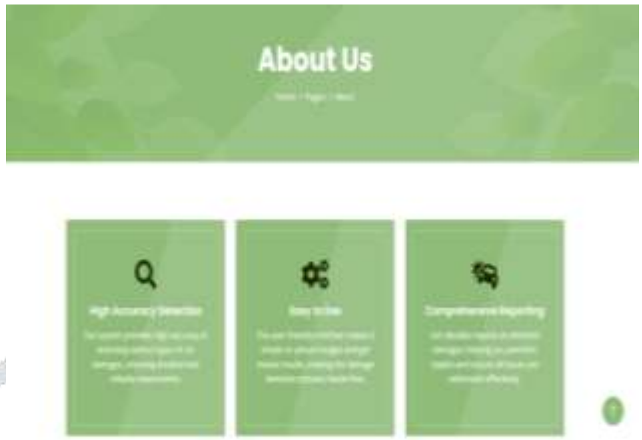

Fig 4 About Page

Fig 5 result page

This is a results page generated by an automated system for analyzing images, pertaining to car damage detection. The details about the image are as follows:

- The close-up captures a damaged car door.
- The door's surface exhibits scratches and dents.
- Text labels indicate that the system has identified moderate scratches with a confidence level of 0.17 and minor dents with a confidence level of 0.1.

The image depicts a truck that has sustained significant damage from an accident, particularly at the front.

- Text appears above the truck, likely indicating a recognized object along with its confidence score. The detection has a confidence score of 0.49, indicating moderate certainty about it.
- A heading beneath the image suggests that it is the output of an image analysis or object detection process.

- Under the "Result" heading, a label identifies the detected objects in the image.
- Another detected object is listed as "severe-broken," with a high confidence score of 0.92.

The image illustrates damage to a car following an accident, with the model identifying various types of damage:

- It has recognized a moderate dent on one of the vehicles with a confidence score of 0.39, which signifies a 39% likelihood that the detected area is indeed a moderate dent.
- A moderate scratch is found with a confidence score of 0.17, indicating a lower certainty compared to the dent.
- A minor scratch is noted with a confidence score of 0.1.
- The model has detected a potentially severe break with a very low confidence score of 0.09.

The image again reveals car damage after an accident, with the model pinpointing three kinds of damage and assigning a confidence score to each:

- A severe break in the vehicle's structure is identified with a confidence score of 0.31, indicating a 31% chance that the detected region is a severe break.
- A moderate dent is detected with a confidence score of 0.1, suggesting lower certainty compared to the severe break.
- Additionally, the model identifies a moderate level of breakage with a very low confidence score of 0.06.

VI. CONCLUSION

The Car Damage Detection system utilizing Yolov8 represents a notable progress in the automation of vehicle damage evaluation, efficiently identifying and categorizing car damages from photographs. The project has successfully achieved its goals, offering a reliable tool for insurance firms, auto repair shops, and vehicle owners to swiftly evaluate damages, thus facilitating the claims and repair processes. Significant milestones include attaining a high level of accuracy with the Yolov8 algorithm, creating a user-friendly web interface based on Flask for easy image uploads and result accessibility, and ensuring secure storage of data. Comprehensive testing demonstrated the system's effectiveness, performance, and dependability across different situations, confirming its readiness for launch. By employing an extensive dataset from Roboflow, the system is educated to recognize various forms of car damage with an accuracy rate of 85.41%. This deep learning-based system improves the speed, consistency, and objectivity of damage evaluation, providing considerable advantages compared to conventional manual methods.

VII. ACKNOWLEDGMENT

I extend my heartfelt gratitude to The National Institute of Engineering, Mysuru, and its dedicated staff for their unwavering support. A special thanks to my guide, **Smt. K R Sumana**, whose guidance and encouragement were invaluable throughout this journey. I am deeply appreciative of my supportive parents, friends, and classmates, whose encouragement and support played a crucial role. Finally, I extend my sincere thanks to everyone who contributed, both directly and indirectly, to the successful completion of my project.

REFERENCES

[1] Ayesha Siddiqa et. al. , “Automatic Damaged Vehicle Estimator Using Enhanced Deep Learning Algorithm”

[2] Mallikarjuna B .et .al , “Vehicle Damage Detection and Classification Using Image Processing” Volume 2, Issue 9, June 2022

[3] Najmeddine Dhieb .et .al. , “A Very Deep Transfer Learning Model for Vehicle Damage Detection and Localization” DOI: 10.1109/ICM48031.2019.9021687

[4] Mohammed Yusuf Jamal Aziz Azmi .et .al ,“Vehicle Damage Detection Using Deep Learning” DOI : https://www.doi.org/10.56726/IRJMETS29626

[5] Maria Raap .et .a. ,“Vehicle Damage Detection using Semi-Supervised Object Detection” 22nd September 2021

[6] Qinghui Zhang .et .al. ,“Vehicle-Damage-Detection Segmentation Algorithm Based on Improved Mask RCNN” DOI: 10.1109/ACCESS.2020.2964055

[7] Umer Waqas .et .al. ,“Vehicle Damage Classification and Fraudulent Image Detection Including Moiré Effect Using Deep Learning” 2020 IEEE Canadian Conference on Electrical and Computer Engineering.

[8] Dimitrios Mallios .et .al. ,“Vehicle Damage Severity Estimation for Insurance Operations” Using In-TheWild Mobile Images” Digital Object Identifier 10.1109/ACCESS.2023.3299223 2023-24

[9] Xinkuang Wang et. Al. ,“CarDD: A New Dataset for Vision-Based Car Damage Detection” Image Based Automatic Vehicle Damage Detection” VOL. 24, NO. 7, JULY 2023

[10] Srimal Jayawardena et. al. “Image Based Automatic Vehicle Damage Detection” November 2013.

[11] R.E. van Ruitenbeek .et .al. ,“Convolutional Neural Networks for vehicle damage detection” Volume 9 15 September 2022, 100332.

[12] Priti Warungse .et .al. ,“Car Damage Detection Using Computer Vision” 2023 JETIR November 2023, Volume 10, Issue 11 [13] Dindayal Bhadrecha1 Divyesh Tharakan .et .al. ,“Car Damage Detection Using Deep Learning” Volume: 09 Issue: 06 | June 2022

[14] Phyu Mar Kyu .et .al. ,“Car Damage Detection and Classification” DOI: 10.1145/3406601.3406651

[15] Rakshata P .et .al. , “Car Damage Detection and Analysis Using Deep Learning Algorithm For Automotive” Volume 5, Issue 6, Nov-Dec-2019.