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Full Length Article

Car Damage Identification Using Deep Learning Techniques

Dr J Madhavan[1], M. Jayanthi[2], C. Lakshmi Likhitha[3], P. Mrudhula Reddy[4]
[1]Professor Department Of Electronics And Communication Engineering, Bhoj Reddy Engineering College For Women Hyderabad India.
[2,3,4]B. Tech Students; Department Of Electronics And Communication Engineering, Bhoj Reddy Engineering College For Women Hyderabad India.
Mail Id; mogilijayanthi08@gmail.com[2], likkireddy2844@gmail.com[3], mrudhulareddypannala@gmail.com[4]
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Abstract
Car damage assessment plays a vital role in insurance claim processing, vehicle maintenance, and road safety management. Traditional vehicle damage inspection methods are often time-consuming, expensive, and highly dependent on human expertise, which can result in inconsistent and subjective assessments. With the rapid advancements in deep learning and computer vision, automated car damage detection has emerged as an effective and reliable solution for accurate vehicle inspection.
This project presents a deep learning-based approach for Car Damage Detection using YOLOv8 (You Only Look Once Version 8), a state-of-the-art object detection algorithm. The proposed system is trained to detect and localize various types of vehicle damage, including dents, scratches, cracks, and broken parts, from input images. YOLOv8 performs real-time object detection with high accuracy by processing images in a single forward pass through the neural network, enabling fast and efficient damage identification.
The model is trained using a labeled dataset of damaged vehicle images and evaluated using standard performance metrics such as Precision, Recall, and Mean Average Precision (mAP). Experimental results demonstrate that YOLOv8 provides accurate, reliable, and efficient detection of vehicle damage, making it well suited for real-world applications such as automated insurance claim assessment, vehicle inspection, and automobile service management. This project highlights the significant potential of deep learning and computer vision technologies in improving the speed, accuracy, and consistency of automated car damage detection systems.

Keywords— *Car Damage Detection, YOLOv8, Deep Learning, Computer Vision, Object Detection, Vehicle Damage Assessment, Image Processing, Insurance Claim Automation, Convolutional Neural Networks (CNN), Mean Average Precision (mAP).*

Introduction
Car damage detection plays an important role in the automobile industry, ‘vehicles are involved in accidents or collisions, they may develop damages such as dents, scratches, cracks, broken lamps, shattered glass, or flat tires. Traditionally, the inspection of such damages is performed manually by technicians or insurance inspectors. However, manual inspection is often time-consuming, subjective, and sometimes inaccurate, especially when dealing with large volumes of vehicles.
With the rapid development of artificial intelligence and computer vision technologies, automated image analysis systems are increasingly being used to solve complex visual recognition problems. Deep learning, particularly convolutional neural networks (CNNs), has shown remarkable success in detecting and classifying objects within images. These models can learn patterns and features from large datasets and perform detection tasks with high accuracy.
Object detection models such as YOLOv8 (You Only Look Once version 8) are widely used for real-time detection tasks. YOLO models can identify multiple objects in an image and locate them using bounding boxes. This capability makes them highly suitable for applications such as vehicle damage detection.
This mini project explores the development of a car damage detection system using deep learning techniques. The system allows users to upload vehicle images, which are then analyzed by the trained YOLOv8 model to detect and classify different types of damages. The detected damage regions are highlighted with bounding boxes along with labels indicating the type of damage.
The proposed system aims to provide an automated, efficient, and reliable solution for detecting car damages from images. Such a system can assist insurance companies, vehicle inspection centers, and automobile service providers in faster damage assessment and decision making.

Literature Survey
Traditional Image Processing Methods
Early research in vehicle damage detection primarily relied on traditional image processing

techniques, including edge detection, image segmentation, and feature extraction. These methods analyze visual characteristics such as scratches, dents, cracks, and deformation patterns in vehicle images to identify damaged areas. Although these approaches laid the foundation for automated vehicle inspection, they have several limitations. Their performance is highly sensitive to variations in lighting conditions, image quality, and viewing angles. In addition, traditional methods struggle to detect complex damage patterns and often fail to generalize across different vehicle models and colors. As a result, their accuracy and reliability are limited, making them less suitable for large-scale, real-world automated vehicle damage detection systems.

Machine Learning Approaches

To overcome the limitations of conventional image processing methods, researchers introduced machine learning techniques for vehicle damage detection. Algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forests were employed to classify vehicle images based on manually extracted features. These approaches demonstrated improved performance by learning patterns from labeled datasets and automating the classification of damaged and non-damaged vehicles. Machine learning methods significantly enhanced detection accuracy compared to traditional techniques and reduced the dependence on rule-based systems. However, they still rely heavily on manual feature engineering, which limits their ability to accurately recognize complex damage patterns under varying real-world conditions.

Deep Learning Techniques

The rapid advancement of deep learning has transformed the field of computer vision by enabling automatic feature extraction and highly accurate image analysis. Convolutional Neural Networks (CNNs) have become the most widely adopted architecture for image classification and object detection tasks due to their ability to learn hierarchical visual features directly from raw images. Deep learning models provide several advantages over traditional machine learning methods, including automatic feature learning, improved detection accuracy, greater robustness, and the capability to identify complex damage patterns without manual intervention. Researchers have successfully applied advanced deep learning architectures such as CNN, ResNet, and YOLO to detect and classify vehicle damage, achieving significantly better performance than conventional image processing and machine learning approaches.

Car Damage Detection Systems

Recent research has focused on developing intelligent car damage detection systems that utilize deep learning techniques for automated vehicle inspection and insurance claim processing. Several studies have proposed CNN-based models capable of identifying various types of vehicle damage, including scratches, dents, broken parts, and cracks, directly from digital images. Object detection frameworks such as YOLO have been widely adopted to accurately locate damaged regions on vehicles in real time. Furthermore, artificial intelligence has been integrated into modern insurance claim processing systems, where automated damage detection helps accelerate claim verification, minimize human intervention, and improve overall operational efficiency. These advancements demonstrate that deep learning-based vehicle damage detection systems offer a reliable, accurate, and practical solution for real-world automotive inspection and insurance applications.

Car Damage Detection Using Deep Learning Techniques

Car damage detection using deep learning techniques is an advanced computer vision application that automatically identifies damaged areas on vehicles from images. Traditional vehicle inspection methods are usually performed manually, which can be time-consuming, subjective, and prone to human error. By using deep learning models, the detection process can be automated, making it faster, more accurate, and reliable.

In this project, a deep learning based object detection model called YOLOv8 (You Only Look Once version 8) is used to identify different types of car damages such as dents, scratches, and broken parts from vehicle images. The system processes input images, analyzes them using a trained neural network model, and highlights the detected damage areas using bounding boxes.

The system first preprocesses the input image to make it suitable for the deep learning model. The YOLOv8 model then extracts important features from the image using convolutional neural networks and predicts the damaged regions. After detection, a post-processing step called Non-Maximum Suppression (NMS) removes duplicate detections and retains the most accurate predictions.

Finally, the detected damage areas are displayed through a web application developed using Flask, allowing users to upload vehicle images and visualize the results easily. This system demonstrates how deep learning and computer vision can be used to automate vehicle inspection processes and support applications such as insurance claim assessment, vehicle maintenance, and accident analysis.

Block Diagram

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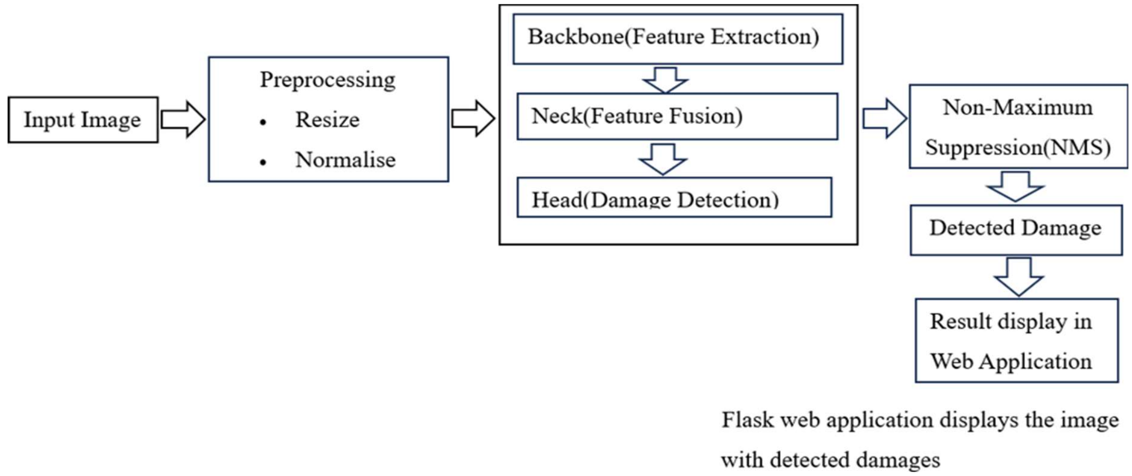

FIG 1; Block diagram

Input Image

Function:

Provides the car image that will be analyzed for damage detection. The system begins with an input image of a vehicle that may contain damage such as dents, scratches, or cracks. The image can be uploaded by the user through the web application interface. The quality and clarity of the input image play an important role in achieving accurate detection results.

Image Preprocessing

Function:

Prepares the input image for processing by the deep learning model. Before feeding the image into the YOLOv8 model, preprocessing operations such as resizing and normalization are

performed. These steps ensure that the image format and size match the input requirements of the neural network. Preprocessing improves the efficiency and accuracy of the detection model.

YOLOV8 Model

Function:

Performs object detection to identify damaged areas in the car image.

The YOLOv8 model is a deep learning based object detection algorithm that processes the image and identifies regions containing car damage. It uses convolutional neural networks to analyze image features and predict object locations in a single pass. This enables fast and accurate detection of damaged regions.

Backbone (Feature Extraction)

Function:

Extracts important features from the input image.

The backbone network is responsible for extracting low-level and high-level features from the image using multiple convolutional layers. These features represent edges, textures, shapes, and patterns that help the model identify damaged areas.

The extracted features are passed to the next stage for further processing.

Neck (Feature Fusion)

Function:

Combines features from different layers of the network.

The neck structure integrates feature maps from multiple layers to improve detection performance. This process helps the model detect objects at different scales and improves accuracy when identifying small or complex damage regions.

Feature fusion ensures better representation of the detected objects.

Head (Damage Detection)

Function:

Predicts bounding boxes and class labels for detected damages.

The head of the YOLOv8 model generates predictions based on the extracted features. It identifies the location of damaged areas and assigns confidence scores to each prediction. The output includes bounding boxes around damaged regions and the classification of the detected damage.

Non-Maximum Suppression (NMS)

Function:

Removes duplicate detections and keeps the most accurate ones.

During detection, the model may generate multiple bounding boxes for the same damage area. Non-Maximum Suppression eliminates overlapping boxes and retains only the most confident prediction. This step improves the clarity and accuracy of the final output.

Detected Damage

Function:

Represents the final detected damaged areas in the image. After applying NMS, the system highlights the detected damage regions by drawing bounding boxes on the image. These boxes indicate the exact location of the damage on the vehicle. This allows users to clearly identify damaged sections of the car.

Result Display in Web Application

Function:

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Displays the final detection result to the user. The Flask web application allows users to upload an image of a vehicle and view the detection results. The processed image with highlighted damage areas is displayed on the webpage. This user interface makes the system interactive and easy to use.

Working Methodology

The working methodology of the car damage detection system involves several steps that process the input image and detect damaged areas using deep learning.

Image Acquisition

The system begins with the acquisition of a car image that may contain visible damage. The image can be uploaded by the user through the Flask web application. The uploaded image acts as the input to the detection system.

Image Preprocessing

The input image is resized to match the input size required by the YOLOv8 model. Normalization techniques are applied to scale pixel values. These preprocessing steps improve model performance and detection accuracy.

Feature Extraction

The YOLOv8 backbone network extracts important visual features from the image. These features include edges, textures, shapes, and patterns related to vehicle damage. Feature extraction helps the model understand the structure of the image.

Feature Fusion

The neck layer combines feature maps from different network layers. This allows the model to detect damage at different scales. Feature fusion improves the detection of small or partially visible damages.

Damage Detection

The YOLOv8 head predicts bounding boxes and class labels for potential damage areas. Each prediction includes the location of the damage and a confidence score. The model processes the entire image in a single pass for fast detection.

Non-Maximum Suppression

Multiple overlapping predictions may occur during detection. Non-Maximum Suppression removes redundant boxes and keeps the most accurate one. This ensures clean and reliable detection results.

Result Visualization

The detected damage areas are highlighted using bounding boxes. Labels and confidence scores may also be displayed. This helps users easily identify damaged regions in the vehicle image.

Results and Discussion

Working

The Car Damage Detection System operates by taking an input image of a vehicle and processing it using a trained deep learning model. The system utilizes computer vision techniques along with Convolutional Neural Networks (CNNs) to identify damaged regions.

Initially, the input image is uploaded through a web-based interface. The image is then preprocessed by resizing it to a fixed resolution (e.g., 640×640 pixels), normalizing pixel values, and converting it into a format suitable for the model.

The processed image is passed to a deep learning model (such as YOLOv8 or CNN-based object detection), which detects damaged regions and classifies them into categories like scratches, dents, or shattered glass. Bounding boxes are drawn around the detected damage areas.

The model outputs:Damage Type Confidence Score Severity Level

Estimated Repair Cost

The backend processes these outputs and displays them on the user interface along with the annotated image.

Results

This section presents the experimental results obtained from testing the Car Damage Detection System on different vehicle images.

The system was implemented on a local machine with an Intel Core i5 processor, 8GB RAM, and executed using Python with deep learning frameworks. The model demonstrated reliable performance in detecting visible damages with high confidence.

Damage Type: shattered glass

Confidence: 96.92%

Severity Level: High

Estimated Repair Cost: ₹12000

Figure 2, Shattered glass detection (High Severity)

In figure2 the system successfully detects severe windshield damage in the given car image. A bounding box is drawn around the affected region, clearly highlighting the shattered glass. The model predicts the damage type as shattered glass with a high confidence score of 96.92%. Based

on the extent of cracks and impact spread, the severity level is classified as High, and the estimated repair cost is ₹12,000. The result demonstrates the model's ability to accurately identify major damages with high reliability

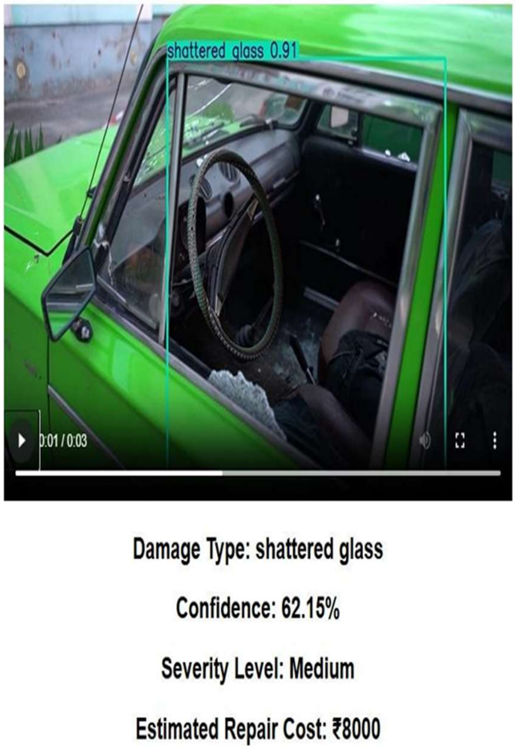

Figure 3; Shattered glass detection(Medium Severity)

In figure 3 the system identifies moderate damage on the car window. The detected region is enclosed within a bounding box, indicating the damaged portion. The model classifies the damage as shattered glass with a confidence score of 62.15%. Due to comparatively lesser crack density and partial visibility, the severity is categorized as Medium, with an estimated repair cost of ₹8,000. This shows the system's capability to handle varying damage intensities, though confidence may decrease with less prominent features.

Performance Analysis

The system showed consistent performance across different test cases. High-quality images resulted in better confidence scores, while images with noise or lower visibility slightly reduced accuracy.High severity damages were detected with confidence > 90%

Medium severity damages showed moderate confidence (~60–80%).Detection speed was fast, making the system suitable for real-time applications. The bounding box detection and classification were accurate in both cases, demonstrating the robustness of the model.

Conclusion

The primary objective of the **Car Damage Detection Using Deep Learning Techniques** project was to develop an intelligent and automated system capable of accurately detecting vehicle damage from images using advanced deep learning algorithms. In this work, the YOLOv8 object detection model was employed to identify and localize different types of vehicle damages, including scratches, dents, cracks, and broken parts. A Flask-based web application was developed to provide a simple and user-friendly interface through which users can upload vehicle images and obtain instant damage detection results.

The trained YOLOv8 model processes the uploaded image, detects damaged regions, and highlights them with bounding boxes, enabling users to easily identify the affected areas of the vehicle. Compared with traditional manual inspection methods, the proposed system significantly reduces inspection time, minimizes human effort, and improves the accuracy and consistency of damage assessment. The integration of deep learning with an interactive web application demonstrates the practical application of artificial intelligence in the automotive sector, particularly for vehicle inspection and insurance claim processing.

Overall, the developed system successfully demonstrates that deep learning-based object detection techniques can effectively identify vehicle damages from images with high accuracy and reliability. The proposed solution has the potential to assist insurance companies, automobile service centers, fleet management organizations, and vehicle owners by providing a fast, efficient, and automated approach to vehicle damage assessment, thereby improving operational efficiency and reducing processing time.

Future Scope

Although the proposed system achieves accurate vehicle damage detection using deep learning, there are several opportunities for further enhancement to improve its performance, scalability, and practical applicability.

Improvement of Dataset and Model Accuracy: The performance of the proposed model can be further enhanced by training it on a larger and more diverse dataset that includes various vehicle models, colors, lighting conditions, camera angles, weather conditions, and damage categories. A more comprehensive dataset would enable the model to learn richer visual features, resulting in improved accuracy and better generalization for detecting scratches, dents, cracks, broken parts, and other types of vehicle damage.

Integration with Mobile Applications: Future versions of the system can be integrated into Android and iOS mobile applications, allowing users to capture images of damaged vehicles directly using smartphone cameras. The captured images can be processed instantly to provide real-time damage detection results, making the system more accessible and convenient for vehicle owners, insurance companies, and automobile service providers.

Real-Time Damage Detection Using Video Input: Currently, the proposed system processes only static images. Future research can extend the model to analyze real-time video streams captured from surveillance cameras, dashboard cameras, or mobile devices. This enhancement would enable continuous vehicle inspection in parking lots, service centers, toll plazas, and traffic monitoring environments.

Automatic Damage Severity Estimation and Repair Cost Prediction: The system can be enhanced to estimate the severity of detected damages by analyzing the size, location, and extent of the damaged regions. Based on this assessment, machine learning models can be incorporated to predict approximate repair costs, thereby assisting insurance companies and automobile repair centers in generating faster and more accurate repair estimates.

Integration with Insurance Claim Processing Systems:
The proposed system can be integrated with online insurance claim management platforms to automate the vehicle inspection process. Customers would be able to upload images of damaged vehicles, after which the system would automatically detect and classify the damages, reducing manual verification efforts and accelerating claim approval procedures.

Detection of Individual Vehicle Components and Detailed Damage Analysis: Future versions of the system can be designed to first identify individual vehicle components such as bumpers, doors, fenders, headlights, windshields, mirrors, and hoods before detecting damage on each component. This would provide more detailed information regarding the exact location, type, and extent of damage, enabling more accurate repair planning and comprehensive vehicle condition assessment.

Integration of Advanced Deep Learning Models: Future research may also investigate the use of more advanced object detection architectures, such as YOLOv11, EfficientDet, DETR, or transformer-based vision models, to further improve detection accuracy, robustness, and inference speed. Ensemble learning techniques and model optimization methods can also be explored to enhance performance in challenging real-world scenarios.

Explainable Artificial Intelligence (XAI): Incorporating Explainable AI techniques would improve the transparency of the damage detection process by providing visual explanations for model predictions. This would increase user trust and facilitate the adoption of AI-based vehicle inspection systems in insurance and automotive industries.

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