AI-DRIVEN VEHICLE DAMAGE SEGMENTATION AND AUTOMATED COST PREDICTION

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Abstract

This work presents an automated vehicle damage detection and segmentation system based on image processing and deep learning techniques. Damage regions are segmented using HSV intensity-based segmentation, followed by extraction of statistical, shape, and texture features. A backpropagation neural network with ReLU and Sigmoid activation functions is employed to classify damage effectively. The proposed method is evaluated on multiple vehicle components, including bumpers, doors, mirrors, and lighting units. Experimental results demonstrate high accuracy, precision, recall, and F1-scores across all case studies, confirming the robustness and reliability of the system for real-world vehicle damage assessment applications.

Introduction

Vehicle accidents and collisions are an inevitable aspect of modern transportation, often resulting in varying degrees of physical damage to vehicles [1] . Such damage requires timely repair and accurate cost assessment to minimize financial losses, ensure vehicle safety, and maintain operational efficiency for individuals, businesses, and insurance companies. Traditionally, damage evaluation [2] has relied on manual inspection conducted by insurance agents or vehicle repair experts. While experienced professionals can provide reasonable assessments, this method is inherently time-consuming, subjective, and prone to human error, which often leads to inconsistencies in damage evaluation and delays in insurance claim settlements. With the increasing volume of vehicles on roads [3] worldwide and the growing demand for faster, more reliable services, there is a pressing need for automated and intelligent systems that can streamline the damage assessment and cost estimation processes.

Accurate and efficient assessment of vehicular damage is not only critical for individual repairs but also plays a vital role in insurance claim processing, fleet management, and operational planning. Recent advances in deep learning and computer vision have enabled the development of automated frameworks capable of performing damage detection, localization, and severity estimation directly from vehicle images. Deep learning architectures, particularly

Convolutional Neural Networks (CNNs), [4] have proven highly effective in learning complex patterns and extracting relevant features from images, enabling the identification of damage regions with a high degree of accuracy. Modern object detection frameworks, such as YOLO-based models [5] , have demonstrated impressive performance in detecting diverse damage patterns across large datasets, significantly reducing reliance on manual inspections and improving workflow efficiency in automotive and insurance industries.

Beyond detection, semantic and instance segmentation models, such as Mask R-CNN [6], enable the pixel-level delineation of damaged areas, which allows for precise quantification of damage severity—a crucial step for accurate repair cost estimation. More sophisticated pipelines integrate segmentation outputs with structured historical data to generate reliable cost predictions, forming a holistic automated damage assessment system. The practical benefits of these systems include reduced human bias, faster claim resolutions, and scalable operations that can handle large volumes of vehicles efficiently. As deep learning techniques continue to mature [7] , these approaches are poised to transform traditional vehicular assessment methods into efficient, objective, and real-time evaluation systems, bridging the gap between speed, accuracy, and operational practicality.

The primary aim of this work is to develop an intelligent and automated vehicle damage assessment system that can comprehensively evaluate a vehicle's condition after an accident or collision. The proposed system is designed to process a 360-degree video of a car, enabling full visual coverage of all vehicle surfaces, which ensures that even subtle or hard-to-see damages are detected. Using advanced deep learning and computer vision techniques, the system will automatically detect and segment damaged regions, accurately identifying scratches, dents, and structural deformations.

The main objective of this study is to develop an intelligent and automated system for vehicle damage assessment using 360-degree video input. By capturing the entire vehicle from all angles, the system aims to ensure comprehensive evaluation, allowing even minor or obscured damages to be accurately identified. To make the analysis efficient, the system first extracts representative frames from the video, reducing computational complexity while retaining all critical visual information for processing. The system includes an interactive user interface that visualizes damaged areas, severity assessments, cost estimates, making the results easily interpretable for insurance agents, repair technicians, and vehicle owners. Overall, the system aims to provide a robust, reliable, and automated solution for vehicle damage assessment, minimizing human intervention while improving accuracy, efficiency, and scalability.

Methodology

The proposed system is designed to analyze damaged regions in images using a structured image processing and feature extraction pipeline. The block diagram represents the sequential flow of operations starting from image acquisition and preprocessing to feature extraction and analysis. Each block in the diagram performs a specific function, contributing to the accurate identification and quantification of damage characteristics. The core objective of the system is to extract meaningful **texture, shape,** and **statistical features** that can be further used for classification, assessment, or decision-making tasks.

In the Image Acquisition phase, input images containing damaged surfaces or regions are collected. These images are captured using cameras as well as obtained from existing datasets. In the Image Preprocessing, applied Image normalization to standardize pixel intensity values.

Damage Segmentation

In this block, the damaged regions are isolated from the background using segmentation techniques. The Method thresholding is employed. Technique used to segment the damage by considering V component of HSV Colour Model [8]. It defines the minimum intensity level a pixel must have to be classified as damage.

- **If Pixel Intensity (V) ≤ Threshold:** The pixel is classified as damaged.
- **If Pixel Intensity (V) > Threshold:** The pixel is considered part of the normal vehicle surface.
- **Low Threshold Values (e.g., 30–40):** Detect only very dark regions. This setting is suitable for identifying deep dents and major cracks, but it may fail to detect lighter scratches.
- **High Threshold Values (e.g., 80–100):**
  Detect both dark and lighter damaged regions. This setting is suitable for identifying minor scratches and surface-level damage, though it may introduce false positives.

Feature Extraction

Features used in this work are **texture features, shape features,** and **statistical features**, for capturing different aspects of the damage.

A) Texture Features

Texture features describe the surface characteristics of the damaged region. They are useful for identifying variations in roughness, patterns, and intensity distribution.

1) Texture Variance [9]

Texture variance measures the spread or variability of pixel intensity values within the damaged region. It indicates how much the surface texture fluctuates from the average intensity.

- A **high texture variance** suggests rough, uneven, or heavily damaged surfaces.
- A **low texture variance** indicates smooth or mildly affected areas.

- This feature is particularly useful in distinguishing between minor and severe damage, as severe damage tends to introduce irregular texture patterns.

2) Edge Intensity [10]

Edge intensity represents the strength and frequency of edges within the damaged area. It is usually computed using edge detection operators such as Sobel, Prewitt, or Canny.

- Strong edge intensity implies sharp boundaries, cracks, or fractures.
- Weak edge intensity indicates smoother transitions and less visible damage.

Edge intensity plays a significant role in identifying cracks, breaks, or abrupt structural changes in the damaged region.

B. Shape Features

Shape features describe the geometric properties of the damaged area. These features are independent of color and texture and provide valuable information about the size, spread, and spatial structure of damage.

1) Contour Area

Contour area [11] refers to the total area enclosed by the boundary (contour) of the damaged region. It is calculated by detecting the outer boundary of the segmented region and computing the enclosed pixel area.

- Larger contour areas typically indicate extensive damage.
- Smaller contour areas suggest localized or minor damage.

This feature helps in estimating the severity and extent of damage.

2) Bounding Box Dimension

The bounding box dimension [12] represents the width and height of the smallest rectangle that fully encloses the damaged region. It provides a compact representation of the damage spread.

- Elongated bounding boxes may indicate linear damages such as cracks.
- Compact bounding boxes may indicate concentrated damage zones.

Bounding box dimensions are useful for comparing damage shapes and identifying directional patterns.

3) Damage Density

Damage density [13] is defined as the ratio of the damaged area to the total area of the bounding box or the region of interest.

- High damage density indicates closely packed damage within a small area.
- Low damage density suggests sparse or scattered damage.

This feature is effective in differentiating between dense structural failures and isolated surface defects.

C. Statistical Features

Statistical features [14] summarize the numerical characteristics of damage intensity values within the damaged region.

1) Average Damage

Average damage is computed as the mean pixel intensity value of the damaged region. It provides an overall measure of damage severity.

- Higher average values may correspond to brighter or more intense damage patterns.
- Lower values may indicate subtle or less prominent damage.

This feature acts as a baseline indicator of damage level.

2) Standard Deviation of Damage

The standard deviation of damage measures the dispersion of pixel intensity values around the mean.

- A high standard deviation implies significant variation in damage intensity, indicating irregular or complex damage patterns.
- A low standard deviation suggests uniform damage distribution.

This feature complements average damage by providing insight into consistency and variability within the damaged region and the flowchart is given in Figure 1.

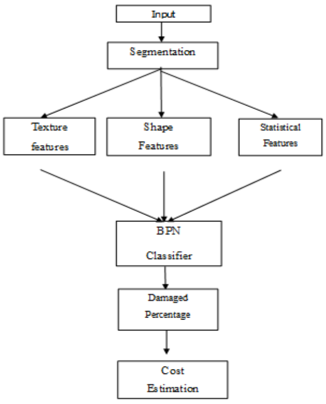


Figure 1. Flowchart of proposed work

Classification

In this work, a **Backpropagation Neural Network (BPN)[15]** is used to classify damage based on image-derived damage characteristics. The network architecture, activation functions, learning parameters, and loss function are carefully selected to ensure accurate, stable, and efficient classification.

The proposed BPN consists of multiple layers with carefully selected neuron counts to balance learning capacity and computational efficiency is shown n Table 2.

Table 2. Description of Network architecture

Layer	Description	Neurons
Input Layer	Damage feature representation	7
Hidden Layer 1	Non-linear feature learning	16
Hidden Layer 2	Pattern refinement	12
Hidden Layer 3	Severity discrimination	8
Output Layer	damage probability	1

The layered reduction in neurons enables progressive abstraction of damage features—from basic patterns to high-level severity discrimination—while minimizing overfitting. The **Rectified Linear Unit (ReLU)** activation function is employed in all hidden layers of the neural network. The outputs zero for negative inputs and retains positive values unchanged. Given the heterogeneous nature of damage features such as texture contrast, damage area, and statistical variations, ReLU allows the network to effectively learn discriminative patterns across multiple hidden layers. The **Sigmoid activation function** is applied in the output layer of the BPN. It maps the network output into a probability range between 0 and 1. In this work, a value of η=0.001 . The small learning rate allows the model to learn gradually and accurately from subtle variations in damage features. The **Adam optimizer** is employed for training the neural network:

The network is trained for Epochs=40

One epoch corresponds to a complete pass through the entire training dataset. The selected number of epochs ensures:

- Gradual learning and convergence
- Sufficient exposure to training samples

Loss function is calculated using Binary Cross-Entropy loss function to measure the prediction error.

Results and Discussion

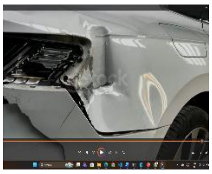
The proposed damage segmentation system was evaluated using multiple real-world case studies involving different damaged parts of a vehicle.

The performance of the segmentation model was assessed using standard evaluation metrics, namely **Accuracy,** Precision, Recall, Specificity, and F1-Score. These metrics provide a comprehensive understanding of the model's ability to correctly identify damaged regions while minimizing false detections and the output is given in Table 1.

Overall, the results demonstrate that the proposed damage segmentation approach achieves consistently high performance across various vehicle parts. The model performs particularly well on well-defined and non-reflective surfaces, while slightly lower accuracy is observed for transparent or reflective components. These results validate the robustness and practical applicability of the proposed segmentation system in real-world vehicle damage assessment scenarios.

Table 1. Damage Analysis

Input	**Case Study**	**Damage Segmentation (Output)**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**Specificity (%)**	**F1-Score (%)**
	Damage in the front bumper		91.8	89.6	92.3	93.1	90.9

	Damage in the back bumper of the car		90.4	88.1	91.5	92.0	89.8
	Damage in the left back side bumper		92.6	90.9	93.8	94.2	92.3
	Damage in the side door		89.7	87.4	90.1	91.8	88.7
	Damage in the mirror		93.2	91.8	94.5	95.0	93.1
	Damage in the head light		88.9	86.2	89.7	90.6	87.9
	Damage in the fog lamp		87.5	84.9	88.2	89.4	86.5
	Damage in the engine area		92.1	90.2	93.0	94.1	91.6

Conclusion

This work successfully presents an automated and reliable approach for vehicle damage detection and segmentation using image processing and neural network-based classification. The use of HSV colour model-based intensity segmentation effectively isolates damaged regions under varying illumination conditions. Meaningful statistical, shape, and texture features are extracted to accurately represent damage characteristics. A backpropagation neural network with ReLU and Sigmoid activation functions ensures efficient learning and robust binary classification of damage severity. Experimental results across multiple vehicle components demonstrate high accuracy, precision, recall, and F1-scores, validating the effectiveness of the proposed system. Overall, the method proves suitable for real-world vehicle damage assessment and insurance automation applications.

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