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Explainable AI-Based Vehicle Damage Assessment and Insurance Decision Support System

Jeenus C Jino[1], Devsankar V Babu[2], Anandhakrishnan[3], Ashish Krishna[4], Sudharma G[5], Anjitha P[6]
Student, Department of Computer Science and Engineering[1,2,3,4]
Assistant Professor, Department of Computer Science and Engineering[5,6]
Thejus Engineering College, Thrissur, Kerala, India
jeenusjino@gmail.com, devsankarvb@gmail.com,
anandhakrishnan9128@gmail.com, ashishkrishna925@gmail.com

Abstract: *Vehicle insurance claim processing still depends heavily on manual inspection by human surveyors, which is slow, subjective, and difficult to scale. Existing deep learning systems largely stop at detecting or segmenting damage, and offer no repair cost estimation, no explanation of their predictions, and no clear recommendation on the claim itself. This paper proposes an Explainable AI-based Vehicle Damage Assessment and Insurance Decision Support System that connects damage detection and segmentation, damage type classification, repair cost estimation, fraud risk assistance, and a claim recommendation with a confidence score into one pipeline. Explainability is built in through Grad-CAM, which highlights the image regions behind a prediction, and SHAP/LIME, which expose the factors that drive the cost and decision outputs. The system finally generates an explainable report for both customers and insurance staff. The design is based on a survey of recent work on vehicle damage assessment and is planned for implementation using YOLOv11, OpenCV, and the CarDD dataset together with a custom vehicle image dataset.*

Keywords: *Vehicle insurance*

I. INTRODUCTION

Motor insurance claims require an assessment of how badly a vehicle is damaged, what the repair will cost, and whether the claim should be approved. In most settings this is done by a surveyor who reviews photographs or inspects the vehicle in person, which makes claim settlement time-consuming and dependent on individual judgement. Advances in computer vision, supported by public resources such as the CarDD dataset [1], have made it possible to detect and segment damaged regions automatically.

However, a detector alone does not settle a claim. A deployed system must also estimate repair cost, advise on repair versus replacement, and justify its output to the customer and the insurer. Deep neural networks are black boxes, and a claim decision that cannot be explained is unlikely to be trusted. Explainable AI (XAI) methods such as Grad-CAM [2], SHAP [3], and LIME [4] can address this gap by showing which image regions and which factors influenced a result. Modern one-stage detectors in the YOLO family [5] provide the speed needed for a practical claims workflow.

Existing vehicle insurance claim systems rely either on manual inspection or on AI models that only detect damage. These systems lack transparency, repair cost estimation, and clear decision support, which makes claim processing slower and less reliable. Manual inspections are time-consuming, and the predictions of AI models come without any explanation. A high dependence on human surveyors reduces efficiency, support for repair or replacement decisions is limited, and trust in AI-based claim processing remains low.

This work presents an Explainable AI-based Vehicle Damage Assessment and Insurance Decision Support System. The main objective is to detect vehicle damage accurately, estimate repair costs, and provide transparent insurance claim recommendations. The proposed system provides vehicle damage detection and segmentation, damage type classification, repair cost estimation, explainable AI using Grad-CAM and SHAP/LIME, and insurance decision

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support with report generation. The scope covers vehicle damage assessment and claim decision-making, with future potential for real-time analysis, fraud detection, and smart insurance applications.

The remainder of this paper is organized as follows. Section II reviews related work, Section III presents the design of the proposed system, and Section IV concludes the paper and outlines future work.

II. LITERATURE SURVEY

Research on automated vehicle damage assessment can be grouped into three directions: detection and segmentation, cost estimation and claim automation, and explainable or multimodal approaches. Each surveyed work below is introduced by its first author, followed by its topic, and Table I summarises them in the same order.

A. Damage Detection and Segmentation

Wang et al. [1] addressed the lack of large, high-quality datasets by introducing CarDD, a high-resolution collection annotated for detection and segmentation. Sarath P et al. [6] used Mask R-CNN together with transfer learning and ensemble learning to identify fine-grained vehicle damage. Katayev et al. [7] proposed DamageNet, which combines dilated convolution, a feature pyramid network, and Mask R-CNN to segment different damage patterns more accurately. Moon et al. [8] designed an encoder–decoder network for the irregular shapes and varied scales of damage masks. Dalal et al. [9] proposed a severity-aware YOLOv8 instance segmentation framework tuned with Harris Hawks optimization to separate severity levels. Hasan et al. [10] reviewed AI-based vehicle damage detection across classification, detection, segmentation, and salient-object detection, and pointed out the remaining research gaps. Pérez-Zarate et al. [11] compared Mask R-CNN, Faster R-CNN, and one-stage detectors in an insurance-company case study, where false positives and small or irregular damage were the main difficulties.

B. Cost Estimation and Claim Automation

Jayaseeli et al. [12] applied Mask R-CNN to detect damaged regions and estimate severity for insurance and repair applications. Qaddour and Siddiqa [13] improved Mask R-CNN with transfer learning and deployed it as a web-based damage estimator. Kannan et al. [14] proposed CDA-Net with CDA-YOLOv5, which uses vehicle make and model, damaged parts, damage type, and severity. Fernando et al. [15] combined computer vision with natural language processing to identify make and model, damaged components, severity, and repair estimates. Atanasious et al. [16] built an Insurtech platform that applies object detection and damage estimation to automate claim management. Aithal et al. [17] estimated repair cost directly with deep learning, and Chethan et al. [18] used YOLOv5 to detect and categorise scratches, dents, cracks, and broken components. Zhang et al. [19] presented a video-based damage assessment system that detects and segments damage and returns damaged components and repair costs, while Anitha et al. [20] built a multi-task pipeline covering image quality, part segmentation, damage detection, severity classification, and cost estimation. Ouf et al. [21] proposed a classification-based framework for damage categorisation and repair-cost estimation, and Rampa and Vignesh [22] presented DamageDetect, an AI-powered assessment and repair cost estimator.

C. Explainable and Multimodal Approaches

Cole and Govil [23] investigated XAI techniques to improve the interpretability of vehicle damage models, since the black-box nature of deep learning reduces transparency and user trust. Phuengpanyaloet et al. [24] combined visual damage assessment with structured text reporting in a multimodal framework. Miao et al. [25] proposed MMLM-CA, which couples visual damage information with insurance policy documents so that a multimodal large language model can support automated claim adjudication.

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TABLE I: SUMMARY OF SURVEYED WORK

Ref.	First Author	Topic	Problem Tackled	Solution Proposed
[1]	Wang et al.	Car damage dataset (CarDD)	Lack of large, high-quality vehicle damage datasets	CarDD dataset with high-resolution images and annotations for detection and segmentation
[6]	Sarath P et al.	Car damage assessment with Mask R-CNN	Identifying fine-grained vehicle damage automatically	Mask R-CNN with transfer learning and ensemble learning
[7]	Katayev et al.	Car damage segmentation (DamageNet)	Accurate segmentation of different damage patterns	Dilated convolution, FPN, and Mask R-CNN
[8]	Moon et al.	Vehicle damage segmentation	Irregular shapes and multiple scales of damage	Encoder–decoder network for multi-scale jagged masks
[9]	Dalal et al.	Severity-aware YOLOv8 segmentation	Distinguishing severity levels and irregular damage	Harris Hawks-tuned YOLOv8 instance segmentation
[10]	Hasan et al.	Systematic review of AI damage detection	Fragmented research on automated damage detection	Review of classification, detection, segmentation, and salient-object detection
[11]	Pérez-Zarate et al.	Insurance company use case	False positives; small or irregular damage	Comparison of Mask R-CNN, Faster R-CNN, and one-stage detectors
[12]	Jayaseeli et al.	Damage detection and cost evaluation	Manual evaluation of exterior damage	Mask R-CNN for damaged regions and severity estimation
[13]	Qaddour and Siddiqa	Automatic damaged vehicle estimator	Slow, expensive claim assessment	Improved Mask R-CNN with transfer learning and a web-based system
[14]	Kannan et al.	CDA-Net car damage analysis	Need for automated damage and cost assessment	CDA-YOLOv5 using make/model, parts, damage type, and severity
[15]	Fernando et al.	Claims processing with CV and NLP	Manual, time-consuming claim processing	Computer vision with NLP for make/model, components, severity, and estimates
[16]	Atanasious et al.	Insurtech claim management platform	Inefficient image-based claim assessment	Object detection and damage estimation platform
[17]	Aithal et al.	Damage detection and repair cost estimation	Manual inspection and repair-cost estimation	Deep learning-based detection and cost estimation
[18]	Chethan et al.	Damage detection and cost estimator	Slow manual damage assessment and classification	YOLOv5 detection and categorisation of scratches, dents, cracks, and broken parts
[19]	Zhang et al.	Video-based car damage assessment system	Slow on-site inspection by insurance inspectors	Video detection and segmentation returning damaged components and repair costs
[20]	Anitha et al.	DNN-based damage assessment	Delays, cost, and subjectivity in claims	Multi-task pipeline: image quality, parts, damage, severity, and cost
[21]	Ouf et al.	Vehicle damage classification	Manual assessment needs time, effort, and resources	Damage classification and repair-cost

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				estimation framework
[22]	Rampa and Vignesh	DamageDetect cost estimator	Need for automated assessment and cost estimation	AI-powered assessment and repair cost estimator
[23]	Cole and Govil	Explainable AI for damage detection	Black-box models reduce transparency and trust	Study of XAI techniques for vehicle damage models
[24]	Phuengpanyaloet et al.	Multimodal-multitask assessment	Separate visual and textual reporting systems	Multimodal vision-language framework with structured reporting
[25]	Miao et al.	MMLM-CA claim adjudication	Combining visual damage with policy information	Multimodal LLM for claim adjudication

III. DESIGN

A. Existing System and Its Limitations

In the existing workflow, the user uploads vehicle images and an AI model detects and segments the damaged areas. The detected damage is classified into types such as dent, scratch, crack, broken headlight, bumper damage, and windshield damage. A surveyor then reviews the images and estimates the damage and repair cost manually, and the claim decision (approve, reject, or request additional inspection) is taken on the basis of manual evaluation and expert judgement. The limitations of this arrangement are that the process is time-consuming, it offers no explainability, the AI provides no accurate cost estimation, it depends heavily on human experts, and decisions can be inconsistent.

B. Proposed System Overview

The proposed system extends the existing pipeline so that cost estimation, explanation, fraud risk checking, and the decision itself are produced together with the damage analysis. Fig. 1 shows the overall architecture, and each stage is described below.

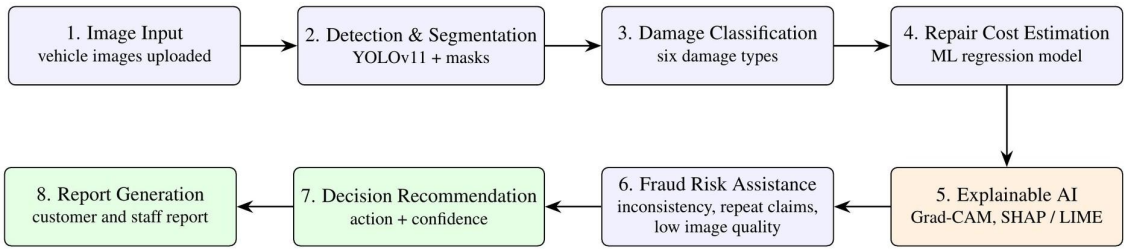


Fig. 1 Architecture of the proposed Explainable AI-based vehicle damage assessment and insurance decision support system.

C. Image Input

The user uploads one or more photographs of the damaged vehicle. Images are resized and normalised before being passed to the detection stage, and a basic image-quality check supports the later fraud-risk stage.

D. Damage Detection and Segmentation

A YOLOv11-based model detects damaged regions and produces instance masks, in the same spirit as earlier Mask R-CNN and YOLO-based work [6], [14], [18], [26]. The mask gives the pixel extent of each damaged area, which is needed for severity and cost estimation. The CarDD dataset [1] and a custom vehicle image dataset are planned for training.

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E. Damage Classification

Each detected region is assigned one of six damage types: dent, scratch, crack, broken headlight, bumper damage, or windshield damage.

F. Repair Cost Estimation

A machine learning model estimates the repair cost from the outputs of the previous stages. For a damaged region d with mask Md in an image of size H × W, the area ratio is

$$r_d = \frac{|M_d|}{HW} \tag{1}$$

and the feature vector xd combines the damage type, the area ratio rd, the estimated severity, and the affected vehicle part. The estimated cost of the claim is the sum of the per-region estimates,

$$\hat{C} = \sum_d f_\theta(\mathbf{x}_d) \tag{2}$$

where fθ is the regression model. This estimate also supports the choice between repair and replacement.

G. Explainable AI

Two kinds of explanation are provided. Grad-CAM [2] highlights the image regions that influenced a prediction. For class c and feature map Ak of the last convolutional layer, the channel weights and localisation map are

$$\alpha_k^c = \frac{1}{Z}\sum_i\sum_j \frac{\partial y^c}{\partial A_{ij}^k}, \quad L_{\text{Grad-CAM}}^c = \text{ReLU}\left(\sum_k \alpha_k^c A^k\right) \tag{3}$$

SHAP [3] and LIME [4] explain the tabular side of the system, that is, which factors drive the cost estimate and the decision. In SHAP, the output is written as an additive attribution over M features,

$$g(\mathbf{z}') = \phi_0 + \sum_{i=1}^{M} \phi_i z_i' \tag{4}$$

where φi is the contribution of feature i and φ0 is the base value.

H. Fraud Risk Assistance

This stage flags claims that need a closer look by checking for inconsistencies, repeated claims, and low image quality. It assists the reviewer and does not make an accusation by itself.

I. Decision Recommendation

The system recommends one of the following actions together with a confidence value: Approve Claim, Request Additional Inspection, Repair Preferred, or Replacement Preferred. A confidence of 92% is an example of the form this output takes. The recommendation is shown next to its explanation so that a human reviewer can accept or override it.

J. Report Generation

Finally, an explainable report is generated for the customer and for insurance staff. It combines the detected damage, the damage types, the estimated cost, the Grad-CAM and SHAP explanations, the fraud-risk indicators, and the recommended decision.

K. Planned Evaluation

The system will be assessed stage by stage. Detection and segmentation can be measured with mean average precision and intersection over union, classification with accuracy and F1-score, cost estimation with mean absolute error against reference repair costs, and the final recommendation against decisions taken by human surveyors. Grad-CAM maps will be inspected qualitatively against the annotated damage regions.

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L. System Specifications

The hardware and software environment planned for the implementation is listed in Table II.

TABLE II: PLANNED HARDWARE AND SOFTWARE SPECIFICATIONS

Component	Specification
Processor	Intel Core i5 / AMD Ryzen 5 or higher
Memory	8 GB RAM (16 GB recommended)
Storage	256 GB SSD or higher
GPU	NVIDIA GTX 1650 / RTX 3050
Operating system	Windows 11 / Ubuntu
Language	Python 3.11+
Frontend	React.js, HTML, CSS, JavaScript
Backend	FastAPI / Flask
Database	PostgreSQL / MySQL
AI frameworks	TensorFlow / PyTorch, YOLOv11, OpenCV
XAI tools	Grad-CAM, SHAP, LIME
Datasets	CarDD, vehicle damage images, custom vehicle image dataset

M. Expected Advantages

Compared with the existing detect-then-review workflow, the proposed system is expected to deliver clear benefits. Faster, automated claim processing is expected, together with transparent AI decisions through explainable AI and accurate damage detection and repair cost estimation. The system also supports repair and replacement decisions, reduces manual effort, and improves customer trust. These benefits are design goals of the framework. Their size will be established by the planned evaluation described above.

IV. CONCLUSION AND FUTURE WORK

This paper proposed an Explainable AI-based vehicle damage assessment and insurance decision support system that integrates damage detection, cost estimation, and decision support in one pipeline, with Grad-CAM and SHAP/LIME explanations at its core. By making each prediction explainable, the system aims to improve transparency, efficiency, and claim-processing accuracy, and to enhance customer trust while supporting insurance professionals. Future work will implement and evaluate the full pipeline on CarDD and the custom dataset, and extend it with real-time analysis and further advanced AI features such as stronger fraud detection and smart insurance applications.

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