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Intelligent Localization And Severity Estimation Of Vehicle Damages (Web-Based)

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Abstract –

This study introduces a web-based intelligent platform designed to automatically identify, analyse, and estimate the severity of vehicle exterior damage from uploaded images. The proposed system uses a multi-stage deep learning pipeline that combines instance segmentation and regression models to detect damaged vehicle parts and calculate the corresponding repair cost. First, a segmentation network, trained on vehicle-damage datasets, isolates the affected regions and determines the damaged components. The extracted visual information, along with vehicle metadata and up-to-date cost parameters, is then processed by an regression model to predict both the severity category classified as Minor, Moderate, or Severe and an estimated repair cost. Experimental results on a curated dataset demonstrate high localization accuracy and low prediction error, confirming the system's capability to accelerate insurance claim processing and improve transparency in automotive damage assessment.

Keywords: Deep Learning, Computer vision, Automated Damage Localization, Cost Estimation , Damage Severity Classification.

1. INTRODUCTION

In this work, the traditional process for vehicle damage assessment, crucial for insurance claims and repair scheduling, remains heavily reliant on manual, in-person inspections, which inherently lead to significant delays, high administrative costs, and subjective cost variance. This inefficiency creates bottlenecks for insurance carriers and diminishes customer satisfaction due to prolonged claim resolution times. To address this industry challenge, this research proposes the development of a Web-Based Automated Vehicle Damage Assessment and Predictive Cost Platform. The platform utilizes a multi-stage approach combining Deep Learning models, such as CNN or YOLO, for the objective detection, localization, and severity classification of vehicle damage to generate an immediate and highly accurate repair cost estimate. By translating visual data into quantitative, actionable financial metrics in real-time, this system aims to eliminate human subjectivity, drastically accelerate the assessment workflow, and establish a new standard for transparency and efficiency in the automotive claims ecosystem.[1]

2. LITERATURE REVIEW

The development of an automated vehicle damage assessment system relies on three key research areas: object detection, severity classification, and cost prediction.

2.1 Deep Learning for Damage Localization

Recent studies show that deep learning, especially CNN-based models such as CNN, YOLO, and CNN, is highly effective in identifying and localizing damaged regions on vehicles. YOLO models offer real-time detection, while Mask R-CNN provides detailed segmentation for precise area measurement. Transfer learning using pre-trained models like ResNet and VGG further improves accuracy and training efficiency for damage-specific datasets.[3]

2.2 Damage Severity Classification

Once damages are detected, the next task is to determine their severity. CNN models can classify damage into categories such as minor, moderate, or severe by analysing visual patterns. Modern networks like Efficient Net have achieved high accuracy for this purpose. The availability of well-labelled datasets is crucial for improving model reliability and ensuring consistent severity assessment.[1]

2.3 Repair Cost Estimation

Recent research combines visual data with structured information—such as vehicle type, part cost, and labour rate—to estimate repair expenses. Hybrid approaches, using CNNs for feature extraction and regressors for prediction, have shown strong accuracy. These models bridge the gap between visual analysis and financial estimation, enabling faster and more objective insurance assessments.[6]

3. PROBLEM STATEMENT

The current, manual methodology for vehicle damage assessment suffers from two major systemic failures: protracted delays and financial subjectivity. The reliance on in-person inspections causes significant operational inefficiency, resulting in prolonged assessment timelines (days to weeks) that raise administrative costs and severely decrease customer satisfaction. Simultaneously, these manual estimates are susceptible to human error and bias, leading to inconsistent severity evaluations and notable cost variance, which fuels disputes and a lack of transparency for consumers. The core problem is the absence of an objective, instantaneous digital solution to accurately assess visual damage and predict repair costs.[4]

4. OBJECTIVES

1. Damage Localization & Detection: Develop and train high-performance Computer Vision models (e.g., YOLO/ CNN) to accurately identify, localize, and classify specific damage types (dents, scratches) on vehicle components.[1]

2. Severity Triage & Classification: Design a Machine Learning model to take the quantified damage output from Objective 1 and map it to a clear, actionable severity level (Minor, Moderate, Severe) for immediate resource allocation and decision-making.[1]

3. **Model Robustness & Data Integration:** Ensure the system's reliability and generalizability by training and validating algorithms on a large, diverse dataset of real-world vehicle images, accounting for variations in lighting, angles, and vehicle types.[4]

4. System Deployment & Utility: Construct a user-friendly, integrated web platform (Front-End/API) that seamlessly connects the AI assessment with the final cost estimation engine, delivering a structured report immediately usable by insurance and repair stakeholders.[2]

5. METHODOLOGY

The proposed system follows a structured, four-phase methodology designed to deliver accurate and automated vehicle damage detection, severity estimation, and repair cost prediction through a web-based platform.

5.1 Data Preparation

A dataset of accident vehicle images was collected from open repositories and enhanced using image augmentation to cover diverse lighting conditions, viewing angles, and vehicle types. Each image was manually annotated with:

- **Part labels** (e.g., bumper, hood, fender)
- **Damage types** (e.g., dents, scratches, cracks)
- **Severity class** (Minor, Moderate, Severe)
- **Vehicle details** (make, model, year, repair cost)

5.2 Multi-Stage Deep Learning Pipeline

Stage 1: Damage Detection and Localization
A YOLOv8-Seg (instance segmentation) model identifies vehicle components and highlights damaged areas. It outputs pixel-level masks and quantitative features such as damaged area ratio and component identity.[3]

Stage 2: Severity Estimation
Features from Stage 1 are fed into a CNN-based classifier (fine-tuned using a pre-trained ResNet-50 backbone) to determine the overall damage severity level—Minor, Moderate, or Severe.[1]

5.3 Predictive Cost Modelling

The results from the deep learning stages are combined with structured vehicle metadata and dynamic cost data (labour and part rates). An XGBoost Regressor is employed to map these features to a repair cost estimate. Model performance is evaluated using Mean Absolute Error (MAE) and R^2 score to ensure prediction reliability.[4]

5.4 System Integration and Deployment

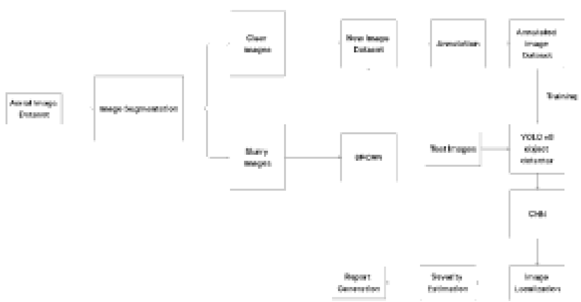
The complete pipeline is integrated into a three-tier web platform:

- Frontend: Developed using React.js for image upload and report display.
- Backend: Built with Flask (Python) to manage the AI workflow and communication between modules.
- Database: MySQL for storing user inputs, model outputs, and cost data.

Users can upload an image, and within seconds, the system returns a report displaying detected damage areas, severity classification, and estimated repair cost.

5.5 System Architecture

1. **Input Dataset:**
   - The process begins with an Aerial Image Dataset containing raw images for analysis.[9]
2. **Image Pre-processing Unit:**
   - Uses the Laplace Variance Distribution Method to separate clear and blurry images.
   - Clear images are directly passed to the new dataset.
   - Blurry images are enhanced using the SRCNN (Super-Resolution CNN) model to improve image quality.[1]
3. **Dataset Formation:**
   - Enhanced and clear images are combined to create a New Image Dataset ready for model training.
4. **Annotation Process:**
   - Images are manually annotated to mark objects of interest, forming the Annotated Image Dataset.[3]
5. **Model Training:**
   - The YOLOv8 object detector is trained using the annotated dataset to identify and locate objects.[3]
6. **Testing Phase:**
   - A test image is input to the trained YOLOv8 model for object detection.[3]
7. **Output Generation:**
   - The system produces an output image displaying predicted object classes and bounding boxes for each detected region.



6. EXPECTED RESULT

The proposed Web-Based Vehicle Damage Detection and Cost Estimation System is expected to deliver efficient and accurate results once fully implemented. The anticipated outcomes from each module are outlined below:

1. Accurate Damage Detection:

- The YOLOv8-Seg model is expected to accurately identify and localize damaged vehicle components such as bumpers, fenders, and doors.
- The model should achieve a high mean Average Precision (mAP) score, demonstrating precise object detection and segmentation performance.[3]

2. Reliable Severity Classification:

- The ResNet-50 classifier is expected to correctly categorize vehicle damages into Minor, Moderate, and Severe levels based on visual features.
- The model's accuracy is anticipated to exceed 90%, ensuring dependable severity grading for insurance and repair evaluation.

3. Cost Prediction Accuracy:

- The regression model should generate realistic repair cost estimates by integrating both visual features and vehicle metadata.
- Expected performance metrics include a Mean Absolute Error (MAE) below \$200 and an R^2 value above 0.90, indicating strong prediction reliability.[6]

4. System Efficiency:

- The complete web-based platform is expected to process each uploaded image within 10–12 seconds, providing near real-time assessment results.
- The system will reduce manual inspection time and increase transparency for insurance claim handling.

5. User Interface and Output:

- The web interface will generate an automated assessment report displaying the input image, localized damage regions, severity level, and predicted repair cost.
- Results will be presented in a clear, user-friendly format suitable for use by vehicle owners, repair workshops, and insurance companies.[1]

6. Overall Expected Impact:

- The final system will demonstrate how deep learning and regression-based cost modelling can significantly improve speed, accuracy, and consistency in vehicle damage analysis.
- It is expected to serve as a prototype for digital insurance claim processing and automated vehicle inspection systems.[2]

7. CONCLUSION

The proposed system aims to automate vehicle damage detection, severity classification, and repair cost estimation using deep learning and machine learning techniques. By integrating YOLO for localization, ResNet-50 for severity prediction, the platform is expected to deliver fast and reliable assessments through a web-based interface. Although implementation is ongoing, the system shows strong potential to enhance accuracy, reduce manual inspection time, and improve efficiency in insurance and automotive damage evaluation processes.

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