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Automated Car Damage Recognition and Cost Estimation using CNN

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ABSTRACT: This project focuses on improving vehicle damage assessment efficiency and user experience through the development of an AI-powered web application. The system is designed to streamline workflows for users by automating tasks such as damage detection, severity classification, and repair cost estimation. It leverages Convolutional Neural Networks (CNN) and Detectron2 to accurately identify and segment damaged vehicle parts, while providing users with detailed results, including estimated repair costs derived from a predefined dataset. The application further enhances efficiency by eliminating manual inspections, reducing processing time, and improving accuracy. Built with Flask for backend development, it ensures seamless data handling and scalability. Ultimately, the integration of advanced AI and data analytics improves decision-making and operational outcomes, offering a reliable solution for insurance automation, automobile services, and fleet management.

KEYWORDS: Vehicle Damage Detection, Convolutional Neural Networks (CNN), Detectron2, Repair Cost Estimation, Image Preprocessing, Flask Framework, Insurance Automation.

I. INTRODUCTION

This project aims to develop an advanced web application designed to enhance vehicle damage assessment and improve operational efficiency. The system includes specialized tools for users, enabling them to upload vehicle images and receive precise damage detection, severity classification, and repair cost estimates. Leveraging Convolutional Neural Networks (CNN) and Detectron2, the application transforms complex damage data into clear, actionable insights. It also streamlines the resolution of damage assessment tasks, ensuring accurate and prompt results that enhance user satisfaction and operational efficiency. Built with Django for backend development and MySQL for database management, the system integrates advanced AI and analytics to improve decision-making and drive better outcomes. Ultimately, it offers a reliable solution for insurance automation, automobile services, and fleet management.

II. LITERATURE SURVEY

[1] Efficient Feature Selection and Classification for Vehicle Detection

X. Wen, L. Shao, W. Fang, and Y. Xue, "Efficient Feature Selection and Classification for Vehicle Detection", IEEE Trans. Circuits Syst. Video Technol., 2015.

The paper presents an efficient approach for feature selection and classification in vehicle detection, addressing the challenges of high-dimensional data processing in real-time traffic systems. The authors develop an optimized framework that enhances detection accuracy while minimizing computational costs. By integrating advanced machine learning techniques with intelligent feature selection, the method improves performance in complex urban scenarios. The proposed solution effectively balances precision and efficiency, making it suitable for intelligent transportation and automated surveillance. Experimental results demonstrate robust vehicle detection, showcasing the method's ability to handle dynamic environments with varying lighting and occlusion conditions, ultimately contributing to more reliable and scalable traffic monitoring systems.

[2] Deep Learning Using Linear Support Vector Machines

Yichuan Tang, "Deep Learning Using Linear Support Vector Machines," ICML Workshop on Representation Learning, 2013.

This paper explores the use of linear Support Vector Machines (SVMs) as the output layer in deep learning models, replacing traditional softmax classifiers. The author demonstrates that combining deep neural networks with linear SVMs can improve classification performance while maintaining computational efficiency. The approach leverages the margin-maximizing properties of SVMs to enhance feature learning in deep architectures. Experimental results show that this hybrid method achieves competitive accuracy on benchmark datasets, suggesting that SVM-based deep learning offers a promising alternative to conventional deep classification models. The technique is particularly effective in scenarios where discriminative feature separation is critical for performance.

[3] KNN Normalized Optimization and Platform Tuning Based on Hadoop

C. Ma and Y. Chi, "KNN Normalized Optimization and Platform Tuning Based on Hadoop," in IEEE Access, vol. 10, pp. 81406-81433, 01 August 2022.

This paper introduces an optimized K-Nearest Neighbors (KNN) algorithm enhanced with normalization techniques and fine-tuned for Hadoop-based big data platforms. The authors address scalability and efficiency challenges in traditional KNN by proposing a distributed computing framework that improves classification accuracy while reducing computational overhead. Their method leverages Hadoop's parallel processing capabilities to handle large-scale datasets effectively. Experimental results demonstrate significant performance gains in speed and precision compared to conventional KNN implementations. The optimized approach proves particularly useful for real-world applications requiring high-dimensional data analysis, offering a scalable solution for machine learning tasks in big data environments.

[4] Rapid Object Detection Using a Boosted Cascade of Simple Features

P.A. Viola and M.J. Jones, "Rapid Object Detection Using a Boosted Cascade of Simple Features," CVPR, 2001.

This paper presents a fast and efficient object detection framework using a boosted cascade of Haar-like features. The authors introduce a machine learning approach that combines AdaBoost for feature selection with a cascaded classifier structure to rapidly discard non-object regions. Their method achieves real-time detection speeds by focusing computation on promising image areas while maintaining high accuracy. The algorithm is particularly effective for face detection, demonstrating robustness to variations in lighting, expression, and orientation. The cascade architecture significantly reduces computation time compared to sliding window approaches, making it practical for real-world applications. This work became foundational for many subsequent real-time computer vision systems.

III. METHODOLOGY

The proposed system is designed to automate and optimize the process of vehicle damage assessment using computer vision and deep learning techniques. The methodology is divided into several interconnected modules that work together to capture input, analyze damage, predict severity, and present the results to the user. The system employs **Convolutional Neural Networks (CNN)** and **Detectron2** to ensure accurate detection and segmentation of damaged vehicle components.

3.1 System Overview

The Intelligent Vehicle Damage Detection System is a web-based application designed to automate the process of vehicle damage analysis using artificial intelligence. The system leverages deep learning models—primarily Convolutional Neural Networks (CNN) and Detectron2—to detect damaged components in vehicle images, assess the severity of damage, and estimate repair costs based on a predefined dataset.

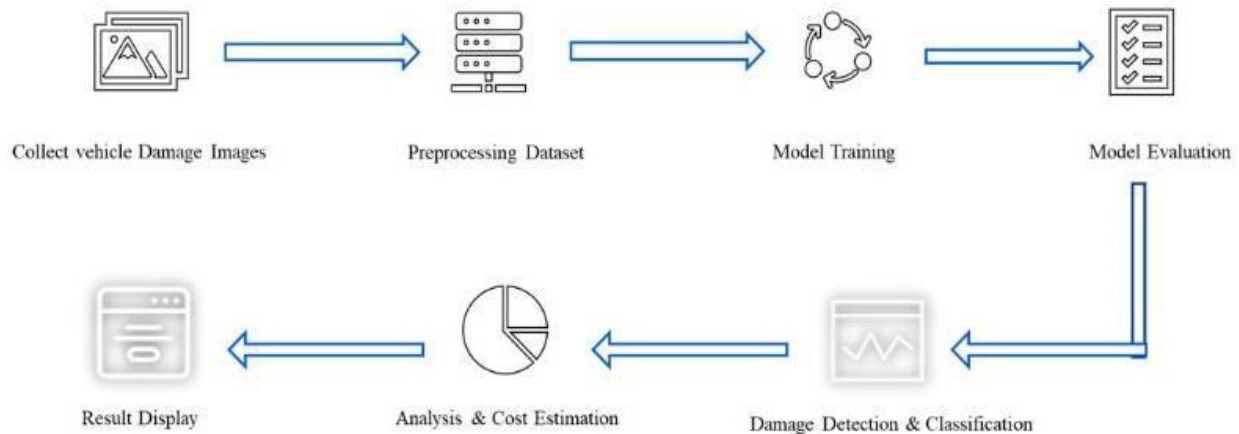


Figure -1: Architecture of the System

The architecture is modular and includes the following major components:

3.1.1 Image Upload and Preprocessing

This module initiates the process by capturing or uploading images. It ensures images are standardized through preprocessing steps like resizing, noise reduction, and normalization to improve analysis accuracy.

3.1.2 Damage Detection and Segmentation

Using Detectron2, the system identifies and segments damaged areas on vehicle components such as bumpers, fenders, doors, and hoods. CNNs are used to learn complex visual patterns that distinguish damaged from undamaged parts.

3.1.3 Severity Classification and Cost Estimation

Once the damaged regions are identified, they are analyzed for severity. The system classifies the damage as Minor, Moderate, or Severe based on predefined visual thresholds. It then estimates the cost using a mapped dataset that associates damage types and locations with average repair costs

3.1.4 Result Display and Reporting

The output is visualized through an intuitive user interface that presents a summary of findings—highlighted damage regions, severity level, and cost estimate. This empowers users to make informed decisions quickly and confidently.

3.2 Workflow Overview

The proposed AI-based vehicle damage detection system follows a structured and modular workflow to ensure accurate assessment, real-time prediction, and user-friendly interaction. The overall process is divided into several key stages:

1. **Image Upload:** The user begins by uploading an image of the damaged vehicle through a web interface. The system validates the image format and quality to ensure it meets the criteria for further processing.

2. **Image Preprocessing:** Once uploaded, the image undergoes preprocessing tasks such as resizing, normalization, contrast enhancement, and noise reduction. This step prepares the image for efficient and accurate analysis by the detection model.
3. **Damage Detection using CNN and Detectron2:** The preprocessed image is passed through a Convolutional Neural Network (CNN) integrated with Detectron2. This model detects and segments the damaged regions of vehicle components (e.g., doors, bumpers, fenders) and highlights them with bounding boxes.
4. **Severity Classification:** The system analyzes the identified damaged regions and classifies them into categories: Minor, Moderate, or Severe, based on visual patterns and feature extraction. This classification helps prioritize repair actions.
5. **Repair Cost Estimation:** Using a predefined dataset that maps vehicle parts to estimated repair costs, the system calculates the probable repair cost. This adds transparency and helps users make informed decisions.
6. **Result Visualization:** The system compiles the results and presents them to the user through an intuitive user interface. This comprehensive output ensures users receive actionable insights quickly and efficiently.

IV. SYSTEM IMPLEMENTATION

4.1 List of Modules

- Image Upload & Preprocessing Module
- Vehicle Damage Detection Module
- Damage Level Prediction Module
- Result Display Module

4.1.1 Image Upload & Preprocessing Module

The Image Upload and Preprocessing Module serves as the entry point of the system. Users can upload images of damaged vehicles through the web interface. Once uploaded, the image is validated and processed to ensure compatibility and quality. Preprocessing involves resizing the image to a fixed input dimension, normalizing pixel values for consistent lighting, and applying noise reduction techniques to remove unwanted artifacts. These steps are essential to enhance the image quality, allowing the deep learning models to extract accurate features during analysis.

4.1.2 Vehicle Damage Detection Module

The Vehicle Damage Detection Module utilizes a pre-trained Convolutional Neural Network (CNN) integrated with the Detectron2 framework to identify damaged vehicle parts. This module processes the preprocessed image to detect components such as doors, bumpers, and fenders. Using bounding boxes and segmentation masks, it highlights the damaged areas with precision. The CNN model is trained on a dataset of annotated vehicle images, allowing it to learn visual patterns associated with various types of damage. This module performs the core task of localizing and identifying vehicle damage, forming the foundation for subsequent analysis.

4.1.3 Damage Level Prediction Module

Once the damage is detected, the image is passed to the Damage Level Prediction Module, which evaluates the severity of the identified damage. The system analyzes the size, shape, and texture of the affected regions to classify them as Minor, Moderate, or Severe. This classification is based on features extracted from the CNN and compared against patterns in the training dataset. In addition to classification, the module performs repair cost estimation. A predefined dataset maps vehicle parts to standard repair costs, and the system uses severity levels as multipliers to provide an accurate cost range. This dual output—severity and cost—adds significant value for users in decision-making processes.

4.1.4 Result Display Module

The final component is the Result Display Module, which compiles the findings and presents them through a user-friendly web interface. It displays the original image with highlighted damage regions, labeled with severity levels and corresponding cost estimates. The interface is designed to be clean and intuitive, ensuring that users can easily interpret

the results even without technical expertise. It also allows for exporting or saving the assessment report for future reference or submission to insurance agencies or repair shops.

V. RESULT AND DISCUSSION

The final processed image, along with detected damages, is displayed to the user. The module provides a summary of the detected parts, their damage levels, and the predicted repair cost range. Damage classifications are clearly shown, enabling users to make informed decisions about repairs. This module ensures that the results are presented in an easily interpretable and actionable format.

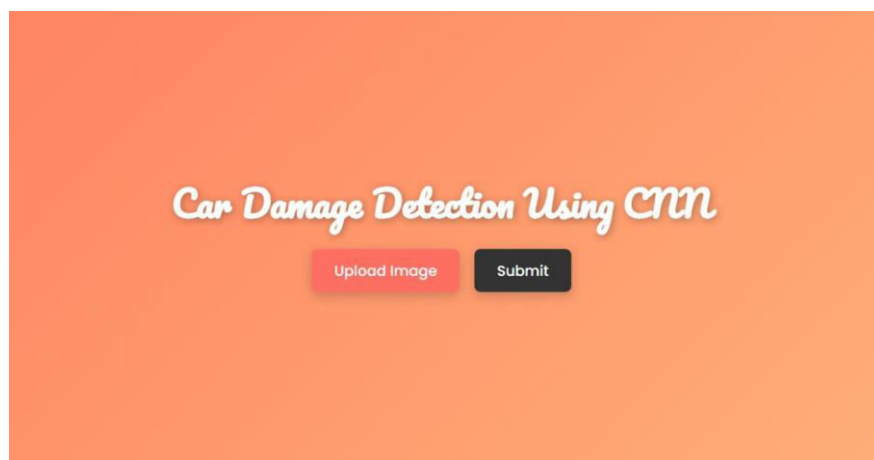


Figure 1: Image Upload and Preprocessing

Users upload an image of the damaged vehicle, which is then processed by the system. First, the system validates the image format and quality to ensure it meets the required standards. Next, image preprocessing techniques, such as resizing and normalization, are applied to standardize the input. Additional steps like noise reduction and contrast enhancement are performed to improve the clarity of the image. Finally, the processed image is sent to the damage detection model for analysis and further evaluation.

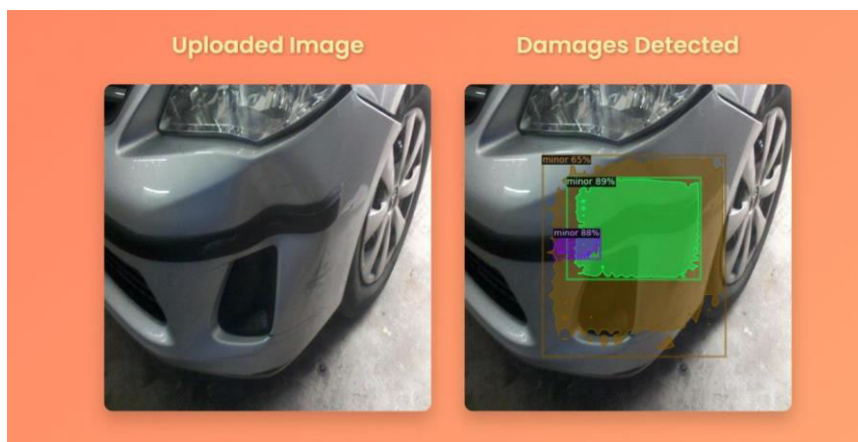


Figure 2: Vehicle Damage Detection

The system uses Detectron2, powered by a trained CNN model, to detect and segment damaged parts of the vehicle. It identifies key components such as bumpers, doors, and hoods, analyzing them for any signs of damage. Bounding boxes are generated to highlight the affected areas, and the results are stored for further classification. The

damage is then categorized based on the specific part involved and visualized for the user's reference. This end-to-end process includes image analysis, damage detection, classification, and result visualization, ensuring a comprehensive assessment of the vehicle's condition.

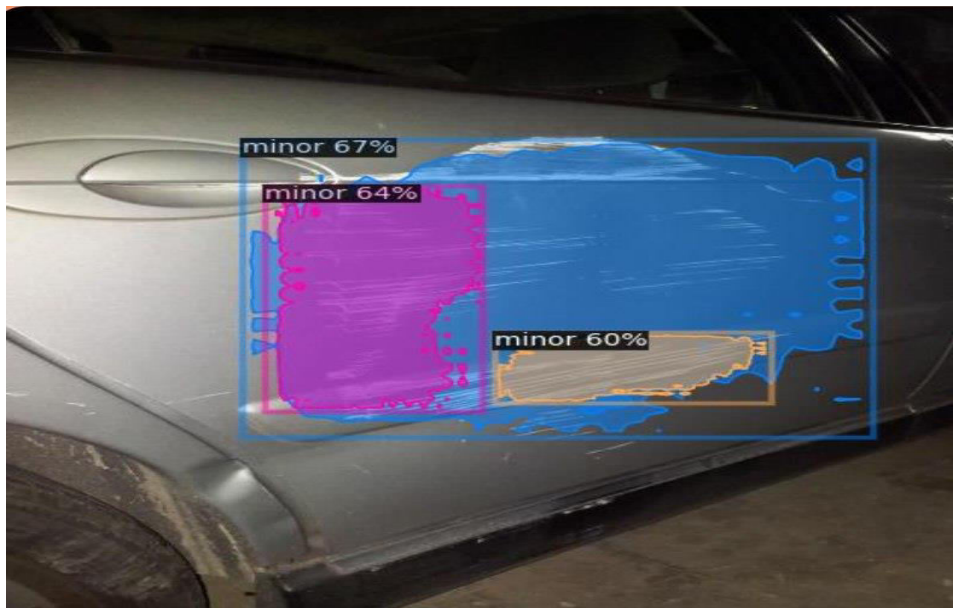


Figure -3: Damage Level Detection

The model assesses the severity of the detected damage, classifying it as Minor, Moderate, or Severe based on extracted image features. This prediction is made using training data from a diverse range of vehicle damages, ensuring accurate and reliable results. Additionally, the system estimates the repair cost by referencing a predefined dataset where each vehicle part has a specific cost associated with its damage classification. Once the damage level and repair cost are determined, the results are forwarded to the display module for user review. This step ensures users receive a clear understanding of the damage extent and potential repair expenses.

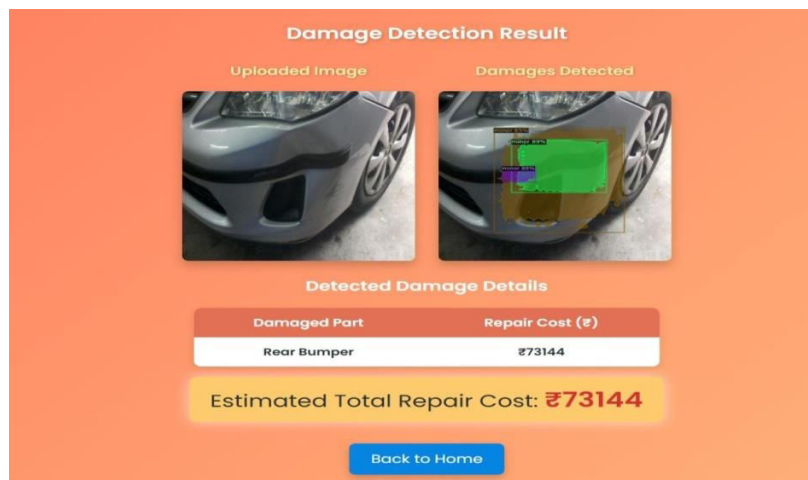


Figure -4: Result Display

The system presents the final processed image with highlighted damage areas, allowing users to visually assess the affected parts. Alongside the image, the damage classification such as Minor, Moderate, or Severe is clearly displayed.

A detailed summary lists each detected vehicle component (e.g., bumper, door, hood) along with its corresponding damage level for transparency. Additionally, the estimated repair cost range, calculated based on predefined part-specific repair data, is provided to give users an understanding of potential expenses. This comprehensive output ensures users have all necessary information visual, categorical, and financial to make informed decisions about vehicle repairs.

VI. CONCLUSION

The proposed system effectively optimizes and streamlines business operations by integrating key modules within two distinct administrative layers: Main Admin and Secondary Admin. The Main Admin handles critical tasks such as customer communication, managing queries, and overseeing inventory. These processes are directly tied to real-time data from the database, ensuring that all customer-facing activities are efficient and accurate.

In contrast, the Secondary Admin is designed solely for observational purposes, where it can view Sales Data and Leads Data in visual formats like charts and reports. This layer has no active role in the management or alteration of system data, allowing for clear separation of responsibilities and ensuring that operational decisions remain within the Main Admin's domain.

Through this architecture, the system enhances overall business efficiency by automating and centralizing data flow, enabling informed decision-making, and fostering better coordination between departments. The integration of the database, managed using Flask for backend development, ensures that all modules remain updated in real-time, further improving the system's reliability and performance. Ultimately, the project demonstrates the power of a well-structured, role-specific administrative system in driving business success and operational improvement.

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