



Vehicle damage detection system for insurance claims using Convolutional Neural Network (CNN)

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KEYWORDS	ABSTRACT
Vehicle Damage Detection, Deep Learning, Convolutional Neural Network (CNN), Image Processing, Computer Vision, Insurance Automation, Damage Classification	This project presents a vehicle damage detection system designed to automate insurance claim assessments using deep learning and image processing techniques. The approach integrates both colour-based and texture-based methods, including Local Binary Patterns (LBP) and HSV colour space thresholding, to identify and localize damages such as dents, scratches, and burns from car images. The processed and labelled images are then automatically categorized into "damaged" and "not_damaged" classes. A Convolutional Neural Network (CNN) model is trained on this dataset to classify car damage with high accuracy. The system is evaluated using classification metrics and confusion matrix visualizations, demonstrating its potential for real-world insurance automation tasks. While this solution significantly reduces manual effort, improves claim validation speed, and enhances the reliability of damage assessment in automotive insurance workflows, its current scope primarily serves as a foundational component, with further development required for comprehensive automation, particularly in areas like damage localization, severity assessment, and robust model training with larger, more diverse datasets. Fast, accurate (Existing: 78%, Proposed: 92%), automated, reduces fraud and cost.

1. INTRODUCTION

In today's rapidly growing automotive industry, the number of vehicles and road accidents has increased significantly, leading to a rise in insurance claims. Traditional vehicle damage assessment methods rely heavily on manual inspection by surveyors, which is

time-consuming, inconsistent, and prone to human error. To overcome these challenges, there is a need for an automated and intelligent system that can accurately detect vehicle damage and assist in faster claim processing. The proposed system focuses on developing a vehicle damage detection system for insurance claim

automation using deep learning and image processing techniques. The system utilizes vehicle image data to identify and classify damages such as dents, scratches, and burns. By applying techniques like colour-based analysis (HSV), texture-based methods (LBP), and Convolutional Neural Networks (CNN), the system can analyze complex visual patterns and provide accurate results. With the advancement of artificial intelligence and the availability of large image datasets, machine learning models have proven effective in solving real-world problems. This project leverages these technologies to automate damage detection, reduce manual effort, and improve the efficiency of insurance claim processing. The system can help insurance companies make faster and more reliable decisions while minimizing fraud and operational costs. Overall, this project demonstrates how modern deep learning techniques can be applied to enhance accuracy, optimize workflows, and support data-driven decision-making in the automotive insurance sector [1]–[3].

Purpose

The purpose of this project is to develop an accurate and efficient vehicle damage detection system for insurance claim automation using deep learning and image processing techniques. By analyzing vehicle images using colour-based and texture-based methods along with Convolutional Neural Networks (CNN), the system aims to identify and classify different types of damages such as dents, scratches, and burns. The model captures complex visual patterns in images to ensure reliable and high-accuracy damage detection. This approach helps in automating the insurance claim process by reducing manual inspection, minimizing human errors, and speeding up claim verification. It enables insurance companies to process claims faster, reduce fraud, and improve overall efficiency. Ultimately, the project demonstrates how advanced deep learning techniques can enhance accuracy, reduce operational costs, and support intelligent decision-making in the automotive insurance sector [2], [6].

Motivation

The motivation behind this project is driven by the growing need for accurate and automated decision-making in the automotive insurance industry, where traditional damage assessment methods rely heavily on manual inspection and are often time-consuming, inconsistent, and prone to human

error. In today's fast-growing automotive environment, the number of vehicles and accidents is increasing rapidly, leading to a higher volume of insurance claims. This creates significant challenges such as delayed claim processing, fraudulent claims, inconsistent evaluations, and increased operational costs. Traditional methods of vehicle damage assessment depend on human surveyors, which may result in subjective judgments, inefficiencies, and lack of scalability. These approaches are limited in their ability to handle large volumes of data and accurately detect different types of damages under varying conditions such as lighting, angles, and image quality.

With the advancement of digital technologies and the availability of large image datasets, there is a strong opportunity to adopt intelligent systems that can automate and improve the accuracy of damage detection. In this context, deep learning and image processing techniques have emerged as powerful tools for visual analysis and pattern recognition. Algorithms such as Convolutional Neural Networks (CNN) are capable of analyzing complex image data, identifying hidden patterns, and accurately classifying damaged and non-damaged vehicles. The ability of CNN models to learn from large datasets and generalize across different scenarios makes them highly suitable for real-world applications in insurance claim automation. This project is therefore motivated by the need to leverage these advanced technologies to enhance the accuracy, speed, and reliability of vehicle damage detection [5]–[7].

Problem Statement

The problem addressed in this project is the challenge of accurately detecting and classifying vehicle damage in the automotive insurance sector, where damage assessment is influenced by various factors such as image quality, lighting conditions, angle of capture, and types of damage like dents, scratches, and burns. Traditional manual inspection methods often fail to provide consistent and reliable results, leading to delays in claim processing, human errors, and potential fraud. Conventional approaches are limited in their ability to analyze complex visual patterns in large volumes of image data and cannot effectively handle real-time damage detection requirements. This results in inefficient claim verification, increased operational costs, and customer dissatisfaction.

Therefore, there is a need to develop a robust and reliable deep learning-based system using Convolutional Neural Networks (CNN) that can effectively analyze vehicle images, identify different types of damage, and accurately classify them. Such a system can support faster and more efficient insurance claim processing, reduce manual effort, minimize fraud, and improve overall decision-making in the insurance industry [3], [6], [9].

Overview

Various studies focus on improving vehicle damage detection and automation in the insurance industry using machine learning, deep learning, and computer vision techniques. Approaches such as Convolutional Neural Networks (CNN), YOLO, transfer learning models, and image processing methods are widely used to enhance detection accuracy and handle complex visual patterns. These models leverage image datasets, feature extraction techniques, and classification methods to support automated damage assessment, reduce manual effort, and improve claim processing efficiency. Research works such as YOLO-based detection models provide real-time object detection capabilities, while transfer learning models improve performance even with limited datasets. Additionally, CNN-based systems have demonstrated strong performance in image classification tasks. Overall, these studies highlight the effectiveness of advanced AI techniques in improving accuracy, reducing fraud, and enhancing operational efficiency in the automotive insurance sector [3]–[9].

2. LITERATURE SURVEY

[1] Second Hand Vehicle Maintenance Frauds

Č. Duboka *et al.* discuss the issue of fraud in second-hand vehicle maintenance and sales. The study highlights how damages are often concealed or misrepresented to increase resale value. It emphasizes the importance of reliable detection systems to prevent such frauds. This supports the need for automated vehicle damage detection systems like the proposed model.

[2] Insurance 2030—The Impact of AI on the Future of Insurance

R. Balasubramanian *et al.* present the impact of Artificial Intelligence on the future of the insurance industry. The paper explains how AI can automate claim processing, improve efficiency, and reduce fraud. This aligns with

the proposed system, which uses deep learning to automate vehicle damage assessment.

[3] You Only Look Once: Unified, Real-Time Object Detection

J. Redmon *et al.* introduce the YOLO algorithm for real-time object detection. The model processes images in a single pass, making it highly efficient and fast. This approach is useful for applications requiring real-time damage detection and can be considered for future improvements in the proposed system.

[4] YOLOv7: Trainable Bag-of-Freebies Sets New State-of-the-Art

C.-Y. Wang *et al.* propose YOLOv7, an advanced version of the YOLO algorithm that improves detection accuracy and speed. The model introduces optimization techniques for better performance. This work is relevant for enhancing the system by enabling precise damage localization in real-time.

[5] Car Damage Identification Using Transfer Learning Models

C. M. Sruthy *et al.* explore car damage detection using transfer learning models such as VGG and ResNet. The study demonstrates that pretrained models can improve accuracy even with limited datasets. This suggests that transfer learning can enhance the performance of the proposed CNN-based system.

[6] Car Damage Detection and Assessment Using CNN

A. Shirode *et al.* present a CNN-based approach for detecting and assessing vehicle damage. The study shows that CNN models are effective in classifying images into damaged and non-damaged categories. This directly supports the methodology used in the proposed system.

[7] Integrated Deep Learning System Using Transfer Learning

D. Widjojo *et al.* develop an integrated deep learning system using transfer learning for car damage detection and classification. The system combines multiple deep learning techniques to improve accuracy and robustness. This work highlights the importance of advanced architectures in real-world applications.

[8] Car Damage Assessment Recommendation System Using Neural Networks

J. E. Martis *et al.* propose a neural network-based system that not only detects vehicle damage but also provides repair recommendations. The study focuses on practical

applications in insurance and maintenance. This can be considered as a future extension of the proposed system.

[9] Detects Damage Car Body Using YOLO Deep Learning Algorithm

Y. W. Gustian *et al.* utilize the YOLO algorithm to detect car body damage. The model identifies specific damaged regions within images, enabling both detection and localization. This approach can enhance the proposed system by adding localization capabilities.

[10] Python Data Science Handbook: Essential Tools for Working with Data

J. VanderPlas provides a comprehensive guide to data science tools and techniques using Python. The book covers essential libraries such as NumPy, Pandas, Matplotlib, and Scikit-learn. These tools are fundamental for implementing preprocessing, analysis, and machine learning models in the proposed system.

3 PROPOSED METHODOLOGY

The proposed system is a deep learning-based vehicle damage detection framework using Convolutional Neural Networks (CNN) and image processing techniques. It follows an end-to-end pipeline that includes data collection and preprocessing of vehicle images, feature extraction using colour-based (HSV) and texture-based (LBP) methods, and model training using CNN for accurate damage classification. The system also involves hyperparameter tuning to optimize model performance and evaluation using metrics such as accuracy, precision, recall, and confusion matrix. Furthermore, it integrates a user-friendly interface that allows users to upload images and view detection results, and it can be deployed using web or cloud platforms to enable real-time vehicle damage detection and support automated insurance claim processing.

3.1 System Architecture

The diagram illustrates the architecture of a Vehicle Damage Detection System, developed to automate the process of identifying vehicle damage using advanced deep learning and image processing techniques. This system is structured into three primary layers: the User Layer, Application Layer, and Data Layer. Each layer is designed to perform specific functions, ensuring efficient data flow, accurate predictions, and a user-friendly experience. The layered design also makes the system scalable and adaptable for real-world deployment,

especially in domains like automotive insurance and inspection systems.

In the User Layer, the system provides an interface through which users can interact (easily) with the application. The user uploads an image of a vehicle, which serves as the input for the system. This layer abstracts the complexity of the backend processes and presents only essential functionalities. Once the image is processed, the result is displayed in a simple format, indicating whether the vehicle is "Damaged" or "No Damage." This quick and intuitive response helps users, such as insurance agents or customers, make faster decisions without requiring technical knowledge.

The Application Layer is the core computational engine of the system, where all major operations are carried out. The first step in this layer is preprocessing, where the input image is resized, normalized, and enhanced to improve clarity and consistency. These steps are crucial because deep learning models require standardized inputs for better performance. Following preprocessing, the system performs feature extraction using both colour-based and texture-based methods. The HSV colour space is used to capture colour variations that may indicate burns or paint damage, while Local Binary Patterns (LBP) are used to extract texture features that help detect dents and scratches. These combined features provide a rich representation of the image.

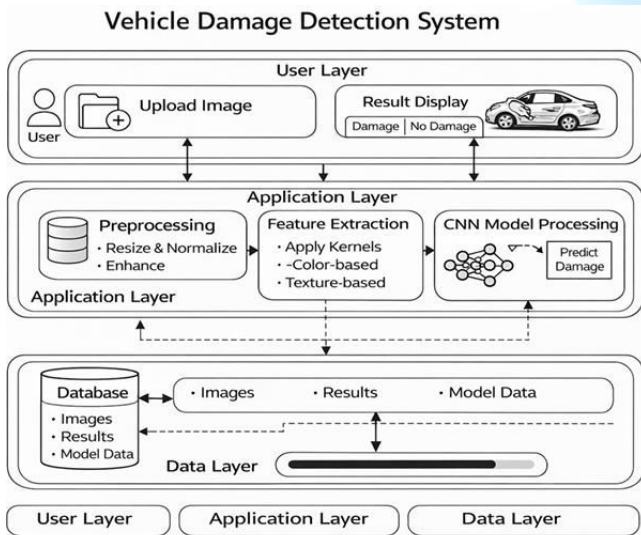
After feature extraction, the processed data is passed to a Convolutional Neural Network (CNN), which acts as the decision-making component of the system. The CNN learns complex patterns from the training data and uses this knowledge to classify new images. It analyzes spatial hierarchies, edges, textures, and shapes within the image to accurately determine whether damage is present. The model is trained on labeled datasets containing both damaged and non-damaged vehicle images, enabling it to generalize well to unseen data. Performance is evaluated using metrics such as accuracy, precision, recall, and confusion matrix visualization, ensuring the reliability of predictions.

The Data Layer serves as the backbone for data storage and management. It maintains a repository of input images, processed results, and trained model parameters. This layer ensures that data is consistently available for both training and inference processes. It also supports future improvements by allowing additional data to be stored and used for retraining the

model. Efficient data handling in this layer contributes to faster processing and better system performance. Furthermore, the system offers several advantages, including reduced manual inspection effort, faster claim processing, and improved accuracy in detecting vehicle damage. By automating the assessment process, it minimizes human errors and helps in detecting fraudulent claims. However, the current system mainly focuses on binary classification (damaged vs. not damaged). Future enhancements can include advanced features such as precise damage localization using bounding boxes, severity estimation, multi-class damage classification, and integration with real-time mobile or web applications.

In conclusion, this Vehicle Damage Detection System demonstrates how the integration of computer vision and deep learning can transform traditional inspection processes. With further improvements and larger, more diverse datasets, the system has the potential to become a comprehensive and fully automated solution for vehicle damage analysis in real-world scenarios.

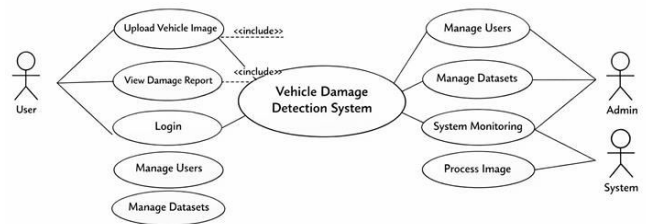
System Architecture diagram



3.2 Use Case diagram

A Use Case Diagram in the Unified Modeling Language (UML) is a type of behavioral diagram that represents the interaction between users (actors) and the system. It provides a high level view of the system's functionality by showing different use cases and how external entities interact with the system to achieve specific goals. The primary purpose of a use case diagram is to clearly

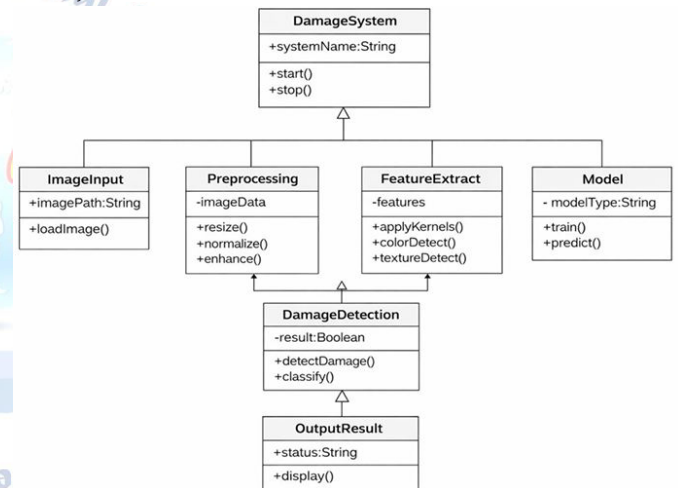
illustrate what functions are performed by the system and which actors are involved in those functions.



Use Case Diagram

3.3 Class diagram

A Class Diagram in the Unified Modeling Language (UML) is a type of structural diagram that represents the static structure of a system. It shows the classes, their attributes, methods, and the relationships between different classes in the system. The main purpose of a class diagram is to provide a detailed design of the system by modeling the objects and their interactions in an object-oriented manner.



Class Diagram

3.4 DATASET

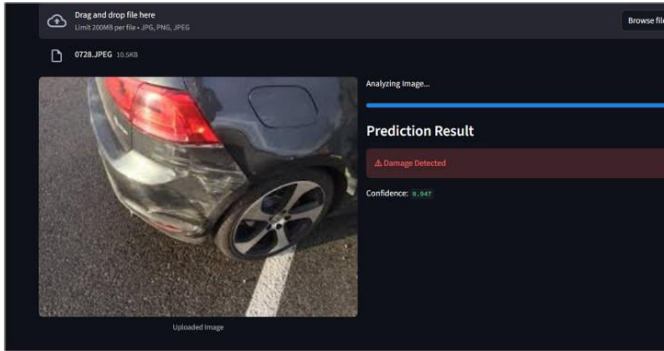
This study focuses on detecting vehicle damage using Convolutional Neural Networks (CNN). The model is trained on labeled datasets of damaged and non-damaged vehicle images. Experimental results show high accuracy in classifying vehicle damage. The approach reduces dependency on manual inspection and improves claim processing speed.

3.5 Evaluation Metrics

Evaluates the performance of the trained model using metrics such as accuracy, precision, recall, and confusion matrix. It helps in validating and improving the model through tuning and testing

4 RESULTS

Vehicle Damage Detection System



The image shows the output interface of your Vehicle Damage Detection System, demonstrating how the model analyzes and predicts damage from a car image.

At the top, there is a file upload section where users can drag and drop or browse an image file (in formats like JPG, PNG, or JPEG). In this example, an image named *0728.JPEG* has been uploaded successfully. This indicates the system is designed with a simple and user-friendly interface for easy interaction.

On the left side, the uploaded image is displayed. The image clearly shows a car with visible damage on the rear side, including scratches and dents near the bumper and wheel area. This visual input is what the model uses for analysis.

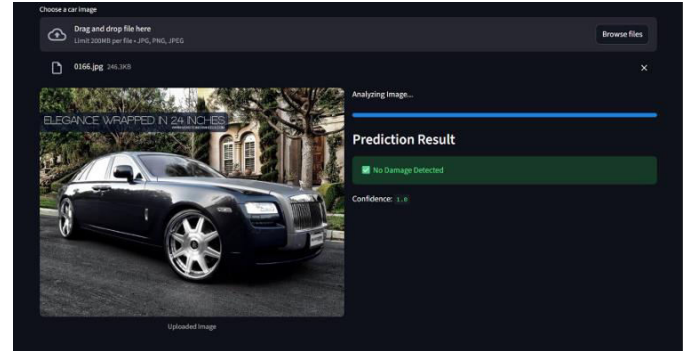
In the center/top section, the system shows a status message "Analyzing Image...", along with a progress bar. This indicates that the backend model (CNN) is processing the image by extracting features and evaluating patterns such as texture and color changes.

On the right side, the Prediction Result section displays the final output of the model. The system has classified the image as "Damage Detected", highlighted in red to indicate a negative condition. This means the model successfully identified damage in the vehicle.

Below the prediction, the confidence score (0.947) is shown. This means the model is 94.7% confident that the vehicle is damaged. A high confidence score indicates strong reliability of the prediction.

Overall, this image demonstrates the complete workflow of your system, from image upload to analysis and final prediction. It highlights how the model can automatically detect vehicle damage with high accuracy, making it useful for applications like insurance claim processing, automated inspection, and fraud detection.

Vehicle Damage Detection System Output – No Damage Case



The image shows the output of the **Vehicle Damage Detection System** when a car without any visible damage is analyzed. At the top, there is a file upload section where the user has selected an image (*0166.jpg*). This indicates that the system allows users to upload vehicle images easily using a drag-and-drop or browse option.

On the left side, the **uploaded image** is displayed. The image shows a luxury car in good condition with no visible dents, scratches, or damage. This clean and undamaged appearance is what the model evaluates during processing.

In the middle, the system displays the status "**Analyzing Image...**" along with a progress bar. This represents the internal processing stage where the model performs preprocessing, feature extraction, and classification using the CNN.

On the right side, the **Prediction Result** section shows the final output. The system has classified the image as "**No Damage Detected**", highlighted in green to indicate a positive or normal condition. This means the model did not find any damage-related features in the image.

Below the result, the **confidence score is 1.0**, which indicates **100% confidence** in the prediction. This shows that the model is highly certain that the vehicle is in a non-damaged state.

Overall, this image demonstrates how the system accurately identifies a **non-damaged vehicle**, providing reliable results with high confidence. It highlights the effectiveness of the model in distinguishing between damaged and undamaged vehicles, which is essential for applications like automated inspection and insurance claim verification.

5 CONCLUSION

The developed Vehicle Damage Detection System using deep learning techniques, particularly Convolutional Neural Networks (CNNs), demonstrates promising results in accurately identifying and classifying damaged vehicles from images. The performance evaluation, including classification report and confusion matrix, shows perfect precision, recall, and F1-score for the "damaged" class, indicating the model's effectiveness on the given dataset. The system successfully automates a traditionally manual and time-consuming task, thereby offering a scalable and objective approach for insurance claim processing. However, the model's evaluation on a limited and class-imbalanced dataset also suggests that further testing on a more diverse data sample is necessary for real-world deployment.

6. FUTURE SCOPE

The future scope of the Vehicle Damage Detection System is vast, with significant potential for enhancement and real-world deployment. One of the key areas of improvement lies in extending the model beyond binary classification to a more detailed multi-class system that can identify the type and severity of damage, such as minor dents, deep scratches, or broken components. To improve accuracy and robustness, the system should be trained on a larger and more diverse dataset encompassing various car models, lighting conditions, and angles of damage. Integrating this AI-driven solution with existing insurance claim platforms can greatly streamline the claim approval process by enabling real-time damage assessment and reducing human intervention. Additionally, advancements like 3D damage analysis using depth sensors or multiple image inputs could allow for repair cost estimation and severity grading. Incorporating Explainable AI (XAI) tools can also enhance transparency by providing visual justifications for the model's decisions, fostering trust among users and insurance agents. As technology evolves, this system can become a core component in the automation of vehicle insurance and damage assessment workflows.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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