20CS713 PROJECT PHASE I

DAMAGED CAR DETECTION USING MULTIPLE CONVOLUTIONAL NEURAL NETWORKS WITH FLASK WEB APP

A PROJECT REPORT

Submitted by

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in partial fulfillment for the award of the degree

of

BACHELOR OF ENGINEERING

IN

COMPUTER SCIENCE AND ENGINEERING

R.M.K. ENGINEERING COLLEGE

(An Autonomous Institution)
R.S.M. Nagar, Kavaraipettai-601 206



November 2023

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ACKNOWLEDGEMENT

We earnestly portray our sincere gratitude and regard to our beloved Chairman Shri. R. S. Munirathinam, our Vice Chairman, Shri. R. M. Kishore and our Director Shri. R. Jyothi Naidu for the interest and affection shown towards us throughout the course.

We convey our sincere thanks to our **Principal**, **Dr. K. A. Mohamed Junaid**, for being the source of inspiration in this college.

We reveal our sincere thanks to our **Professor and Head of the Department**, **Computer Science and Engineering**, **Dr. T. Sethukarasi**, for her commendable support and encouragement for the completion of our project.

We would like to express our sincere gratitude for our Project Guide Mr. M. P. Karthikeyan M.Tech., (Ph.D.,) Assistant Professor for his valuable suggestions towards the successful completion for this project in a global manner.

We take this opportunity to extend our thanks to all faculty members of Department of Computer Science and Engineering, parents and friends for all that they meant to us during the crucial times of the completion of our project.

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ABSTRACT

Vehicles get damaged due to various reasons such as accidents, collisions, natural disasters, and wear and tear. The issue affects many businesses, including automakers, insurance companies, car rental companies, and individual vehicle owners. For insurance companies to file a compensation claim, they must quickly and accurately detect the damage to the vehicles involved in the accident. This project is designed to create an application to diagnose car damage using multiple CNNs and Flask Web. This project uses advanced image processing tools and machine learning algorithms to quickly analyze images and highlight damaged areas. The system uses the power of CNNs to accurately identify and describe various vehicle damages such as dents, scratches, and deformations from input images. Adding to the importance of CNN-based damage to pipelines, we created a web application using Flask that allows users to easily upload images and receive instant damage assessments. The system is divided into two parts: training the model and submitting the model to the website. Using this technology has the potential to improve the insurance process, improve the vehicle's performance, and increase customer satisfaction through speed. Speed up and streamline the process.

Keywords: Convolutional Neural Network (CNN), Car Damage Detection, Flask Web Application, Image Classification.

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CHAPTER 1

INTRODUCTION

1.1 Problem Statement

Car damage detection is an important task in many applications, such as insurance claims processing and vehicle inspection. However, it can be a difficult task, especially when the damage is minor or difficult to see. The problem is significant, as inaccurate or delayed damage assessments can lead to increased costs for insurers, longer processing times for claims, and customer dissatisfaction.

1.2 Project Scope and Objective

This project aims to develop a computer vision system that can identify and classify car damage from images. Here is an outline of the project's scope and objectives:

1.2.1 Scope of the Project

The project scope involves developing a Convolutional Neural Network (CNN) model to detect car damage from images and integrating it into a Flask-based web application for user-friendly accessibility and real-time inference.

1.2.2 Objective of the Project:

To develop a system that can accurately and reliably detect damaged cars using multiple Convolutional Neural Networks (CNNs). CNNs are a type of machine learning algorithm that is well-suited for image classification tasks. CNNs have been used to successfully detect damaged cars in a variety of settings. The goal of this project is to develop a system that can accurately and reliably detect damaged cars using multiple CNNs. The system should be able to detect damage of all types and severities, even in challenging conditions such as poor lighting or occlusion.

1.3 Literature Survey

The research paper [1], authored by Q. Zhang, X. Chang, and S. B. Bian, The main result is a methodology to estimate quickly and easily repair costs of vehicles involved in road accidents. Real-world accidents analyzed in this paper are Crashworthiness Data System (NASS CDS Database)- field research teams located across a country study about 5000 crashes a year; Audaplus estimation system which used data about costs of the vehicle parts and the time necessary to replace it based on manufacturer's information. This study has developed a retrospective methodology to estimate easily repair costs of vehicles involved in road accidents with the front zone involved. Using residual deformation measurements based on Tumbas and Smith's protocol, it is viable to estimate deltaV and absorbed energy for the vehicle involved in an accident.

The research paper [2], authored by MaleikaHeenaye–Mamode Khan, Mohammad Zafir Hussein SkHeerah, and ZuhairahBasgeeth, Has deployed an application in this paper for the automatic detection and classification of vehicle damages, which can be used by insurance companies to process claims or by the police department to record accidents. Manually identifying the types and severity of vehicle damage after an accident can be time-consuming. An automated damage detection application can help with insurance claims. Convolutional Neural Networks (CNN) have had great success in object classification. However, CNN has not been thoroughly investigated or applied for multiclass classifications of vehicle damages. In this paper, pre-trained CNN models, MobileNet, and VGG19 are adapted and used in transfer learning on the large-built dataset. This application achieved a Mobile Net accuracy of 70% and a VGG19 accuracy of 50%.

The research paper [3], authored by NajmeddineDhieb, Hakim Ghazzai, Hichem Besbes, and Yehia Massoud, proposes efficient and streamlined deep learning-based architectures for vehicle damage identification and localization in this paper. For feature extraction, the proposed solution incorporates deep learning, instance segmentation, and transfer learning techniques. Its goal is to automatically detect vehicle damage, locate it, classify its severity levels, and visualize it by contouring its exact location.

The research paper [4], authored by UmerWaqas, NimraAkram, Soohwa Kim, Donghun Lee, and JihoonJeon, considers the problem of car damage classification in this paper, where classifications include medium damage, huge damage, and no damage. For classification, the Mobile Net model is proposed using deep learning techniques and transfer learning. Furthermore, moving toward automation comes with a variety of challenges; users can upload bogus images such as screenshots or take screenshots of computer screens, for example. To address this issue, a hybrid approach is proposed in which only authentic images are provided as input to an algorithm for damage classification. To detect fraudulent images, moiré effect detection and metadata analysis are used. Damage classification accuracy is 95%, and moiré effect detection accuracy is 99%.

The research paper [5], authored by AtharvaShirode, Tejas Rathod, ParthWanjari, and AparnaHalbe, If the vehicle is insured, an insurance agent will go to the customer's home to investigate and prepare a report. Book review is a time-consuming process. However, thanks to significant advances in deep learning algorithms, it can be used to solve these problems in the insurance industry. Two CNN models are used in the proposed solution. VGG16 is used to diagnose damage to the vehicle as well as the location and severity of the damage. Mask RCNN is used to isolate damaged areas. Both models provide reasonable estimates of vehicle damage, allowing insurance companies to submit insurance claims without wasting resources and time on manual checks.

The research paper [6], authored by Sruthy C M, Sandra Kunjumon, and Nandakumar R, This study used the transfer learning models Inception V3, Xception, VGG16, VGG19, ResNet50, and Mobile Net from Kera's library to train our model to predict damage and compare their efficacy. The proposed dataset is trained with these pre-trained models to achieve maximum accuracy and speed with minimal loss so that the model can be used to predict claims in real life. When compared to other models, MobileNet is more accurate and has a faster training time. The accuracy in forecasting damage and categorizing it into different types was 97.28%, which is significantly better than previous results in a similar test set.

1.4 Hardware Requirements

Any kind of internet connection like WIFI, modem data, etc., to allow the browser interfaces to connect to the website. The website can be accessed through any device like a computer, laptop, tablet, etc.

• Cpu: Intel i5 processor with 64-bit operating system

• Ram: 8GB

• Storage: ITB Storage

• Internet: Wireless adapter (Wi-Fi)

1.5 Software Requirements

Some of the software interfaces which you can use to access our website are

Opera

• Google Chrome

Virtual Studio Code

MySql

• Version control system (e.g., Git)

• Web development tools (HTML, CSS, JS, Flask web).

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CHAPTER 2 SYSTEM ANALYSIS

2.1 Existing System

The Existing approaches try to estimate damage costs directly from images, noting that they lack scalability due to the need for repeated operations and updates as new car models are released. By using separate methods for damage estimation and cost estimation, the model becomes more robust. This means that the model can detect and identify the damaged vehicle in the image without the need for updating and reworking, and maintain its accuracy and validity promptly. This approach reduces the maintenance burden and makes the system versatile in handling many vehicles regardless of model changes, making it beneficial in the long term.

2.1.1 Disadvantages of Existing System

- 1. Traditional car damage detection methods rely on manual inspection by human experts.
- 2. Manual inspection is time-consuming and susceptible to human error.
- 3. These methods may not effectively detect hidden or internal damages.
- 4. Limited scalability is a challenge, as traditional methods require specialized expertise.
- 5. Subjective human judgment can lead to inconsistent evaluations and disputes.
- 6. Manual processes slow down insurance claims and repair procedures.
- 7. Delays and inefficiencies in the assessment and repair workflow are common with manual methods.

2.2 Proposed System

The planning process involves various computer vision systems for damage detection and assessment. It uses semantic segmentation to detect damaged vehicles and measure the extent of damage. Computer vision features were extracted to find the location and severity of damage to each exterior panel. This information then provides the information necessary to provide accurate estimates of damage costs. By combining these technologies, the system provides a way to assess and evaluate damage to the vehicle, improving the accuracy and efficiency of repair and maintenance cost estimates.

2.2.1 Advantages of Proposed System

- 1. Systems enable swift and accurate identification of damage types, including dents, scratches, and structural issues.
- 2. Swift identification facilitates prompt repair and maintenance actions.
- 3. Comprehensive methodology streamlines and enhances the efficiency of the assessment process.
- 4. Improved speed and accuracy of damage cost estimation is a key benefit.
- 5. Advanced computer vision techniques reduce reliance on manual inspection.
- 6. Reduced human error potential ensures consistent and objective evaluations

CHAPTER 3

SYSTEM DESIGN

3.1 System Architecture

The proposed system architecture for Damaged Car Detection using Multiple Convolutional Neural Networks with Flask Web App involves collecting a labeled dataset, training multiple CNNs, developing a Flask web application for user interaction, deploying the trained models in the web application, and processing and displaying the results to users.

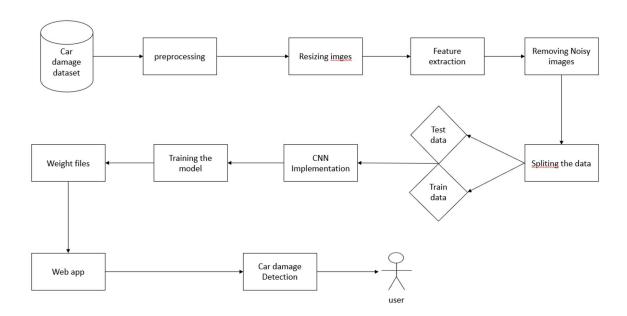


Figure 3.1 System Architecture

3.2 Use Case Diagram

This diagram represents the user's interaction with the Flask web application and the CNN model for car damage detection. The user uploads an image, which is then preprocessed, and the CNN model is applied to detect the damage. The detection result is sent back to the user. The Flask web application also loads the CNN model and classifies the image.

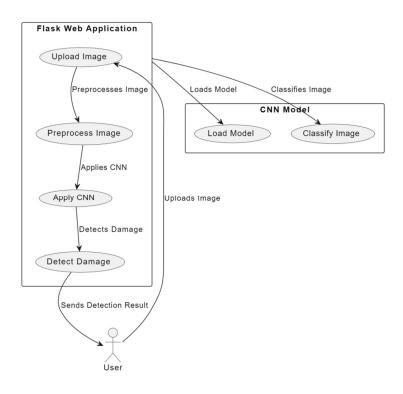


Figure 3.2 Use Case Diagram

3.3 Class Diagram

This class diagram represents a vehicle collision detection using neural network (CNN) in a Flask web application. Vehicle class represents details of the vehicle such as make, model, and year. The DamageDetection class is responsible for detecting damage in the vehicle image and creating the DamageReport object. The CNN class is used to load pre-trained CNN models, pre-process traffic images, and predict damage and reliability. FlaskApp class plays the main role and uses CNN and DamageDetection class to detect damage in the traffic image.

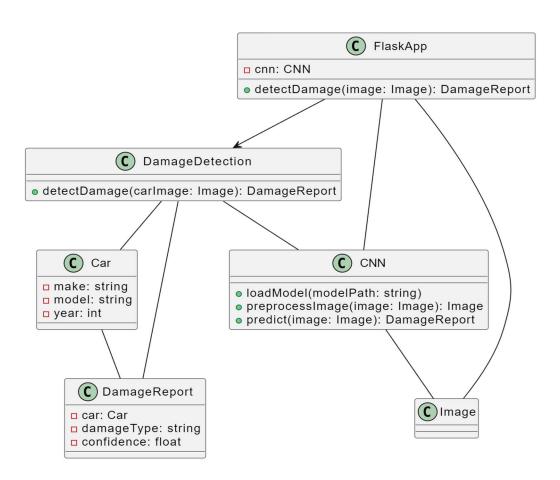


Figure 3.3 Class Diagram

3.4 Data Flow Diagram

This Diagram shows the flow of information and interaction between different components in the investigation of vehicle damage. The user uploads the image to FlaskApp and then passes the image to DamageDetection. The DamageDetection component uses CNN to predict damage types by loading pre-trained models and preliminary images and predicting damage types. The Damage Detection component also retrieves vehicle details from vehicle to vehicle. Finally, the DamageDetection component creates a DamageReport, which is stored by FlaskApp in the DamageReport resource.

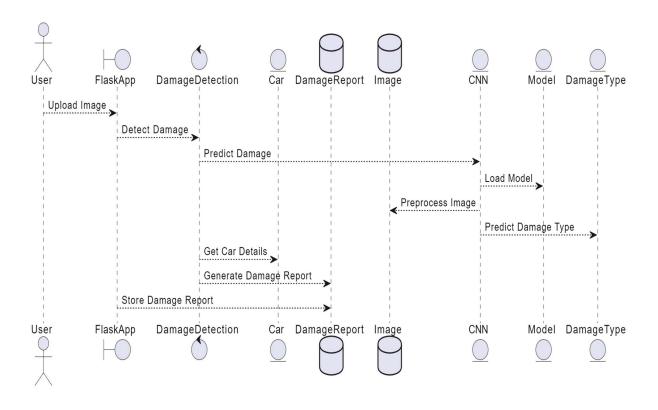


Figure 3.4 Data Flow Diagram

3.5 Activity Diagram

This activity diagram represents the process of car damage detection using a Convolutional Neural Network (CNN) with Flask web. The image of the car is captured and preprocessed. Then, a trained CNN model is loaded to classify the car damage into one of the five classes: A, B, C, D, or Unknown. Depending on the damage class, the corresponding message is displayed.

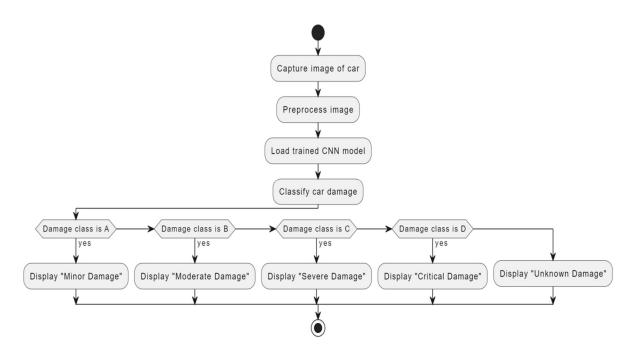


Figure 3.5 Activity Diagram

CHAPTER 4

SYSTEM IMPLEMENTATION

4.1 Modules

Car damage detection system using Convolutional Neural Networks (CNN) with a Flask web app, you will need to set up different modules to handle various tasks. Here are the main modules you might find in such a system:

- **Dataset Preprocessing Module:** This module is responsible for preprocessing the dataset and preparing it for training the CNN model. It may include tasks such as data loading, data augmentation, and splitting the dataset into training and testing sets.
- **Feature Extraction:** Extract features from the preprocessed images using techniques such as edge detection, color histograms, and texture analysis Prepare the feature vector representation for training the CNN model.
- CNN Model Training Module: This module is used to define the architecture of the CNN model and train it on the preprocessed dataset. It involves defining the layers of the CNN, compiling the model, and fitting it to the training data.
- **Model Evaluation Module:** This module is used to evaluate the performance of the trained model on the test dataset. It may include functions for calculating metrics such as accuracy, precision, recall, and F1 score.
- Flask Web App Module: This module is responsible for creating the Flask web application. It will handle user requests, display the input form for uploading images, and process the uploaded images using the trained CNN model. It will display the results of the car damage detection to the user.
- User Interface: Design a user-friendly interface that allows users to easily upload images for car damage detection. Display the results of the analysis in a clear and visually appealing manner, providing users with comprehensive information about the detected damages and their severity.

4.2 Module Description

- Dataset Preprocessing Module: This module focuses on preparing the car damage dataset for training the Convolutional Neural Network (CNN) model. It handles tasks such as data loading, resizing, normalization, and the division of data into training and testing sets. It also incorporates data augmentation techniques to enhance the diversity of the dataset, ensuring robust training of the CNN model.
- Feature Extraction: The feature extraction module leverages pre-trained CNN models, such as VGG16 or ResNet, to extract meaningful and relevant features from the car images. It involves fine-tuning the pre-trained models on the specific car damage dataset, enabling the extraction of distinctive features related to different types and extents of car damage.
- CNN Model Training Module: In this module, the architecture of the CNN model is defined, incorporating the extracted features from the previous module. The layers are customized and optimized to facilitate accurate detection of various types of car damage. The module also entails the training of the CNN model using the preprocessed dataset and the extracted features, with a focus on achieving high accuracy and robust performance in car damage identification.
- Damage Detection: Implement a component that identifies and localizes areas of damage within car images. Train the CNN model to differentiate between different types and extents of car damage, such as scratches, dents, and major structural damage. Integrate algorithms that can accurately classify and highlight the regions of the car that have been damaged. Provide an intuitive and informative visual representation of the detected damage areas for users to comprehend the severity and extent of the damage.

CHAPTER 5

CONCLUSION

Integrating a convolutional neural network (CNN) model into a Flask-based vehicle damage detection system demonstrates the feasibility and ease of use of flight theory. The system is expected to provide effective solutions for vehicle damage detection, thereby simplifying the insurance payment process and improving the overall user experience. Our approach can help reduce the time it takes insurance companies to resolve claims. This saves both parties time and money while increasing customer satisfaction. Further improvements could include refining the model and exposing the dataset to allow for a more comprehensive analysis of different vehicle damage scenarios.

"The art of repair is the art of honoring"

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SCREENSHOTS

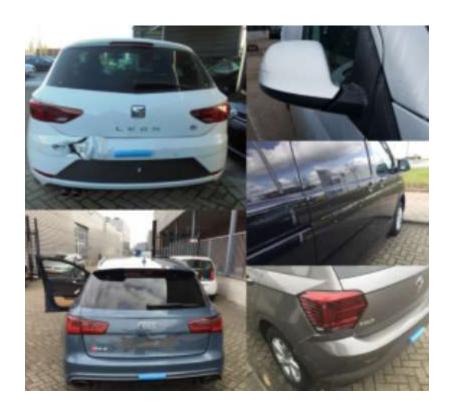


Fig 7.1 Damaged Car- Image 1



Fig 7.2 Damaged Car- Image 2



Fig 7.3 Damaged Car Detected