

CNN Approach for Car Damage Detection in Insurance Claims

Prof. Soniya Dhotre¹, Kushal Agrawal², Shardul Potdar³, Preetam Patil⁴

¹Prof. Soniya Ravindra Dhotre, Computer Engineering, Sinhgad Academy of Engineering

²Kushal Manoj Agrawal, Computer Engineering, Sinhgad Academy of Engineering

³Shardul Surendra Potdar, Computer Engineering, Sinhgad Academy of Engineering

⁴Preetam Babaso Patil, Computer Engineering, Sinhgad Academy of Engineering

ABSTRACT

The automotive industry is witnessing a growing demand for advanced safety and maintenance systems to enhance vehicle safety and reduce maintenance costs. Car damage detection plays a pivotal role in achieving these objectives. This abstract provides an overview of the concept of car damage detection, its importance, and the technologies and methodologies involved. Car damage detection refers to the process of identifying and assessing physical damage to a vehicle, such as dents, scratches, cracks, or structural deformities. It is essential for various stakeholders, including car owners, insurance companies, and automotive service providers, as it enables timely repair and maintenance, facilitates insurance claims, and ensures road safety.

Key Words: CNN, Mask R-CNN, Image Analysis, Computer Vision, Machine Learning, Deep-Learning

1. INTRODUCTION

The increasing number of vehicles on the roads has led to a surge in accidents, underscoring the need for efficient car damage detection processes in the automotive industry, insurance sector, and vehicle maintenance services. Traditionally, the assessment of car damage has been a time-consuming and labour-intensive manual task, prompting the exploration

of AI-powered solutions to streamline and automate the process.

Car insurance companies can use damage detection systems to streamline the claims process. Instead of relying solely on human adjusters to assess the damage, AI can quickly and accurately determine the extent of damage, expediting claims and reducing fraud. Car dealerships and repair shops can employ damage detection systems to assess the condition of vehicles, making it easier to identify and prioritize repairs or maintenance tasks. This can enhance the overall safety and performance of vehicles. Buyers and sellers of used cars can benefit from damage detection systems to assess the condition of a vehicle before purchase. This helps ensure transparency and fair pricing in the used car market. Companies with vehicle fleets can use these systems for regular inspections and maintenance scheduling. This reduces downtime and increases the efficiency and safety of the fleet.

CNNs, a class of deep learning models, have garnered significant attention due to their exceptional performance in various image-related tasks, making them a promising candidate for automating car damage assessment. By harnessing the power of CNNs, the automotive industry and insurance sector can potentially expedite claim processing, reduce costs, and enhance overall customer experience through faster and more reliable car damage detection.

2. LITERATURE REVIEW

1) **Paper Name:** Car Damage Detection and Assessment Using CNN.

Authors: Atharva Shirole; Tejas Rathod; Parth Wanjari.

Road accidents and collisions are unfortunate events that lead to significant damage to vehicles and potential harm to individuals. Timely and accurate assessment of car damage is crucial for insurance claims, vehicle repairs, and road safety. This paper presents a novel approach for car damage detection and assessment using Convolutional Neural Networks (CNNs). CNNs have shown remarkable success in various computer vision tasks, making them a promising candidate for automating the assessment of car damage. Our proposed system utilizes a large dataset of car images with different types and degrees of damage. We fine-tune a pre-trained CNN model, such as VGG16 or ResNet, on this dataset to develop a specialized car damage detection model. The trained CNN model is capable of identifying the presence and extent of damage in an input image, classifying it into predefined categories, and generating a damage severity score.

2) **Paper Name:** Car Damage Identification and Categorization.

Authors: Sruthy C M; Sandra Kunjumon; Nandakumar R.

In recent years, the automotive industry has seen significant advancements in the field of computer vision and artificial intelligence, leading to the development of innovative solutions for car damage identification and categorization. Accurate and efficient assessment of vehicle damage is crucial for insurance claims processing, vehicle maintenance, and resale value estimation. This abstract provides an overview of the key components and methodologies involved in car damage identification and categorization using computer vision and machine learning techniques. The proposed system

leverages image and video data captured from various sources, including photographs, security cameras, and dashcams, to identify and categorize damage to automobiles.

3) **Paper Name:** Car Damage Detection and Price Prediction using Deep Learning.

Authors: Prof. Reshma Totare, Varad Bhalsing, Mayur Lende, Tejas Maramwar.

This project proposed a solution for vehicle damage detection and cost estimation using deep learning techniques such as convolutional neural networks (CNN) and VGG-16 exchange course. The system can detect and classify damaged vehicles and provide an estimate of repair costs based on the severity and location of the damage. It benefits insurance companies by facilitating the evaluation of documents and individuals by providing independent evaluation of damages. Clinical evaluation shows accuracy and repeatability, making good decisions in vehicle maintenance important.

3. PROJECT SCOPE

Gather a diverse and comprehensive dataset of images or videos featuring cars with various types of damage. This dataset is crucial for training and testing the detection model. Annotations may include bounding boxes around damaged areas, labels indicating the type of damage, and severity scores. Decide on the machine learning or deep learning model to be used for car damage detection. Deploy the software or application on the chosen platform or infrastructure, ensuring scalability and reliability. Plan for ongoing maintenance, updates, and model retraining to keep the system accurate and up to date with new types of damage or changes in data distribution.

4. DEPENDENCIES

Car damage detection systems typically depend on machine learning models, such as deep neural networks, for feature extraction and classification. The dataset should include various types of vehicle damage, different car makes and models, and a range of lighting and environmental conditions. Access to a continuous stream of images or video footage from cameras or other sensors is essential for real-time damage detection.

5. ARCHITECTURE

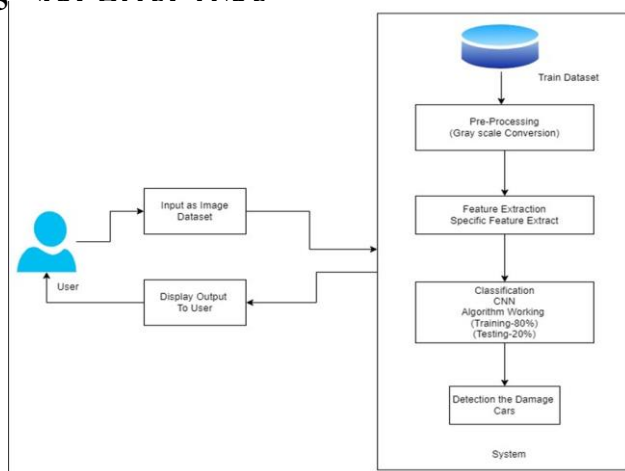


fig. 1.1

a) Input Layer:

You start with an image dataset that contains the images you want to work with. This dataset can include images of various categories or classes, and it forms the basis for the subsequent steps in the process.

b) Pre-processing:

Pre-processing involves preparing the images for analysis. Grayscale conversion is one pre-processing step, where coloured images are converted to grayscale to simplify the data and reduce the computational complexity. Grayscale images contain only shades of gray, removing the color's information.

c) Feature Extraction:

Feature extraction is a critical step in working with image data. It involves selecting or extracting relevant features from the pre-processed images. For image data, this can include extracting texture patterns, edges, shapes, or other characteristics that are important for damage classification.

d) Classification with CNN:

This step involves the use of a Convolutional Neural Network (CNN) for image classification. CNNs are a type of deep learning model specifically designed for image analysis. They automatically learn features from the data and can classify images into different categories or classes. Training a CNN typically involves feeding it the pre-processed image data, fine-tuning the model's parameters, and evaluating its performance.

e) Output to the User:

The output of the CNN classification step is the prediction of the class to which each image belongs. The CNN will assign a class label or a probability score to each image, indicating the likelihood of it belonging to a particular category. In our case, the output has basically two categories, Damaged or not damaged.

6. MATHEMATICAL MODEL

Let S be the Whole system $S = I, P, O$

I-input, P-procedure, O-output, Input(I) I=Text Dataset

Where,

Dataset- Image dataset Classification Using CNN

Algorithm

Procedure (P),

$P=I$, Using I, System detects the damaged car and gives the result.

7. WORKING OF OUR MODEL

1) *Input Layer:*

CNN starts with an input layer that takes the original pixel values of the image. The reference value of each pixel is treated as a separate input neuron.

2) *Convolution Operation:*

Convolution layers are the building blocks of CNN. Layers consist of a series of small filters (also called kernels), usually 3x3 or 5x5 grids. Each filter is applied to the input image by shifting it across the width and height of the image. At each position, the filter evaluates the product between its own value and the value in the input image area it currently occupies. The result of this process is called a specification map or operations map, which shows a specification map or operations map. Some features (edges, textures, images) are included in the ideas.

3) *Activation Function:*

After the convolution process, an element-by-element activation function (usually ReLU - Rectified Linear Unit) is applied to the feature map. Enable the function to show inequality in the network, allowing it to learn complex patterns and representations.

4) *Pooling Layer (Subsampling)::*

The Pooling layer is used to reduce the spatial size of the feature map while preserving the most important information. Maximum pooling is a pooling technique in which the highest value in each region of the image with valid properties is selected, stored, and discarded. Pooling helps reduce computational complexity, increase translation invariance, and decrease the risk of overfitting.

5) *Fully Connected Layers:*

After several layers and compositing processes, the CNN usually results in one or more compositing (wet)

layers. The layers of the feature map into a single circuit, connecting each neuron from the previous layer to the next layer. All layers perform the best extraction and classification.

6) *Output Layer:*

The last link-layer outputs the network. The quantity of neurons within this layer is contingent on the particular task at hand. For example, in image classification there is a neuron for each category and the output represents the probability of the image falling into each category (usually enabled by SoftMax).

7) *Training:*

Teach CNN to use registration data and optimization techniques such as stochastic gradient descent to adjust weights and biases. During training, the network learns features and patterns associated with completing a task by minimizing the loss function that evaluates the variance of predicted and actual results.

8) *Backpropagation:*

Use backpropagation to calculate the slope of the loss function with network parameters (weight and bias). These gradients are used to adjust parameters and rearrange the network function.

9) *Evaluation and Prediction:*

Once the CNN is trained, it can be used to make predictions about new, unseen objects. Generally, the most repeated category in the output layer is selected as the final prediction.

8. SCALABILITY

Scalability includes the system's ability to handle increasing load and adapting to increasing numbers of users without degrading performance. Improved the system to detect damage in other vehicles as well. Techniques such as load balancing, resource optimization

and distributed implementation architectures can improve scalability and resource use.

9. LIMITATIONS

The current system under development is designed to identify damage in cars; however, it has limitations.

- It cannot perform detailed classification of the damage into various categories such as scratches, dents, and other specific types of damage.
- To create an advanced version of this system, enhancements could be made to enable it to not only detect damage but also categorize it more precisely.
- This advanced system could employ advanced computer vision and machine learning techniques to differentiate between different types of car damage, providing more detailed and specific information to users or automating the assessment process for insurance claims and repair estimates.
- By incorporating additional data and more complex algorithms, it could significantly improve the accuracy and usefulness of the damage assessment system.

10. CONCLUSION

The development of a car damage detection system using Convolutional Neural Networks (CNNs) represents a significant advancement in the automotive industry and vehicle maintenance practices. By leveraging the power of deep learning and computer vision, this system addresses critical challenges in car damage assessment and enhances vehicle safety and customer service. This system enhances the traditional Insurance process of manually checking whether the car

is damaged or not. Automating the old traditional procedure not only provides relief to the Insurance Companies but also to the Car Owners. Car Damage Detection is capable enough to classify the difference between legitimate Insurance claims & false ones. Finally, this system is fully capable of identifying the Damaged Cars.

11. FUTURE SCOPE

- 1) *Multi-Modal Fusion*: Integrate text, location, and weather data to enhance car damage detection accuracy.
- 2) *Real-Time Mobile Solutions*: Develop app-based, real-time damage assessment for quick insurance claims.
- 3) *Transfer & Few-Shot Learning*: Explore model adaptation for various vehicles and limited data scenarios.

REFERENCES

1. “Deep learning-based car damage classification “— Kalpesh Patil, Mandar Kulkarni, Anand Sriraman, and Shirish Karande, 2017.
2. “Vehicle Damage Classification and Fraudulent Image Detection Including Moire Effect Using Deep Learning” — Umer Waqas, Nimra Akram, Soohwa Kim, Donghun Lee, Jihoon Jeon — 2020 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)
3. “Automated Detection of Multi-class Vehicle Exterior Damages using Deep Learning” — Maleika Heenaye-Mamode Khan, Mohammad Zafir Hussein Sk Heerah, Zuhairah Basgeeth — IEEE 2021.
4. Qinghui Zhang, Xianing Chang, Shanfeng Bian, “Vehicle-Damage-Detection Segmentation Algorithm Based on Improved Mask RCNN”, IEEE Access (Volume: 8), 2020

5. J. Yang, L. Ji, X. Geng, X. Yang, and Y. Zhao, "Building detection in high spatial resolution remote sensing imagery with the U-rotation detection network," *Int. J. Remote Sens.*, vol. 40, no. 15, pp. 6036–6058, Aug. 2019
6. B. P. Choulagai, H. Ling, P. Sharma, S. R. Mishra, M. Ahmed, and P. B. Chand, "Epidemiology of Road Traffic Accidents in Nepal: Data Review and Qualitative Analysis," *SM Online Scientific Resources*, vol. 1, no. 3, pp. 1–4, 2015.
7. Vijayakumar, T., and R. Vinothkanna." Retrieval of complex images using visual saliency guided cognitive classification." *J Innov Image Process (JIIP)* 2, no. 02 (2020): 102-109.
8. Artan C.T., Kaya T. (2020) "Car Damage Analysis for Insurance Market Using Convolutional Neural Networks". In: Kahraman C., Cebi S., Cevik Onar S., Oztaysi B., Tolga A., Sari I. (eds) *Intelligent and Fuzzy Techniques in Big Data Analytics and Decision Making. INFUS 2019. Advances in Intelligent Systems and Computing*, vol 1029. Springer.