20CS811 PROJECT PHASE II – BATCH 53

Smart Detection of Car Defective Parts with Recommendations

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Abstract

- ✓ The project focuses on developing an integrated system for detecting car damage utilizing multiple Convolutional Neural Networks (CNNs) within a Flask web application framework.
- ✓ Advanced CNN techniques are employed to precisely identify and categorize damage types such as dents, scratches, and deformations from input images.
- ✓ The system incorporates QR code generation and scanning functionalities to encode and retrieve detailed information about the detected damages, improving data accessibility and organization.
- ✓ The user interface, facilitated by Flask, offers a user-friendly platform for image uploads and damage report views.
- ✓ The integrated system has the potential to streamline the detection process and enhance customer satisfaction across the automotive industry.

Key words: Convolutional Neural Network (CNN), Car Damage Detection, Flask Web Application and QR Code Generation.

SCOPE

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.

LITERATURE SURVEY

S.NO	TITLE OF THE PAPER	AUTHOR NAME & YEAR	ALGORITHM	DESCRIPTION
1	Vehicle Damage Severity Estimation for Insurance Operations Using In-The-Wild Mobile Images	Dimitrios Mallios, Li Xiaofei, Niall McLaughlin, Jesus Martinez Del Rincon, Clare Galbraith, Rory Garland- 2023	Mask RCNN, Semantic Segmentation	**Merits:** Detailed damage assessment with semantic segmentation. Integration of structured data improves cost estimation accuracy. **Demerits:** Reliance on user-captured photographs introduces variability. Dependency on historical claims data limits generalization.
2	Vehicle-damage-detection segmentation algorithm based on improved mask RCNN	Q. Zhang, X. Chang, and S. B. Bian- 2020	Mask RCNN	**Merits:** Innovative segmentation for repair cost estimation. Utilization of real-world accident data enhances reliability. **Demerits:** Limited focus on front zone accidents. Reliance on specific deformation measurements.
3	CarDD: A New Dataset for Vision-based Car Damage Detection	Xinkuang Wang, Wenjing Li, Zhongcheng Wu- 2023	CarDD dataset, DCN (Deformable Convolutional neural Network)	**Merits:** CarDD: First large-scale public dataset for car damage detection, addressing data scarcity. Meticulous annotation and statistical analysis enhance dataset robustness. **Demerits:** Model generalization uncertainty. Relatively small dataset size may limit real-world training.
4	Car Damage Assessment Based on VGG Models	Phyu Mar Kyu, Kuntpong Woraratpanya- 2020	Deep learning-based algorithms, specifically VGG16 and VGG19	**Merits:** High accuracy (VGG16: 94.56%, VGG19: 94.35%) showcases transfer learning effectiveness. Technique exploration provides optimization insights for insurance industries. **Demerits**: Overfitting risk due to high accuracy. - Limited generalizability from real-world dataset focus.

LITERATURE SURVEY

S.NO	TITLE OF THE PAPER	AUTHOR NAME & YEAR	ALGORITHM	DESCRIPTION
5	A Very Deep Transfer Learning Model for Vehicle Damage Detection and Localization	Najmeddine Dhieb, Hakim Ghazzai, Hichem Besbes, Yehia Massoud- 2020	Inception-ResNetV2 (pre-trained model). Fully Connected Neural Network	**Merits:** Improves detection, localization, and severity classification for insurance claims. Reduces losses from claims leakage, benefiting insurers financially. **Demerits**: Complexity of implementing deep learning may hinder adoption. Complexity challenges may affect implementation.
6	Car Damage Detection and Assessment Using CNN	Atharva Shirode, Tejas Rathod, Parth Wanjari, Aparna Halbe- 2022	VGG16 (Convolutional Neural Network), Mask R-CNN	**Merits**: Improves vehicle damage detection and classification for insurance claims. Reduces losses from claims leakage. **Demerits:** Complex implementation may hinder adoption. Complexity challenges affect implementation.
7	Car Damage Identification and Categorization Using Various Transfer Learning Models	Sruthy C M, Sandra Kunjumon, Nandakumar R-2021	VGG16, VGG19, ResNet50, MobileNet	**Merits:** Thorough comparison of transfer learning models. MobileNet excels in accuracy and speed. **Demerits:** Limited dataset and testing details. Heavy reliance on pre-trained models.
8	A large-scale car dataset for fine-grained categorization and verification	Linjie Yang, Ping Luo, Chen Change Loy, Xiaoou Tang-2015	CNN, Bayesian methods, SVM	**Merits:** "CompCars" dataset design supports diverse car-related vision tasks. Inclusion of surveillance and web sets broadens dataset's utility. **Demerits:** Limited exploration of challenges in car-related vision. Emphasis on specific applications may restrict dataset's flexibility.

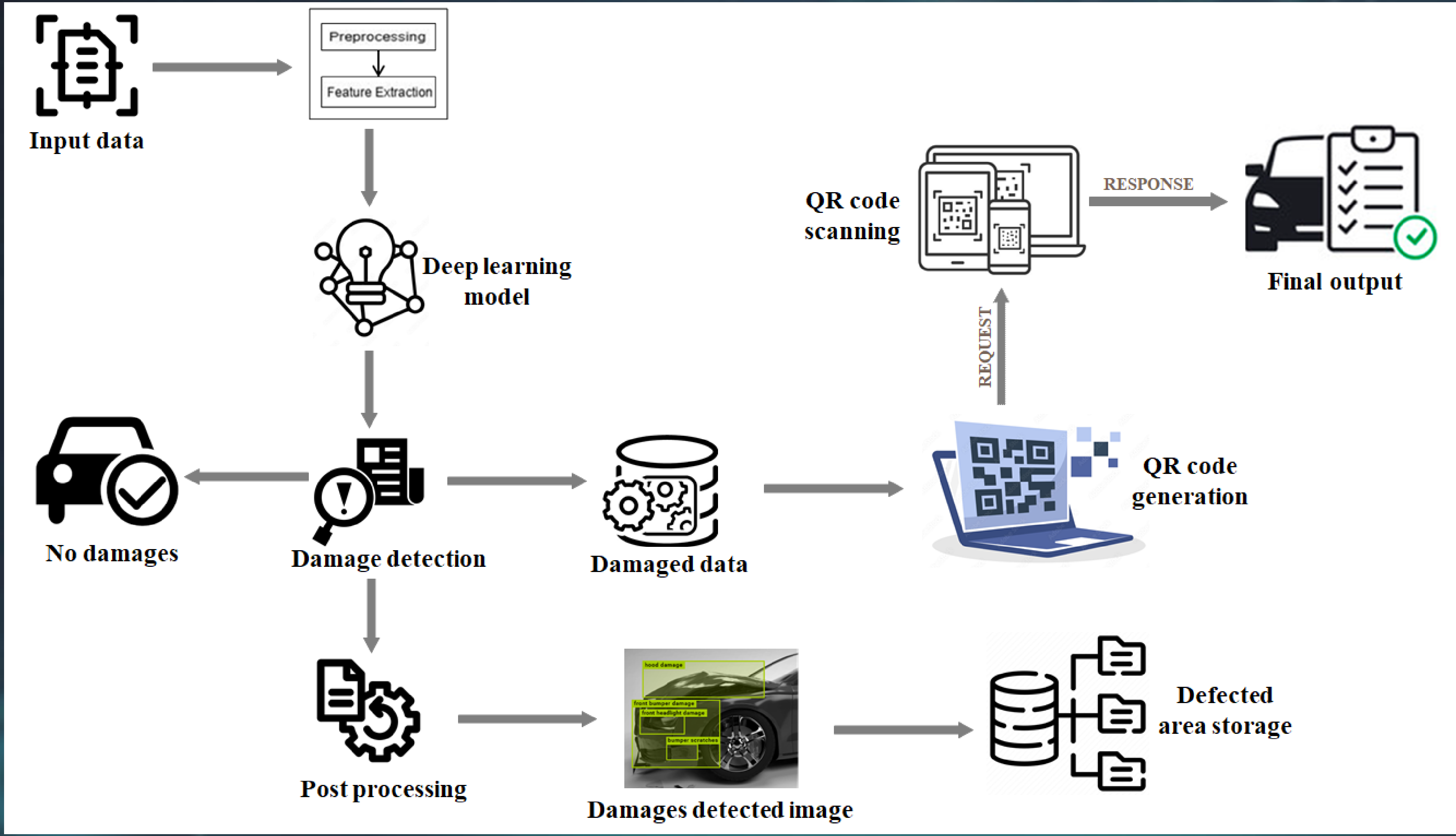
Problem statement

- The detection of defective parts in cars is a crucial task in various 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 primary problem addressed by this project is significant, as inaccurate or delayed damage assessments can lead to increased costs for insurers, longer processing times for claims, and customer dissatisfaction.

PROPOSED SYSTEM

- ✓ The proposed system integrates Convolutional Neural Networks (CNNs) into a Flask web application for car damage detection which utilized to accurately identify and categorize various types of damages.
- ✓ QR code generation and scanning functionalities are incorporated to encode and retrieve detailed information about detected damages, enhancing data accessibility and organization.
- ✓ The system aims to streamline the detection process and boost customer satisfaction within the automotive industry.

System architecture



MODULE DESCRIPTION

1. 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.

2. 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.

Module description

3. 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.

4. Dataset Post-processing Module :

Post-processing in car damage detection refers to the additional steps or techniques applied after the initial detection model has identified potential damage in an image or a set of images. While the primary objective of the detection model is to locate and identify damages in a vehicle, post-processing steps aim to refine, validate, or further analyze the detected results. This aims to improve the accuracy, reliability, and interpretability of the initial detection model's output, enhancing the utility of the system in practical applications

Module description

5. QR Code Generation and Scanning:

In the QR Code Generation and Scanning module, dynamic QR codes are generated to encode specific information related to each detected damage during the inspection process. This dynamic encoding ensures that comprehensive details about the damages are embedded within the QR codes. Scanning these QR codes facilitates quick and convenient access to detailed damage reports, providing stakeholders with instant insights into the nature and extent of each identified issue.

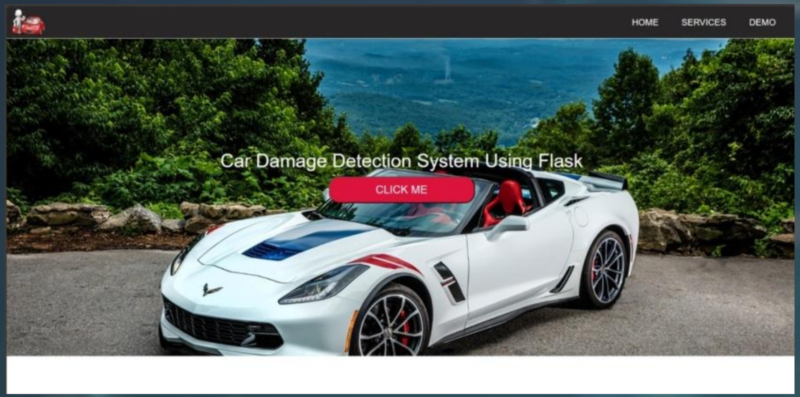
6. User Interface Module:

The User Interface (UI) module in car damage detection plays a crucial role in presenting visual outputs like annotated images and severity classifications. It facilitates real-time user interaction and adjustment of settings while providing information about damage severity and classifications. The UI module also integrates with external systems, enhancing the user experience for stakeholders like insurance assessors and auto repair professionals. Additionally, the inclusion of a QR code output further streamlines information access and retrieval, contributing to the overall efficiency and convenience of the system.

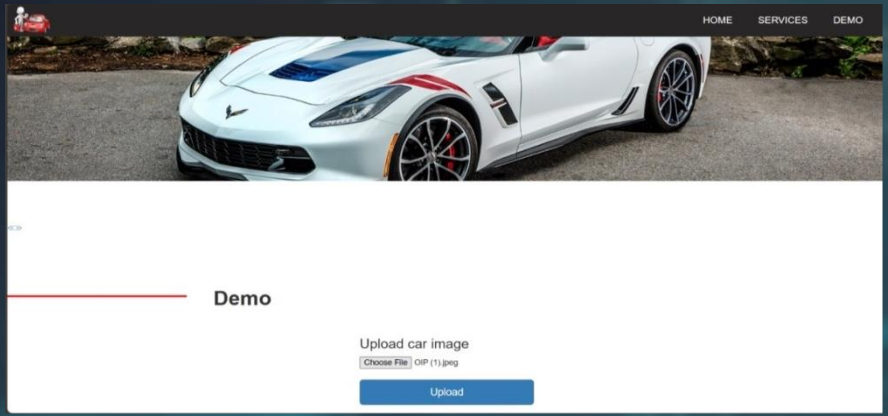
Result & discussion

The system is expected to provide effective solutions for vehicle damage detection, thereby simplifying the process and improving the overall user experience. This system leverages cutting-edge technologies to significantly improve efficiency, ensuring swift and accurate identification of damages. Our trained CNN module used to identify and localize car damage, distinguishing between scratch, dent, and structural issues. Integrate algorithms for precise classification and highlighting, providing an intuitive visual representation for users to assess damage severity and extent. For each detected damage, a unique QR code is generated, encoding information such as damage type, location, severity, and timestamp. The results showed that the proposed convolutional neural network has a powerful ability to detect multiple damages with the recognition accuracy of 92.9%. They successfully identifies and categorizes damages in input images with a high degree of accuracy, providing valuable insights for stakeholders like car manufacturers, insurers, rental companies, and individual owners.

Screenshots



1. Home Page



2. Uploading Input(Damaged Car Images)

3. Output

Conclusion

The Detection of defective parts using deep learning, coupled with QR code integration, presents a robust and innovative solution that revolutionizes the car inspection process. This system leverages cutting-edge technologies to significantly improve efficiency, ensuring swift and accurate identification of damages. The integration of QR codes adds a layer of streamlined documentation, facilitating comprehensive and organized management of car damages. This rich metadata not only aids in tracking the history of damages but also enables efficient communication between stakeholders involved in repair and maintenance activities. As a result, the system not only simplifies the inspection process but also fosters improved collaboration and decision-making among automotive professionals, ultimately enhancing the overall user experience and satisfaction.

References

[1] DimitriosMallios, Li Xiaofei, Niall McLaughlin, Jesus Martinez Del Rincon, Clare Galbraith, Rory Garland, “Vehicle Damage Severity Estimation for Insurance Operations Using In-The-Wild Mobile Images”, IEEE Access (Volume: 11), 2023.

[2] Q. Zhang, X. Chang, and S. B. Bian, “Vehicle-damage-detection segmentation algorithm based on improved mask RCNN,” IEEE Access, vol. 8, pp. 6997–7004, 2020.

[3] Xinkuang Wang, Wenjing Li, Zhongcheng Wu, “CarDD: A New Dataset for Vision-based Car Damage Detection”, IEEE Transactions on Intelligent Transportation Systems (Volume: 24, Issue: 7, July 2023)

[4] Phyu Mar Kyu, KuntpongWoraratpanya, “Car Damage Assessment Based on VGG Models”, IEEE Access, 2020.

[5] NajmeddineDhieb, Hakim Ghazzai, Hichem Besbes, Yehia Massoud, “A Very Deep Transfer Learning Model for Vehicle Damage Detection and Localization”, 31st International Conference on Microelectronics (ICM), 2020.

[6] AtharvaShirode, TejasRathod, ParthWanjari, AparnaHalbe, “Car Damage Detection and Assessment Using CNN”, IEEE Delhi Section Conference (DELCON), 2022

[7] Sruthy C M, Sandra Kunjumon, Nandakumar R, “Car Damage Identification and Categorization Using Various Transfer Learning Models”, 5th International Conference on trends in Electronics and Informatics (ICOEI), 2021.

[8] Linjie Yang et al., “A large-scale car dataset for fine-grained categorization and verification”, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2015.

[9] K. Patil, M. Kulkarni, A. Sriraman, and S. Karande, “Deep learning based car damage classification”, in Proc. 16th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA), Dec. 2017, pp. 50–54.

[10] S. Ren, K. He, R. Girshick, and J. Sun. “Faster R-CNN: Towards real-time object detection with region proposal networks”, 2015.

References

[11] UmerWaqas, NimraAkram, Soohwa Kim, Donghun Lee, JihoonJeon, “Vehicle Damage Classification and Fraudulent Image Detection Including Moiré Effect Using Deep Learning”, IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), 2020

[12] K. He, X. Zhang, S. Ren, and J. Sun. “Deep residual learning for image recognition”. In CVPR (IEEE) , 2016.

[13] Krizhevsky, I. Sutskever, and G. Hinton. “ImageNet classification with deep convolutional neural networks”, In NIPS, 2012.

[14] T.-Y. Lin, P. Dollar, R. Girshick, K. He, B. Hariharan, and S. Belongie, “Feature pyramid networks for object detection”, in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jul. 2017, pp. 320–329

[15] G. Wang and S. Liang, “Ship object detection based on mask RCNN”, in Proc. Radio Eng., IEEE (IGARSS), 2018.

[16] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, “ImageNet: Alarge-scale hierarchical image database”, in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2009, pp. 248–255

[17] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, “YOLOv4: Optimal speed and accuracy of object detection”, 2020, arXiv:2004.10934.

[18] J. Dai, H. Qi, Y. Xiong, Y. Li, G. Zhang, H. Hu, and Y. Wei, “Deformable convolutional networks”, in Proc. IEEE Int. Conf. Comput. Vis. (ICCV), Oct. 2017, pp. 764–773.

[19] M. Tan and Q. V. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks”, in Proc. 36th Int. Conf. Mach. Learn., 2019, pp. 6105–6114.

[20] Tsung-Yi Lin, Piotr Doll’ar, Ross Girshick, Kaiming He, Bharath Hariharan, and Serge Belongie. “Feature pyramid networks for object detection”. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition(CVPR), pages 2117–2125, 2017.

Thank You...