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Automated Damage Detection and Repair Cost Estimation for Automobiles

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Abstract: Accurate damage identification and repair estimation costs are significant to the insurance and automotive industries. Current processes use labor-consuming, human error-prone, visually focused manual checks that commonly introduce inconsistencies. In this work, an AI-based system that applies the Mask R- CNN model is presented for detecting vehicle damage at a surface level and repair cost estimation. The proposed model processes images of vehicles and determines areas damaged, their severity, and reliable cost estimates. Performance analysis shows an accuracy of 88.78% with an F1-score of 0.880, which validates the reliability of the model in damage assessment. The results emphasize the effectiveness of the approach in enhancing cost estimation accuracy, reducing the evaluation process complexity, and facilitating automation.

Index Terms: Damage detection, repair cost estimation, deep learning, Mask R-CNN, image segmentation, vehicle inspection, automotive AI.

I. INTRODUCTION

It is one of the most essential functions in the car business for insurance companies as well as clients to estimate automobile repair cost. Manual estimation is labor-intensive, prone to mistakes, subjective, and often time-consuming while establishing the repair costs.Computer-based car damage estimation is revolutionizing the auto insurance industry by enhancing assessment accuracy and doing away with manual estimates. The application of deep learning techniques has revolutionized the process of how insurance companies process claims and compensations [1].Mask R- CNN, a deep learning framework that combines instance segmentation and object detection, possesses good accuracy, particularly in the identification of smaller targets. It is applied extensively in agriculture, medical imaging, and construction and provides a potential solution to streamlining vehicle damage assessment automation and insurance claims [2].

In this study, we used Mask R- CNN to detect external damages on vehicles in images. The incorporation of this analysis in our system determines the extent and type of the damage by allowing our system to estimate repair cost. The developed computerized approach enhances the efficiency of damage assessments and the validity and reliability of cost estimates for customers and the insurers. This solution reduces and streamlines the estimation of repair costs, with the application of AI-based technology. So it alleviates the bureaucratic burden and helps ensure equality and transparency of insurance and repair works.

A. Motivation

Growing complexity and inefficiencies of traditional car damage detection and insurance claim processing signal the need for new and innovative solutions. AI-based technologies, particularly automation and data analysis-oriented ones, are the key to transforming the way the insurance industry addresses car damage assessment and claim processing.The motivation for this research is due to the potential to investigate AI-based solutions that will improve precision, lower costs, and overall customer satisfaction in insurance processes[3].

New technology in machine learning and artificial intelligence presents actual solutions to these problems.Advanced computer vision systems, especially those based on sophisticated neural networks for image processing, are capable of automatically detecting and evaluating vehicle damage with great accuracy. These AI applications provide repeatable and data-driven estimates, minimizing the subjectivity in human evaluation.

Our system seeks to simplify the process of assessing vehicle damage using advanced image recognition technology. This helps insurers, who can pay out claims more quickly, and vehicle owners, who get their repair estimates more quickly and precisely. By reducing human bias and standardizing the assessment process, we can improve both operational efficiency and customer satisfaction.

B. Contribution of Research Work

This work has four major contributions. It first explores the software of deep learning strategies, particularly Mask R-CNN, for the evaluation and detection of external car damage. The study also provides the design of a system that integrates image segmentation with machine learning algorithms, which allows for accurate estimation of repair cost based on identified damage. This paper develops a model that can indicate the damage in vehicle images within real-time and give cost estimation depending on severity and type of damage. Finally, traditional methods of damage evaluation and manual estimations are compared with this system to show whether the new one is more accurate and efficient.

C.Paper Structure

The paper is dependent as follows: phase 2 gives a brief evaluate of current techniques for damage estimation, highlighting their deficiencies and discussing the demanding situations involved within the automated estimation of repair prices. section 3 info the proposed framework, which involves integrating mask R-CNN for harm localization, even as the very last sub-mission focuses on making use of machine getting to know algorithms for cost estimation. segment four presents the performance assessment of the proposed system, showcasing diverse metrics and supplying a comparison with preceding works to demonstrate the effectiveness of the brand new approach.

II. Related Works

P. M. Kyu et al. [4] utilized VGG16 and VGG19 architectures for car damage detection, localization, and severity assessment, employing transfer learning and L2 regularization. VGG19 demonstrated superior performance compared to VGG16, achieving 95.22% accuracy in damage detection, 76.48% in localization, and 58.48% in severity assessment. The study highlights the benefits of transfer learning over fine-tuning for enhancing model performance.

Sunil Kumar Aithal et al. [5] developed an automated vehicle damage assessment system (VDAS) using Mask R-CNN and YOLOv5 for damage detection and repair cost estimation. YOLOv5 achieved 71.9% accuracy with an F1-score of 0.39 at a confidence threshold of 0.477. The study emphasizes the system's effectiveness in classifying vehicle damages and predicting repair costs.

H. Ahaggach et al. [6] proposed a hybrid approach for predicting car damage repair costs by integrating ontology reasoning with regression models. They developed the Ontology for Car Damage (OCD) using Named Entity Recognition (NER) and Relation Extraction (RE) techniques, which improved accuracy through structured data. Evaluated on over 300,000 records, the Random Forest model with OCD outperformed traditional models, enhancing cost estimation for insurers and repair shops.

M. Zhang et al. [7] introduced an AI-based system for car repair cost estimation using ResNet50 and transfer learning. The system includes modules for car make and model classification (88% accuracy) and damaged vehicle classification (86% accuracy), surpassing previous studies by 11% and 67%, respectively. The study underscores the potential of AI to improve cost estimation accuracy and streamline insurance claims processing.

A. Shirode et al. [8] proposed a vehicle damage detection system using VGG16 for damage classification and Mask RCNN for precise damage localization. The study highlights the capability of deep learning in automating insurance analysis, limiting human effort. Image noise and illumination variations were mentioned as the obstacles, with the suggestion to use images of higher resolution for better results.

M. Dwivedi et al. [9] created a system for car damage classification and detection using pre-trained CNN models and YOLO, achieving 96.39% accuracy and a 77.78% mAP score for damage detection. Their pipeline combines classification and detection, providing a foundation for an automated car damage identification system with potential for improvement through a more diverse dataset.

A. Elbhrawy et al. [10] proposed a Cost Estimation System (CES) for car damage assessment using AI, specifically YOLO and Transformers, to automate damage recognition and cost estimation. The system achieved an average precision of 78.50%, recall of 70.24%, and mAP of 0.66, using a dataset of 2508 car images. This approach enhances accuracy, productivity, and time efficiency while reducing manual inspection costs and mitigating fraud risk in the insurance claims process.

J. D. Dorathi Jayaseeli et al. [11] developed a Mask R-CNN model for automatic car damage detection, focusing on scratches. Trained on annotated car images, the model identifies damaged regions, reducing insurance claim processing costs and fraud. It improves pricing accuracy and eliminates manual assessments, achieving a final loss of 0.3888.

Namam A. Mohammed et al. [12] proposed an end-to-end solution using Mask R-CNN to automate vehicle damage detection and cost estimation. Two Mask R-CNN models were employed: one for detecting vehicle parts and another for identifying damage areas. The system achieved 98.5% accuracy, demonstrating Mask R-CNN's effectiveness in estimating damage costs and improving the insurance claim process.

Harit Bandi et al. [13] explored three transfer learning approaches to detect vehicle damage, its location, and severity, utilizing Convolutional Neural Networks for accuracy optimization. The study achieved accuracy levels ranging from 68% to 87%, with the highest at 87.9%. The research enhances existing methods and highlights potential applications in the vehicle insurance sector, particularly for image recognition and damage estimation.

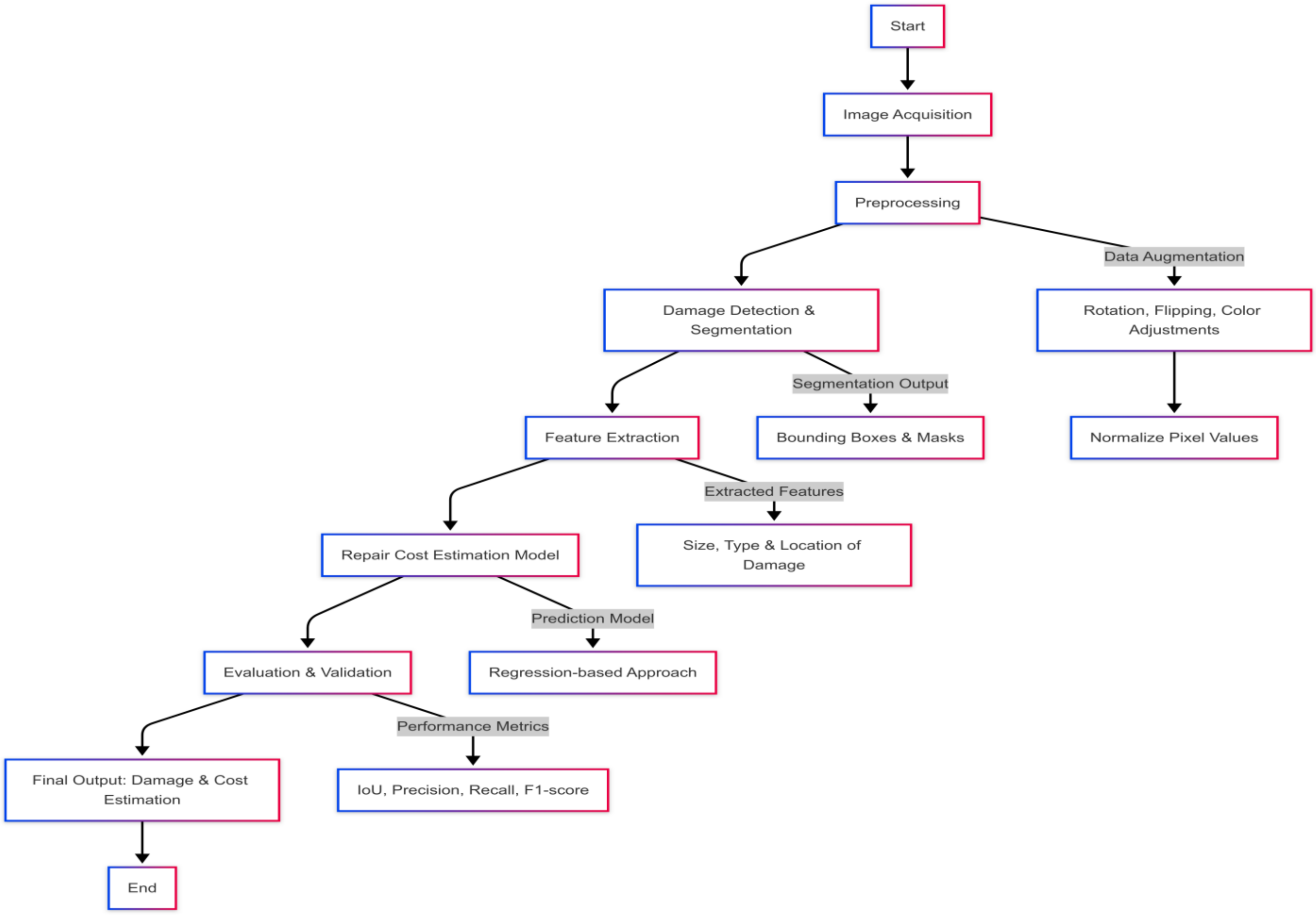
D. Widjojo et al. [1] designed an integrated deep learning system for damage detection and classification of cars using deep transfer learning. Mask R-CNN was employed for segmentation and EfficientNet and MobileNetV2 were compared for classification. With a concatenate simple CNN modification, MobileNetV2 obtained 91% F1 score, increasing accuracy by 9%. The research provides an applied solution for speeding up car insurance claim procedures.

Table I. Summary of Literature Survey

Author(s)	Technique	Pre- processing Methods	Application	Limitations
P. M. Kyu et al. [4]	VGG16, VGG19	Transfer learning, L2 regularization	Car damage detection, localization, and severity estimation.	VGG19 did better than VGG16, but low accuracy for severity estimation.
Sunil Kumar Aithal et al. [5]	Mask R-CNN, YOLOv5	Image processing at high resolution	Automated damage detection and repair cost estimation.	YOLOv5 only had 71.9% accuracy, and F1-score was 0.39.
H. Ahaggach et al. [6]	Ontology reasoning, Regression models	Named Entity Recognition (NER), Relation Extraction (RE)	Semantic reasoning with regression for cost estimation.	Heavy dependence on ontology structure; challenging to integrate.
M. Zhang et al. [7]	ResNet50, Transfer learning	Feature extraction and classification	AI-based vehicle repair cost estimation.	Restricted to vehicle make/model classification and damage classification.
A. Shirode et al. [8]	VGG16, Mask RCNN	Image resizing, normalization	Car damage detection and assessment for insurance claims	Affected by image noise, low resolution, and lighting variations.
M. Dwivedi et al. [9]	Pre-trained CNN, YOLO	Image augmentation, Feature extraction	Vehicle damage classification and detection	Accuracy dependent on diversity of dataset; 77.78% mAP score.
A. Elbhrawy et al. [10]	YOLO, Transformers	Object detection, Feature extraction	AI-based damage identification and cost estimation	mAP of 0.66, recall of 70.24%; dataset limited to 2508 images.
J. D. Dorathi Jayaseeli et al. [11]	Mask R-CNN	Transfer learning, Image annotation	Scratch detection on cars for insurance purposes	Final loss of 0.3888; scratch detection alone.
Namam A. Mohammed et al. [12]	Mask R-CNN (Dual models)	Segmentation, Feature extraction	Automated vehicle damage detection and cost estimation	System only tested on specific datasets; generalization not evaluated.
Harit Bandi et al. [13]	Transfer learning with CNNs	Model fine-tuning	Detection of car damage, location, and severity	Accuracy varies from 68% to 87.9%; no real-world validation.
D. Widjojo et al. [14]	Mask R-CNN, MobileNetV2, EfficientNet, CNN	Deep Transfer Learning, Concatenate CNN	Car Damage Detection and Classification	Limited to specific datasets and scenarios

III. Proposed Methodology

This section discusses the proposed method for the car harm detection and repair price estimation device. It integrates masks R-CNN, a deep learning-based totally



item detection and segmentation model, with a pipeline for the prediction of the repair cost the usage of damage severity and regions detected to compute the overall price of maintenance.

A. Collection of Dataset

The proposed gadget has used the COCO automobile harm Detection Dataset for education and evaluation. It carries labeled pictures with unique annotations of broken regions and categories. There are fifty nine photos within the schooling dataset together with corresponding annotation documents that incorporate facts on the broken place and their categories together with COCO_train_annos.json and COCO_mul_train_annos.json. similarly, the validation set has eleven pix that were used to validate the version in the course of education, and the test set had eight snap shots to test the model on records it has never visible.

B. Pre-processing

Preprocessing includes several steps of making ready the records for the version. pictures will be annotated using bounding boxes drawn around damaged parts, labeled in line with specific categories, such as "headlamp" or "front bumper." records augmentation through rotation, flipping, and different coloration modifications may be carried out for better generalization of the model. Pixel values are normalized in the variety of [0, 1] to ensure constant training. moreover, features important for value prediction—inclusive of the size of the damaged place, type of damage, and area—are extracted to facilitate correct repair fee estimation.

C. Feature Extraction

Feature extraction is an vital part of the automobile harm detection and repair price estimation gadget because it allows in predicting the value of repair according to the detected harm in the pix. The functions extracted consist of the size of the broken region, the sort of harm (e.g., scratch, dent, crack), and its region in the photo (e.g., front bumper, rear door). these functions give a demonstration of the severity and volume of the harm, which can be very important in determining the entire repair fee. The damaged areas are detected and segmented the use of masks R-CNN, with further techniques utilized to numerically quantify and classify them. The measurement of the broken location is determined through assessing the pixels within the bounding containers, even as the kind of damage may be recognized thru predetermined categories. The region of the damage is determined by means of the relative function of the segmented regions in the picture. those functions, whilst processed via a price estimation pipeline, allow for the correct prediction of restore fees for the affected vehicle components.

D. Model

This project focuses on developing a Mask R- CNN based model leveraging the Detectron2 framework for detecting,

Fig. 1. Flow Chart

segmenting, and classifying car damage. The objective is to design an advanced system capable of accurately identifying and localizing damage across various vehicle components, including the hood, bumper, doors, and headlights.

The model is built upon Detectron2's pre-trained Mask R-CNN architecture, integrating a ResNet-50 backbone with a Feature Pyramid Network (R50-FPN). Fine-tuning is performed to enhance accuracy, ensuring precise damage detection and segmentation. Training is conducted using Detectron2's default trainer, with optimization carried out through the Stochastic Gradient Descent (SGD) optimizer, which facilitates efficient convergence. To assess performance, the COCO Evaluator is employed to measure key metrics such as precision, recall, and segmentation accuracy. The model leverages GPU acceleration via cfg.MODEL.DEVICE, significantly improving computational speed and efficiency. Initially, it undergoes 500 iterations (MAX_ITER) as a baseline, with potential refinements based on specific requirements.

Once trained, the model excels in real-time damage detection, producing bounding boxes and segmentation masks to precisely highlight damaged areas. This solution has valuable applications in the automotive industry, particularly in automated vehicle repair cost estimation, insurance claim processing, and vehicle inspections. By automating damage identification and classification, the system enhances workflow efficiency, reduces manual effort, and improves damage assessment accuracy. This advancement represents a significant step forward for the auto repair and insurance sectors.

E. Testing Process

The system's performance is assessed using a test set of eight newly introduced images with simulated damage, processed through the trained Mask R- CNN model. The generated segmentation masks are evaluated against ground truth data using key performance indicators such as Intersection over Union (IoU), precision, and recall to measure the accuracy of damage localization.

Key damage attributes, including size, type, and location, are identified and incorporated into a repair cost estimation model. The predicted costs are then validated against actual repair expenses to ensure the system's reliability and accuracy. This structured approach enhances both the precision of damage detection and the efficiency of cost estimation, reducing manual effort while streamlining workflow operations.

Fig. 2. Damage detection and cost estimation output

IV. Results and Discussions

The performance of the car damage detection and segmentation system was evaluated using several key metrics and visualizations. Below are the details, including the formulas used, figures for graphs, and sample outputs.

A. Perfomance Analysis

The models proposed for car body damage detection and restore price estimation are compared to a lot of parameters in various methodologies and car body parts f1 rankings version accuracy and component-based detection quotes are used for the comparisons.

Formulas Used:

Precision:
Precision is real excessive high-quality predictions divided by way of making all beneficial predictions don't forget

$$Precision = \frac{True\ positives}{True\ positives + False\ positives}$$

Recall (Sensitivity):
Sensitivity is actual great detected among all actual positives

$$Recall = \frac{True\ positives}{True\ positives + False\ negatives}$$

F1 Score:
F1 rating a harmonic propose between don't forget and precision giving a single degree of approaches.

$$F1\ Score = \frac{2 * precision * recall}{precision + recall}$$

As it must be the version plays the recommended mask r-cnn version applied in restore estimation and car damage detection found out stepped forward performance in step with explicit measures of assessment the model consists of f1-score 0.880 accuracy of 0.86 and a consider of 0.901 though it has the proper stability amongst faux negatives and faux positives for damage detection and segmentation.

In addition, the model demonstrates an extremely high accuracy of 88.78%, well classifying different classes of vehicle damages and generating effective segmentation masks to estimate costs accurately. A component-wise evaluation displays varying detection accuracies from 89.23% for doors, 85.56% for the hood, 78.45% for the front bumper, 74.89% for headlamps, and 67.12% for the rear bumper. Such variations indicate that the model responds sensitively to damage patterns with differences across separate vehicle components.

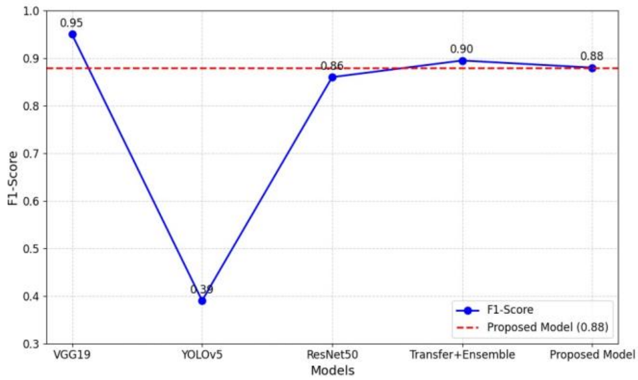


Fig. 3. F1 Score of 6 different models

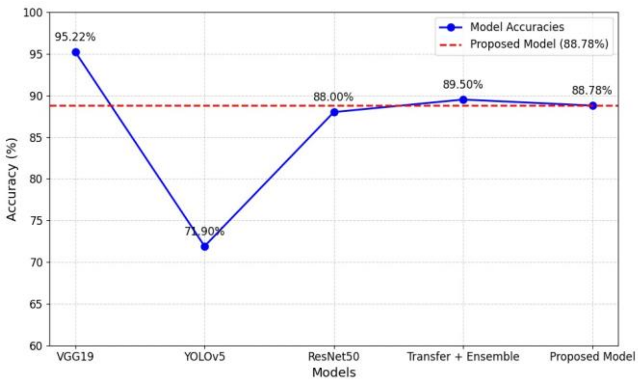


Fig. 4. Accuracy of 6 different models

Table II. Performance Metrics of the Proposed Model

Model	*Value*
Accuracy	*88.78*
Precision	*0.89*
Recall	*0.87*
F1-score	*0.88*

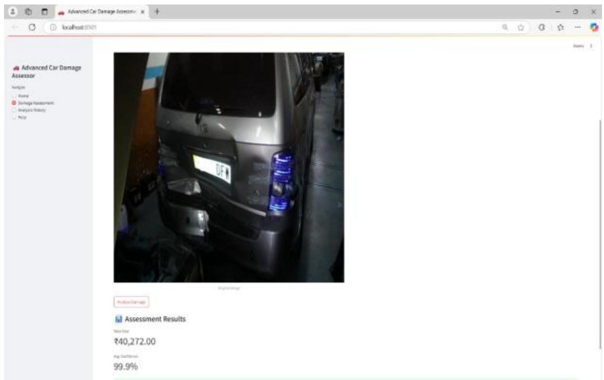


Fig. 5. Web interface displaying cost estimation.

V. Conclusion and Future Work

The automated damage detection and repair cost estimation system employs Mask R- CNN to identify damaged areas and estimate repair costs based on extracted damage features, such as size, type, and location. The model performs well in identifying vehicle damage and estimating the cost of repairs accurately having the potential to make repair quotes easier and automated in the automotive industry the system not only saves manual effort but also increases efficiency and accuracy in costing and damage analysis to further enhance the system increasing the data set to include a larger range of vehicle parts and types of damages is necessary this would improve the models generalization over different scenarios future work would be the addition of other variables such as labor rates part availability and regional price variation in the cost estimation model to make it even more realistic and practical transfer learning techniques will also be explored to fine-tune the model and enhance its overall performance the addition of up-to-date data from repair shops and insurance databases would also improve the robustness of the system which would be better suited for practical applications these additions would make the system a consistent tool for repair estimate automation and cost analysis in the automotive industry.

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