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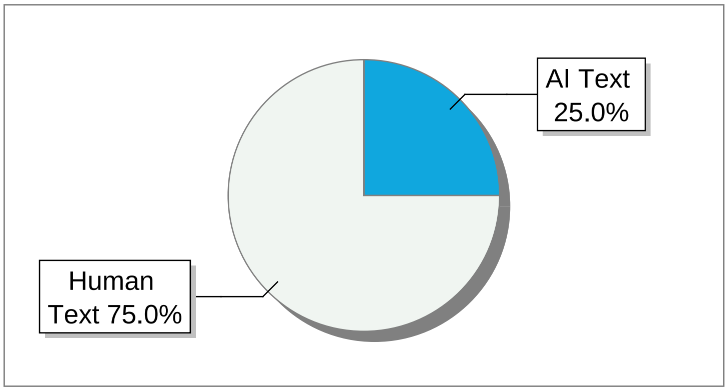


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1 Automated Damage Detection and Repair Cost Estimation for Automobiles Abstract Accurate damage identification and repair estimation costs are significant to the insurance and automotive industries.
Current processes use labor-consuming, human error-prone, 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 8878% with an F1-score of 0880, 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 Estimating the cost of repairing automobile damage is one of the most critical tasks in the automotive industry for both customers and insurance providers.
Manual assessments are tedious, error-prone, subjective, and usually inefficient when determining repair costs.
Automated car damage evaluation is revolutionizing the automobile insurance industry by improving assessment accuracy and reducing manual inspections.
The integration of deep learning techniques has significantly transformed how insurance companies process claims and compensations [1]Mask R- CNN, a deep learning system that blends object detection and instance segmentation, boasts substantial accuracy, particularly in the detection of small targets.
It is applied extensively in industries such as agriculture, medical imaging, and construction, and presents a promising method for simplifying the automation of vehicle damage assessment and streamlining insurance claims[2].
In this study, we used Mask R- CNN to detect external damages on vehicles in images.
The integration of this analysis in our system calculates the type and extent of the damage by enabling our system to estimate repair costs.
The computerized method developed through this study improves the productivity of damage assessments and increases the validity and reliability of cost estimations for customers as well as the insurers.
This solution simplifies and accelerates the repair cost estimation process, through the use of AI-driven technology.
Thus, it reduces administrative workload and promotes fairness and transparency in insurance and repair services.
A Motivation Increasing sophistication and inefficiencies of conventional car damage identification and insurance claim handling indicate the importance of new and innovative solutions.
AI-driven technologies, especially automation and data analysis-focused ones, hold the key to revolutionizing the manner in which the insurance sector approaches car damage evaluation and claim handling.
The motivation behind this research comes from the prospect of investigating AI-led solutions that will improve precision, lower costs, and overall customer satisfaction in insurance processes[3].
Recent developments in artificial intelligence and machine learning technology present promising solutions to these challenges.
Modern computer vision systems, particularly those utilizing advanced neural networks for image analysis, can automatically identify and assess vehicle damage with high accuracy.
These AI tools offer consistent and data-driven estimates, reducing the subjectivity inherent in manual assessments.
Our system aims to streamline the vehicle damage assessment process by implementing cutting-edge image recognition algorithms.
This approach benefits both insurers, who can process claims more efficiently, and vehicle owners, who receive faster, more reliable repair estimates.
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.
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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 9522% accuracy in damage detection, 7648% in localization, and 5848% 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 719% accuracy with an F1-score of 039 at a confidence threshold of 0477.
The study emphasizes the systems 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.
I 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.
R Singh et al.
[8] designed an end-to-end system for automating car insurance claim processing using image-based damage assessment.

The system integrates Mask R- CNN, PANet, and an ensemble model with VGG16 for part and damage localization.
It categorizes damage severity into no damage, minor, and severe, aiding in repair cost estimation.
The proposed method achieves mAP scores of 038 for parts localization and 040 for damage localization, simplifying the claims process for insurers and customers.
M Dwivedi et al.
[9] created a system for car damage classification and detection using pre-trained CNN models and YOLO, achieving 9639% accuracy and a 7778% 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 7850%, recall of 7024%, and mAP of 066, 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 03888.
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 985% accuracy, demonstrating Mask R-CNNs 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 879%.
The research enhances existing methods and highlights potential applications in the vehicle insurance sector, particularly for image recognition and damage estimation.
Kalpesh Patil et al.
[14] investigated deep learning techniques for car damage classification in vehicle insurance processing.
Initially, they trained a CNN but faced challenges due to limited labeled data.
The study then experimented with domain-specific pre-training, fine-tuning, transfer learning, and ensemble learning.
Results indicated that transfer learning outperformed domain-specific fine-tuning, achieving 895% accuracy with the combination of transfer and ensemble learning.
3 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 719% accuracy, and F1-score was 039.
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.
R Singh et al.
[8] Mask R-CNN, PANet, Ensemble with VGG16 Image segmentation and localization Automating car insurance claims using image-based damage assessment Low mAP scores (038 for parts, 040 for damage localization).
M Dwivedi et al.
[9] Pre-trained CNN, YOLO Image augmentation, Feature extraction Vehicle damage classification and detection Accuracy dependent on diversity of dataset; 7778% mAP score.
A Elbhrawy et al.
[10] YOLO, Transformers Object detection, Feature extraction AI-based damage identification and cost estimation mAP of 066, recall of 7024%; 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 03888; 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 879%; no real-world validation.
Kalpesh Patil et al.
[14] CNN, Transfer learning, Ensemble learning Domain-specific pre-training Classification of car damage in vehicle insurance processing Limited labeled data affected model performance.
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.
4 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_annosjson and COCO_mul_train_annosjson.
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 (eg, scratch, dent, crack), and its region in the photo (eg, 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, 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 headlightsFig.
Flow Chart 5 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 cfgMODELDEVICE, 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 systems 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 systems 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 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 proposed automobile damage detection and repair price estimation system become tested the usage of multiple metrics from different fashions and vehicle components.
This analysis consists of F1 rankings, version accuracy comparisons, and element-precise detection fees.
Formulas Used Precision Indicates the proportion of true positive predictions among all positive predictions.
Recall (Sensitivity) Represents the proportion of true positives identified from all actual positives.
F1 Score A harmonic mean of precision and recall, providing a single metric for model performance.
The proposed Mask R-CNN model for repair estimation and auto damage detection demonstrates superior performance according to a number of evaluation measures.
The model achieves an F1-score of 0880, precision of 086, and recall of 0901, ensuring effective balance between false positives and false negatives in damage detection and segmentation.
In addition, the model demonstrates an extremely high accuracy of 8878%, 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 8923% for doors, 8556% for the hood, 7845% for the front bumper, 7489% for headlamps, and 6712% for the rear bumper.
Such variations indicate that the model 6 responds sensitively to damage patterns with differences across separate vehicle components.
Fig F1 Score of 6 different models Fig.
Accuracy of 6 different models Table II.
Performance Metrics of the Proposed Model Model Value Accuracy 8878 Precision 089 Recall 087 F1-score 088 Fig.
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 demonstrates promising results in accurately detecting car damage and estimating repair costs, offering the potential to automate and simplify repair estimates in the automotive industry.
This system not only reduces manual effort but also improves efficiency and accuracy in damage assessment and cost estimationTo further enhance the system, expanding the dataset to include a wider variety of vehicle components and damage types is crucial.
This would improve the models ability to generalize across diverse scenarios.
Future work will focus on incorporating additional factors, such as labor costs, part availability, and regional price variations, into the cost estimation model to increase its realism and practicality.
Additionally, transfer learning techniques will be explored to fine-tune the model and enhance its overall performance.
Integrating real-time data from repair shops and insurance databases would also strengthen the systems robustness, making it more applicable in real-world settings.
These improvements aim to establish the system as a reliable tool for automating repair estimates and cost evaluations in the automotive industry.
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