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Deep Learning Approach for Vehicle Damage Analysis and Repair cost Estimation

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Abstract

As more cars hit the roads, accidents and damage are just part of the deal. Usually, experts handle vehicle damage assessments by hand—lots of waiting, high costs, and sometimes you don't even get the same answer twice. That's why this paper introduces a deep learning system to automate the whole process, from spotting damage on your car to figuring out what it'll cost to fix.

Here's how it works: The system pulls in the YOLOv5 object detection model to scan uploaded photos for damage—think dents, scratches, busted parts, or crumpled panels. Then, OpenAI GPT-4o-mini steps in, crunches the damage data, estimates repair costs, and delivers a straightforward explanation. You don't need any fancy tech skills to use it, either. It's all packed into a web app, with React.js running the front and Python Flask running the back.

KEYWORDS: Vehicle Damage Detection,Deep Learning,YOLOv5,Object Detection,Image processing,Repair Cost Estimation,OpenAI GPT-4o-mini ,Web based System,Artificial Intelligence.

1. Introduction

Traffic keeps growing, so accidents and car damage are more common than ever. When you get in a wreck, figuring out what's broken and how much it'll cost to fix has always been a hassle, not just for car owners, but for insurance companies and repair shops, too. Usually, you need an expert to take a good look at the car and make their judgment. But this old-school way isn't quick, and you might get different answers depending on who inspects the car or how much experience they have.

Now, with deep learning and computer vision, there's a better way. Algorithms like convolutional neural networks are really good at picking things out in images, so it makes sense to let them spot damage and estimate repairs. That's the whole idea behind this project.

Here, we built a web app that does just that. It uses frontend to scan uploaded car photos and spot damage, even giving details on what's wrong and how serious it is. Then, GPT-4o-mini steps in to suggest how much the repair might cost and explains why. All you have to do is upload your pictures, and you'll get an instant, automated damage report—no need to wait for someone to eyeball it.

2. Literature Survey

Deep Learning approaches used in automated Vehicle damage detection and assessment using images has been explored recently. The models can identify patterns in images such as Dents, Scratches, Cracks and Broken parts. Multiple Algorithms are used mainly for Object detection models such as YOLO and they are also applied on different conditions of vehicle damage assessment and detection. Following Studies are highlighted.

Wang et al., 2020 proposed an image based model for vehicle damage detection using convolution neural network for surface level damages like scratches and dents etc. They reported improvement in the accuracy than traditional image processing techniques, however more labelled data was needed to improve their model.[1].

Kumar et al., 2021 conducted an experimental study on classification of vehicle damages using support vector machine and random forest. Features were analyzed on vehicle's image datasets, reported a moderate accuracy but wasn' t able to handle complex damages or illumination changes.[2].

Singh et al., 2022 developed a deep learning based model using YOLO-v3 for real time vehicle damage detection. Multiple damages such as broken or dents were reported with good speed and accuracy. The detection accuracy gets reduced for low quality/blurry images. [3].

Li et al., 2023 proposed an improved object detection based on efficient net with convolution neural networks. Very high accuracy is reported on fine grain damages such as minor scratches but requires high processing power and takes time to train. [4].

Patel et al., 2024 proposed a hybrid deep learning model using CNN and transfer learning for vehicle damage detection. Good generalization on unseen datasets have been reported by author, however requires extensive processing steps and sensitive hyperparameter tuning. [5].

Chen et al., 2024 propose a YOLO-v5 based model for vehicle inspection. Model reported very high accuracy as well as good speed for real time processing. However, model performance heavily depends on dataset diversity. Continuous updations are required to ensure good generalization performance. [6].

Zhou et al. (2023) have proposed an SSD (Single Shot MultiBox Detector) based model of real- time vehicle damage detection. The system achieved a quicker detection time than older methods and also exhibited a good performance under real t ime conditions. The model however exhibited somewhat lower accuracy than YOLO based approaches. [7].

These studies show that deep learning models, particularly those based on the YOLO architecture, are very successful in the area of detecting damage to vehicles. Nonetheless, issues related to the diversity of datasets, high computation requirements, and real-world implementation are yet to be addressed.

The system presented in this paper advances these methods by combining YOLOv5 with a web- based application and a damage estimation module to deliver a feasible and effective system for automating the assessment of damage to vehicles.

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Table-1: Comparison of Existing Vehicle Damage detection Methods

Authors & Year	Model Architecture	Dataset Used	Performance	Result	Limitations
Wang et al., 2020	CNN	Vehicle Image Dataset	Improved accuracy over traditional methods	Effective detection of scratches and dents	Requires large labeled dataset
Kumar et al., 2021	SVM + Random Forest	Vehicle Image Dataset	Moderate accuracy	Basic damage classification	Poor performance on complex damages and lighting variations
Singh et al., 2022	YOLOv3	Vehicle Damage Dataset	High detection speed and accuracy	Real-time damage detection	Reduced accuracy for blurry images
Li et al., 2023	EfficientNet + CNN	Vehicle Image Dataset	Very high accuracy	Detects fine-grained damages	High computational cost and training time
Patel et al., 2024	CNN + Transfer Learning	Vehicle Damage Dataset	Good generalization	Robust performance on unseen data	Requires preprocessing and hyperparameter tuning
Chen et al., 2024	YOLOv5	Vehicle Inspection Dataset	High accuracy and speed	Real-time vehicle inspection	Depends on dataset diversity
Zhou et al., 2023	SSD (Single Shot Detector)	Vehicle Image Dataset	Fast detection	Good real-time performance	Lower accuracy than YOLO models

3. Analysis of Datasets

Here's how the system works: First, it pulls together a bunch of vehicle photos some with dents, others with scratches, broken pieces, or smashed panels. It doesn't just stick to one source, either. The images come from public datasets and various spots online, so there's a good mix.

Every image gets carefully labeled. Damaged spots are marked with bounding boxes, and those labels train the YOLOv5 object detection model.

The data splits into two chunks: 80% goes to train the model, and the remaining 20% is set aside to test how well it actually performs.

Before the model sees anything, there's some prep work. The images get resized, normalized, and run through a few extra tweaks and augmentations. This part's pretty important—it sharpens up the model and helps it spot damage on all kinds of vehicles, not just the ones it saw first.

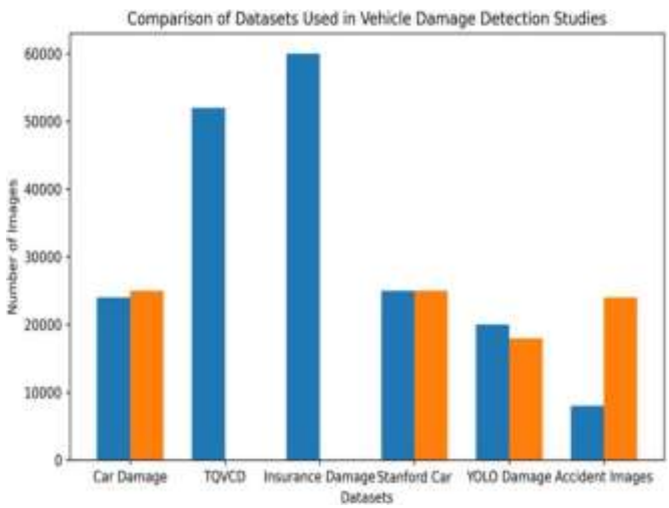

Fig. 1: Dataset distribution used for the Vehicle Damage Detection Models

4. Methodology of Proposed System

Our system is based on detection of the car damage and estimation of cost using deep learning techniques and web technologies. The system models the damages such as scratches, cracks, smash of lamp and glasses, dents on the vehicle image. The objective of this system is the automatic inspection process for vehicle.

At first the user gives input via Web interface by uploading vehicle image and fill in vehicle type, brand, model and damaged part. The uploaded image is pre-processed by a trained deep learning model to identify damage. Different type of damages is identified by YOLOv5 Object detection model as shown below.

Prior to training the model, the dataset is preprocessed in various ways: the images are resized to a fixed resolution, the pixel values are normalized and the data is formatted for use by the model. These preprocessing strategies improve model performance and allow the input data to be more consistent. The data is partitioned into training and testing sets: around 80% are placed in the former, and the rest in the latter.

Following data pre-processing it is used to train the YOLOv5 deep learning model. The model learns how to recognise the different severities/types of vehicle damage by observing shapes, edges and pattern recognition in the images. The model is then integrated into the backend system.

After the user uploads a photo, the photo is processed by the trained model; it detects the type of damage, bounding box, and the confidence score. Moreover, the cost estimation based on GPT-4o-mini utilizes the damage detected and vehicle information to estimate the damage cost and severity (minor, moderate, severe).

The web interface visualizes the result and makes user experience easier.

Object Detection Principle YOLOv5

YOLO (You Only Look Once) is an object detection algorithm that processes images in a single pass to detect objects efficiently. It divides the image into grids and predicts bounding boxes along with class probabilities.

The predicted output can be represented as:

$$y = \sum_{=1}^{N} (\text{Bounding Box} + \text{Confidence} + \text{Class}_{=1})$$

Formula: 1

Where:

- y = final detection output
- Bounding Box = coordinates of detected damage
- Confidence = probability of correct detection
- Class = type of damage (dent, scratch, etc.)
- N = number of detected objects

Loss Function

The YOLO model uses a combined loss function to optimize detection performance:

$$Loss = Lbox + Lobj + Lcls$$

Formula: 2

Where:

- Lbox = bounding box regression loss
- Lobj = objectness loss
- Lcls = classification loss

This loss function ensures accurate localization and classification of vehicle damages.

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Cost Estimation Model

The system also includes an AI-based cost estimation module that predicts repair cost based on detected damages and vehicle details.

$$\text{Cost}=f(\text{Damage Type},\text{Severity},\text{Vehicle Details})$$

Formula: 3

Where:

- Damage Type = dent, scratch, broken,lamo broken,glass shatter
- Severity = minor, moderate, severe
- Vehicle Details = brand, model, year, damage part

The estimation model uses a language model (GPT-4o-mini) to generate realistic repair cost ranges and explanations.

Regularization and Generalization

To improve model performance and avoid overfitting, techniques such as data augmentation, normalization, and proper dataset splitting are used. These methods ensure that the model generalizes well to unseen vehicle images.

4.1 System Architecture

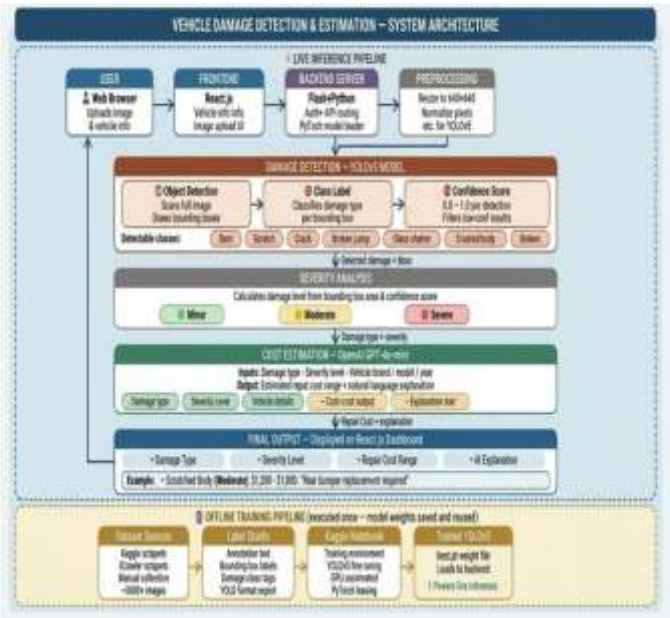


Fig. 2: Vehicle Damage Detection Model Architecture using Deep Learning Models

The architecture is a holistically designed pipeline for vehicle damage detection and repair estimation with deep learning-based web application.

It is a well-organized designed flow where the whole process begins with providing information from the user and ends with the final output to the user.

The first stage takes place between the user and the system via a React.js frontend. The user will have to upload an image of the car along with the essential vehicle information.

The data goes directly to the Flask backend server which handles the API and preprocessing. At this point, the uploaded image is resized and normalized so the deep learning model can work efficiently.

The second step is to detect the damages using YOLOv5 model. The model takes the image, which has gone through the above preprocessing, as the input, then it detects a variety of damages including dent, scratch, broken lamps, crack and glass shattering.

The model will place a box around each potential damage, and also provide a confidence score to indicate the reliability of this detection. After this, a severity analysis is performed based on the detected damages.

Lastly, the system can output repair cost estimation with a GPT-based language model. The user provide many inputs, including the type and severity of the damage, production year, etc, then the programme output an expected price accompanied by a short explanation.

The expected image that user will see through web page comprises damage type, severity level and the predicted price accompanied by the explanation. An offline training pipeline with labelled dataset is also adopted, which makes necessary training to the model by Kaggle and Google Collab.

4.2 Block Diagram

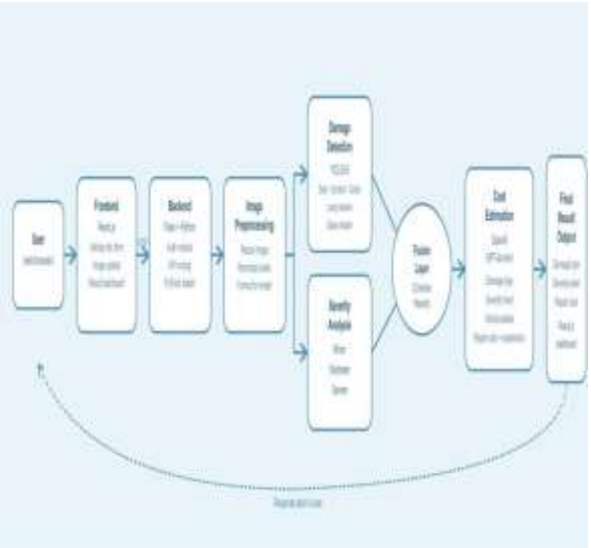


Fig. 3: Block Diagram of the Vehicle damage detection and repair cost estimation

The above block diagram depicts the detailed working flow of the vehicle damage detection and repair cost estimation system where the user needs to enter the image of the vehicle to be tested and then all the images will go into a deep learning based damage detection engine which will automatically identify the location of the damage and then send the image to the intelligent damage repair cost estimation engine followed by delivering the repair amount to the user as output.

The first step of this process is the user input stage. In this stage users can upload images of damaged car via a web interface that was built by React.js (frontend). The frontend application inputs data that needs to be sent to the server (the backend server used Flask and Python) by API calls. Flask's role in this section is to handle the initial request, producer task, handle the passing of data and oversee the stage.

Once the user inputs the data, the image preprocessing occurs and this is an important step before passing the data through the model. Here, the uploaded image is resized to the input scale of the YOLOv5 model.As well as resizing, other operations like normalization and formatting are performed to keep all the input images uniform and consistent.

After that the preprocessed image will be entered into the damage detection part via YOLOv5. It is the main part of this system as one of the fastest object detection algorithms ever. With this system, the object can be detected in a picture from many objects that are classed in a short period. In this system, has it can detect the damage of the vehicle including dents, scratches, broken parts, cracks, and shattered glasses. This model will find the damaged part of the vehicle from the picture and drawing the box as well as classifying label and confidence score, which are a kind of a confidence indicator.

In addition to detection, the damage severity analysis is carried out in terms of damage severity assessment. It makes use of the number of damages and the size of damaged regions, as well as the confidence in the detections, in order to categorize the damage as in the severity analysis module [87], into light, medium or heavy. As this system should provide easy understanding, the results of the detection module and severity analysis are fused together, in a fusion layer [88], combining all the information obtained.

Finally, cost estimation is provided by an AI-based language model (such as GPT-4o-mini, or you can train your own model). The inputs are damage type, level of severity, number of damages, and vehicle information. The output of this stage is an estimated range of repair cost and a short explanation of how this cost is calculated. This step converts detection results into financial figures that are applicable for everyday uses, for example, in insurance or vehicle inspection.

Lastly, this system produces the final output that can then be viewed through the web interface by the user. For this system, the output consists of the identified damage type, its severity level, diagram of estimated repair cost, and the reasoning behind the damage assessment. For the diagram, there is a feedback loop (represented by the dotted arrow) that shows the results are sent back to the user. From this diagram, it is easy to see how deep learning, image processing, and the web interface all contribute to make a fully functioning vehicle damage estimation system.

5. Implementation

This system is an AI-based model that takes vehicle images and identifies damages on them, also predicts cost of repair based on that. It integrates a deep learning model and web application. The webapp is built using python, YOLOv5, OpenCV, NumPy, Flask. Many other libraries such as Base64, UUID, JSON, SQLite, requests etc are used for data processing and backend activities. The training set comprised of labeled data-set of vehicle damages (dents, scratches, cracks, breakages, broken parts) which was accumulated from Kaggle data sets and Google Colab with GPU enabled on GPU. Training, validation data set ratio is 80–20.

Images were resized and normalized as a pre-processing step to make the input clearer. Damage images were used in training with YOLOv5 and learned the damage and then going to put it as object detection with bounding box and confidence score. Annotation, development, and collection of the data were done through Label Studio, VS Code, and iCrawler respectively.

The trained model is then embedded into a web system, where users upload images of the vehicle through a React.js system.

The image is fed into the Flask system and detected, then severity classification and repair cost estimation are done using GPT-4o-mini. The results with highlighted damages are then shown to the users, and stored in SQLite database. This provides an affordable, fast and automated vehicle damage assessment system.

6. Experimental Results

The he designed vehicle damage detection system's effectiveness was tested on a deep learning based system designed for damage detection including dents, scratches, cracks, and broken parts. The YOLOv5 system was trained on the curated dataset and tested on accuracy metrics like precision, recall, and mAP.

Object detection is performed using YOLOv5. It is capable of making multiple damage types into a given image and localize the damages. This was achieved by learning the visual features of the given structure, surface deformation or texture change.

Metrics and visualisations including detection results and confusion matrices were used for performance evaluation. These are used to quantify the accuracy of damage types recognition and make sure the reliable predictions.

Accuracy Calculation

Accuracy measures the overall correctness of the model in detecting vehicle damage.

The formula for accuracy is:

Formula 4:

$$\text{Accuracy} = (TP) / (TP + FP + FN)$$

Where:

- **TP (True Positive)** – correctly detected vehicle damage
- **FP (False Positive)** – incorrectly detected damage where no damage exists
- **FN (False Negative)** – actual damage that the model failed to detect

Higher accuracy indicates better performance of the damage detection model.

6.1 Precision, Recall

Precision and recall are used to evaluate the performance of the object detection model.

Precision

Formula 5:

$$\text{Precision} = TP / (TP + FP)$$

Precision measures how many detected damages are actually correct.

Recall

Formula 6:

$$\text{Recall} = TP / (TP + FN)$$

Recall measures how many actual damages are correctly detected by the model.

Mean Average Precision (mAP)

Formula 7:

mAP = Mean of Average Precision across all classes

mAP evaluates the overall detection performance by considering both localization and classification accuracy across different confidence thresholds.

In this project, mAP@0.5 and mAP@0.5:0.95 are used as standard evaluation metrics for YOLOv5.

6.3 Model Performance Evaluation

The The experimental results show that the proposed system achieves reliable performance in detecting car damages from images. The system uses the YOLOv5 deep learning model to identify damage types such as dent, scratch, broken parts, lamp broken, and glass shatter.

The model is evaluated using object detection metrics such as precision, recall, and mean Average Precision (mAP). The results indicate that the model successfully detects most of the damage regions with high accuracy and minimal false detections. The preprocessing techniques such as image normalization and resizing further improve the stability and performance of the model.

The precision-recall curve results indicate that the model maintains a good balance between precision and recall. The results demonstrate that deep learning–based object detection techniques can improve the accuracy and reliability of automated car damage systems. .

Table-2: Performance metrics for a car Damage Detection

Metric	Value
Precision	0.95
Recall	0.92
mAP@0.5	0.708
mAP@0.5:0.95	0.60

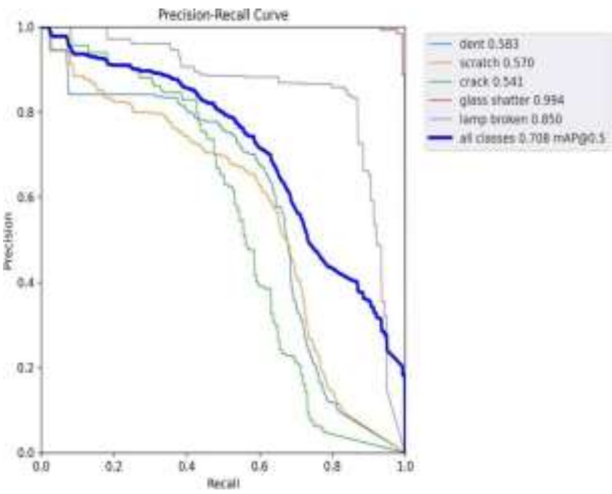


Fig 4: Precision-Recall Curve for

Table 3: Performance Metrics Based on Confidence Analysis

Metric	Value
Precision(Max)	1.00
Recall(initial)	0.85
F1-Score(Max)	0.73
Optimal Confidence	0.298

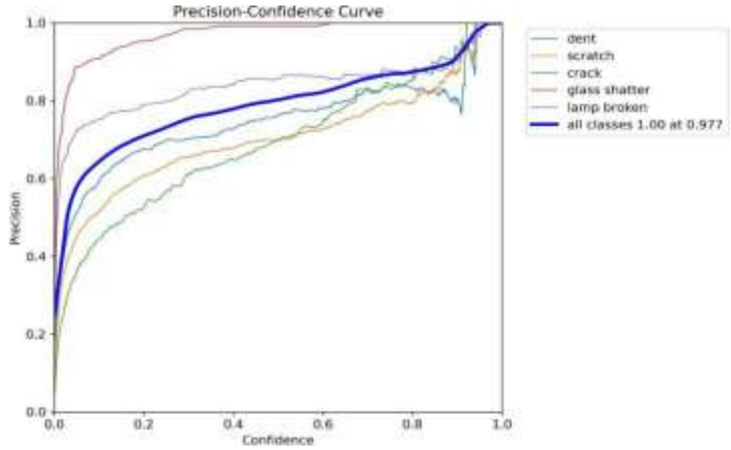


Fig-5: Precision-confidence curve

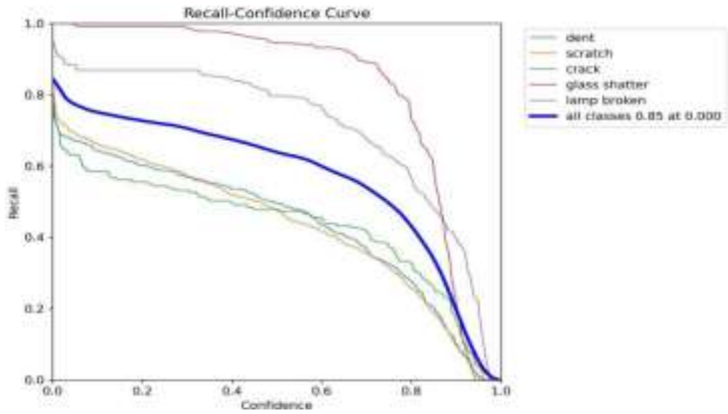


Fig-5: Recall-confidence curve

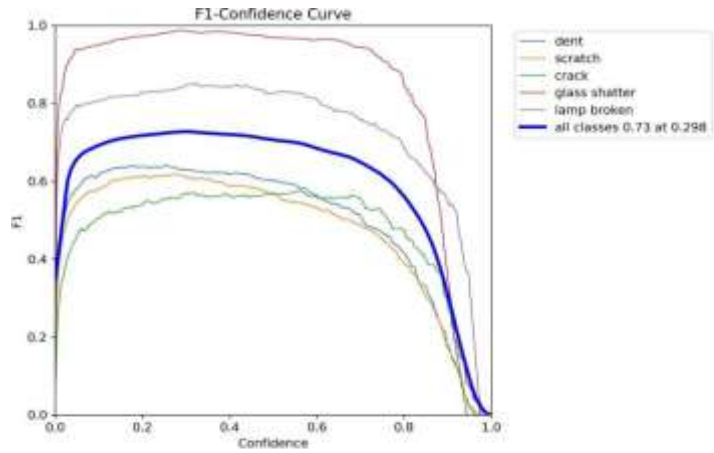


Fig-5: F1-confidence curve

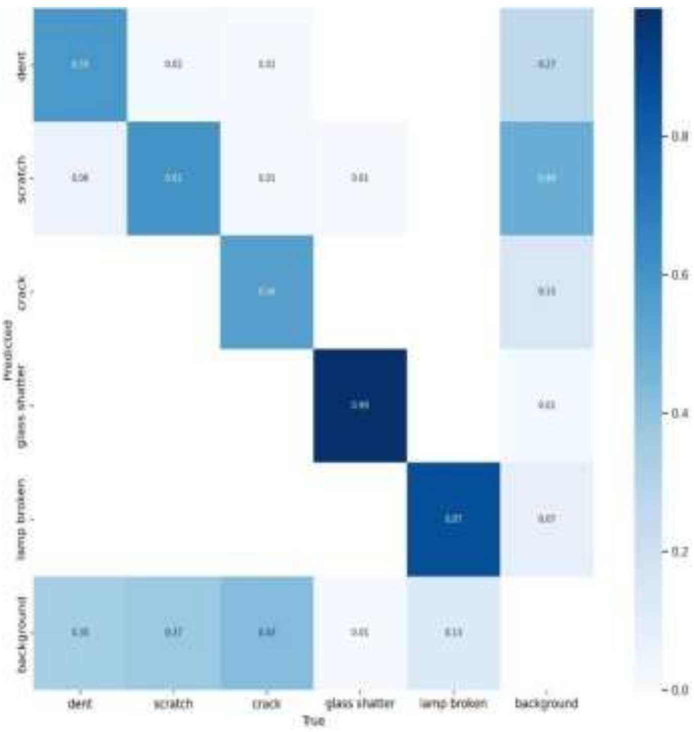


Fig. 7: Confusion Matrix Results for Damage Detection Models

Table 5: Overall Performance Comparison

Class	Images	Instances	Precision (P)	Recall (R)	mAP@ 0.5	mAP@ 0.5:0.95
All	751	1646	0.755	0.707	0.708	0.501
Dent	751	486	0.702	0.570	0.583	0.313
Scratch	751	717	0.656	0.574	0.570	0.311
Crack	751	171	0.610	0.532	0.541	0.320
Glass Shatter	751	134	0.985	0.989	0.994	0.852
Lamp Broken	751	138	0.822	0.870	0.850	0.709

7. Gaps Identified in Existing Research

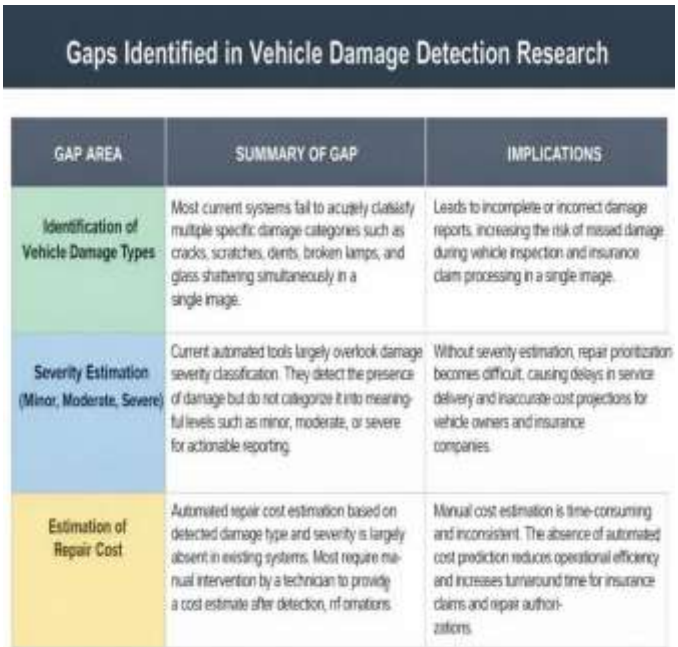
The diagram overviews what research gaps are currently in the field of damage detecting systems in vehicles. The display illustrates these in three sections belonging to three broad research gaps: Damage identification, Damage severity estimation and Damage cost estimation. The rows explain respectively what systems are deficient in today and how this affects 'inspection in the field of vehicle insurance'.

The first gap is the detection of vehicle damage types. Several authorizations used today lack an effective system that can identify and categorize multiple damage types (dents, scratches, cracks, break lamps and glasses damage) with one single image. This shortcoming could seriously hamper damage reporting and lead to overlook substantial damage.

The second type of gap is severity estimation. Most machines detect damage, but the severity is not classified into relevant scale, such as minor, moderate or severe. Without severity, the service provider cannot decide the required repair on time or insurance companies cannot evaluate the urgency of the damage.

The third that the gap shows is an automated repair cost estimator. In most existing systems the technician has to manually assess the extent of the damage and give an estimate of the cost of repair. This introduces inefficiencies into the cost estimation and prolongs the processing time of a claim and repair authorization.

In general, the diagram reveals the fact that although current systems for fault detection are somewhat reliable, they are incomplete in their fault severity recognition, cost estimation, and other functionalities. This set of necessities highlights the apparent requirement for such systems as your project, a system that would provide automatic cost estimated based on severity recognition through fault detection.



Gaps Identified in Vehicle Damage Detection Research

GAP AREA	SUMMARY OF GAP	IMPLICATIONS
Identification of Vehicle Damage Types	Most current systems fail to accurately classify multiple specific damage categories such as cracks, scratches, dents, broken lamps, and glass shattering simultaneously in a single image.	Leads to incomplete or incorrect damage reports, increasing the risk of missed damage during vehicle inspection and insurance claim processing in a single image.
Severity Estimation (Minor, Moderate, Severe)	Current automated tools largely overlook damage severity classification. They detect the presence of damage but do not categorize it into meaningful levels such as minor, moderate, or severe for actionable reporting.	Without severity estimation, repair prioritization becomes difficult, causing delays in service delivery and inaccurate cost projections for vehicle owners and insurance companies.
Estimation of Repair Cost	Automated repair cost estimation based on detected damage type and severity is largely absent in existing systems. Most require manual intervention by a technician to provide a cost estimate after detection, rf omations.	Manual cost estimation is time-consuming and inconsistent. The absence of automated cost prediction reduces operational efficiency and increases turnaround time for insurance claims and repair authorizations.

Fig. 8: Gaps Identified Vehicle Damage Detection and Repair Cost Estimation

8. Future Enhancements Suggested in the Literature

In addition to the improvements made to the vehicle damage detection system it would be beneficial to incorporate larger, more general vehicle damage datasets. We have seen that the current vehicle damage detection systems have been trained on small datasets, specific to vehicle types and types of damage. By increasing the data set, including more vehicle types, sky and weather conditions and types of damage the models' generalization abilities can be improved.

Another possible avenue for advancement is through the use of more sophisticated deep learning architectures, such as hybrid models. The use of enhanced YOLO variants, or the use of models that combines CNN feature extraction with transformers, can improve upon the detection accuracy and refine the other damage patterns like small scratches, cracks, and deformations to the structure.

Researchers further highlight utilizing different methodologies to enhance model performance such as data augmentation, hyperparameter optimization and transfer learning. These enhance the ability of the model to learn different visual cues as well as be more robust in real-world settings with different quality images and distracting backgrounds.

A significant future research area, is the use of XAI methods for vehicle damage detection. It would be useful if the system was capable of providing an explanation for the detected damage, damage severity category and estimated cost, to increase the user trust, particularly in the case of insurance and inspection applications.

Moreover, mobile camera-based damage detection or sensor- based damage detection could be conducted during the future system. The integration with Internet of Things (IoT) and intelligent transportation system could realize this function that aims to monitor the road condition and send instant message.

In summary, these improvements are intended to bring about more reliable, portable, and intelligent vehicle damage detection methods and systems in order to facilitate automatic vehicle inspection, minimize human intervention, and optimize efficacy in the insurance and repairs sectors.

9. Conclusion

In recent few years, the rapid development of artificial intelligence and deep learning methods has opens up new scopes to enhance the current automated vehicle inspection system.

Vehicle damage detection is an integral part for this process and plays a crucial role in lowering the manual checking workload, accelerating Insurance claim settlement, and enhancing the repair decision-making process.

This work develops an automatic vehicle damage recognition and cost assessment system using deep learning algorithms.

Object detection based model is developed which can detect various damages like scratches, dents, cracks, broken lamp and glass damages etc. on vehicle image.

This damage report can be uploaded on website where user can submits vehicle images and gets the report. Model uses object detection with image preprocessing for detecting damage regions and further categorizing into damages.

Along with damage detection, the system will also include severity classification and automatic estimations of repair costs based on other state-of-the-art AI models such as GPT-4o-mini so that the system will not only return the detection result but also supply the damage severity levels and estimated repair costs.

Experimental results show that the desired detection performance with good accuracy and stable results for various kinds of vehicle damage can be got in our scheme. The preprocessing methods and the effective training strategies can help to improve the model‘s performance and generality.

In summary, the system is an efficient, automated, scalable and intelligent system to perform damage evaluation of a vehicle. It can be implemented with less amount of manual intervention, more precise and un-biased results, and better user experience of Web based system.

The project also emphasizes on application of AI in day-to-day activities like vehicle inspection and helps such processes to be quick, reliable and intelligent.

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