

Vehicle Damage Detection and Severity Estimation

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Abstract - Vehicle damage assessment is key to the insurance claim process and for evaluating damaged vehicles. The traditional approach uses manual inspections which are slow, subjective, and often inconsistent due to the many different conditions vehicles are subject to in the real world. This paper proposes an automated system to identify vehicle damage and estimate the severity using deep learning and image processing methods. The authors use a pre-trained YOLOv8 model to find the damage regions, namely dents, scratches, and cracks, using bounding box localization methods. The authors then use the damage zones identified by YOLOv8 to calculate a damage ratio in each zone so that they may be classified as either minor, moderate, or critical damage using a rule-based system. Following this, they have developed a Repair Cost Estimation module to take the severity level of the damage and map it to a predefined repair cost range. Additionally, the authors have used an image hashing method to identify duplicate images submitted and prevent insurance fraud. The findings show that the proposed automated system can successfully identify and classify the severity of vehicle damage and consistently provide accurate cost estimates in real-world conditions. Overall, the proposed automated system provides more efficient vehicle inspection and insurance claims processing by reducing the amount of manual labour and allowing for faster decision making.

Keywords: Vehicle Damage Detection, YOLOv8, Computer Vision, Severity Estimation, Cost Prediction, Image Hashing.

I. INTRODUCTION

Increased vehicle volume has caused a dramatic rise in automobile accidents and damages from items such as scratches, dents, and cracks. The ability to accurately assess the extent of damages is critical for the purpose of vehicle inspections, repair planning, and processing insurance claims. The typical method for assessing vehicle damages has been to have an expert manually assess each vehicle. This process often takes a long time to conduct, is subjective, and has often produced inconsistent results. The manual process can also be affected by environmental conditions including lighting, camera angles, and complex backgrounds.

The use of deep-learning (DL) and computer vision (CV) technology has improved the ability for the automation of vehicle damage detection. DL-based object detection models, such as the YOLO architecture for example, are capable of rapidly and accurately analysing images to identify damaged areas of a vehicle. However, the vast majority of existing damage detection systems do not integrate damage detection with damage severity estimation or cost prediction.

This paper describes a DL-based automated vehicle damage detection and severity estimation system that uses the YOLOv8 object detection model. The system is capable of detecting damaged regions using bounding box localization; measuring the extent of the damage via image analysis; classifying the damage severity using severity classification; and estimating repair costs. The automated vehicle damage detection and severity estimation system also incorporates an image hashing mechanism to detect duplicate image submissions to help prevent fraudulent claims.

This work presents several major original contributions:

- Integration of the YOLOv8 object detection model with severity estimation.
- A new rule-based mapping of damage severity to repair cost.
- The ability to detect tampering via image hashing.
- A complete automated vehicle damage detection and severity estimation system designed for real-time usage.

II. LITERATURE REVIEW

Deep learning and computer vision are the focus of current efforts to automate and improve upon existing methods of assessing vehicle damage. In particular, object detection models (e.g., YOLO) are frequently employed because of their ability to function in real time, accurately and very quickly, to detect many different types of damaged areas in an image of a vehicle. Therefore, they can be used in a wide variety of real-world settings as the basis for operational automated vehicle inspection systems [1].

A number of researchers have developed advanced loss function and optimization algorithms to increase the detection accuracy of automated vehicle damage detection systems. Improved detection accuracy for small or subtle vehicle damage (i.e., scratches or minor dents) is a primary benefit of these techniques and of better handling of class imbalance within vehicle dataset images using one or more of the discussed improved detection strategies. The improvements in training strategies have resulted in faster convergence and improved performance with difficult to detect damage in real-world datasets [2].

A number of research studies have shown improvements in automated vehicle damage detection systems using deep learning techniques, specifically bounding box localization methods. These systems successfully detect various types of vehicle damage (i.e., dents, scratches and/or cracks) in multiple environmental settings. However, the majority of automated vehicle damage detection systems currently available in the literature, primarily focus on detection, but not on integrated estimation of damage severity or cost to repair the detected damage [3].

In some of the reported investigation or applications, proposals have been made to improve the process of estimating damage severity by using (1) multi-stage pipeline processes; (2) damage segmentation techniques; which allows for more granular analysis of vehicle damage via providing a better boundary and severity detection within the segments but at the cost of a larger computational burden and loss of applicability for real-time detection of the damage [4].

Additionally, although a number of recent studies have indicated that ensemble-based approaches can provide higher detection accuracy by combining the predicted outputs from multiple models, these approaches create a more complex and costly processing system than using traditional single model based approaches [5].

Deep neural networks (DNNs) are used in advanced segmentation models to enhance the accuracy of localizing damage. These models provide more detailed damage boundary information and better classify damage severity than previous models. However, DNNs demand large datasets and a lot of processing power, making them inefficient solutions for real time damage localization.

Other studies that have combined damage detection and cost prediction using rule-based approaches produce outputs that classify the severity of the damage and assign a predicted repair cost according to predefined severity levels, but these approaches do not effectively adapt to the constantly changing repair costs in the real world.

The enhancement of performance exhibited by using DNNs in vehicle damage detection can be attributed to the availability of large-scale annotated datasets. The lack of generalizability and robustness of DNN models has been lessened by the use of diverse datasets taken in varying light and environmental conditions. While these advances have improved the ability of detecting damage, most systems currently in existence are limited to damage detection without an integrated system that includes detecting damage, estimating severity of damage, predicting the cost of repair for the damage and detecting damage fraud, indicating the need for a comprehensive system that can produce a complete assessment of vehicle damage in real world situations.

III. PROPOSED SYSTEM

The developed system uses deep learning and image processing technologies to automate how we detect damage to vehicles as well as how to determine how badly they are damaged (or the degree of severity of their damage). The solution analyzes images of vehicles to determine what areas of the vehicle have been damaged (e.g., dents, scratches, and

cracks) by analyzing the image(s) and looking for visually distinguishable areas. For example, once an image has been processed using the proposed image quality and uniformity measurement analysis techniques, a pre-trained YOLOv8 model detects damage areas and creates bounding boxes around those areas so that they can be easily visualized.

The overall goal of this system is to develop a solution that will provide a consistent and efficient way to assess the damage done to a vehicle by eliminating the shortcomings of the current manual inspection process.

To begin with, a set of vehicle images will be processed to remove variability from image quality and increase uniformity of vehicle images prior to processing through the YOLOv8 model, which will detect damaged regions and categorize them into bounding boxes.

Once the bounding boxes identifying damaged areas have been created by and labeled, the extent of the damage can be determined by calculating the ratio of the area of damage to the size of the image.

Following this calculation, the appropriate rule-based method for severity evaluation will be used to evaluate the extent of damage and assign a severity level to that extent (e.g., low, medium, or high).

To add value and utility to the proposed system and to further assist the user, the cost associated with damage will be incorporated by developing a cost estimation model that involves mapping all severity levels to a specified cost range for each level of severity, allowing the user to receive some sense of the financial implications of damage incurred to a vehicle.

In addition, the proposed system will identify duplicate images and evaluate if the duplicate images were submitted by the same person to prevent abuse by identifying duplicate images through the image hashing technique and removing any duplicates from the analysis.

Finally, the proposed solution will employ a web-based interface that allows the user to upload images of their vehicle and receive an analysis of images uploaded to the web interface, including bounding boxes around identified areas of damage, a severity score for the extent of the damage, and an estimated cost associated with repairing the damaged vehicle due to the extent of the damage identified with the bounding boxes.



Figure 3.1 Architecture of the system

Vehicle images will be obtained in different lighting conditions, backgrounds, and orientations. The vehicle images will be pre-processed using various techniques to improve the quality of the images and to ensure consistency in the images so that they can be processed by the model.

The subsequent step will send the processed vehicle images to the YOLOv8 model. YOLOv8 will detect the damaged parts of the vehicle image and create bounding boxes around the detected damaged areas. Using the detected damaged areas, the model can also compute the ratio of damaged areas compared to the total area of the vehicle image.

In addition, the model will estimate the severity of the damage using established rules based on the calculated damage ratio. The estimated severity of the vehicle damage will be categorized as either minor, moderate, or critical. After the estimated severity of the vehicle damage has been calculated, the model will use a pre-established process to predict the approximate cost to repair the damage based on the estimated severity level.

In addition to detecting and assessing the damage to a vehicle image, the system will use image hashing techniques to detect possible image tampering. The location of the image hashing will be conducted by creating a hash value from the vehicle image when it is uploaded and then comparing the hash value to the hash values stored in a database for images that have been uploaded in the past for the same vehicle.

IV. IMPLEMENTATION

An end-to-end vehicle damage detection and severity assessment system is being implemented using deep learning & image processing techniques. The system utilizes deep learning and other image processing methods to process pictures of actual vehicles to identify damage such as dents, scratches, etc.

Vehicle pictures are inputted into the system as a part of the first step in the system's workflow. Vehicle images will be obtained in different lighting conditions, backgrounds, and orientations. The vehicle images will be pre-processed using

various techniques to improve the quality of the images and to ensure consistency in the images so that they can be processed by the model.

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A web-enabled system provides a user with the ability to upload photos of their vehicle and view the analytic results provided. Deployed through a user-friendly interface, the results show all areas where damage was detected, the assessed severity of the damage, and an estimated repair cost in an easy-to-read manner. The entire process from the upload of the photo until the result shows will be completely automated and designed to create a positive user experience.

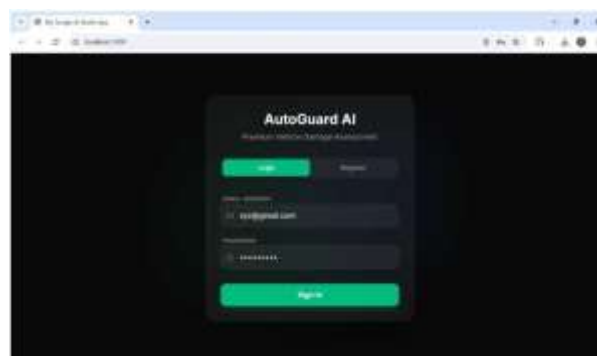


Figure 5.1: User Authentication Screen with Login Credentials Input

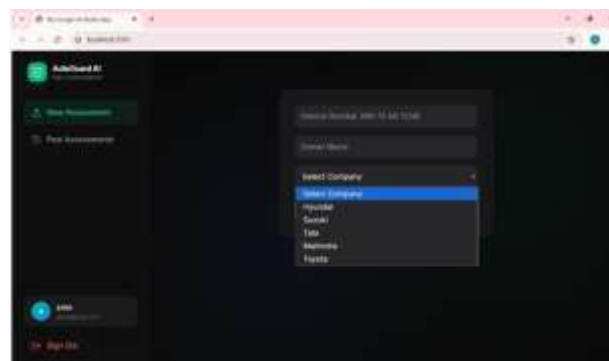


Figure 5.2: Vehicle Details Entry with Manufacturer Selection

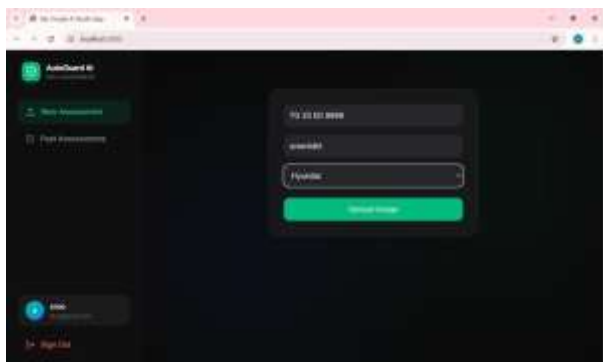


Figure 5.3: Vehicle Information Input with Image Upload Option



Figure 5.4: Image Selection Dialog for Uploading Vehicle Damage

V. RESULTS AND DISCUSSION

To determine how well the Vehicle Damage Detection and Severity Estimation System works, the following evaluation methods are used: (1) accurate detection of damaged areas from uploaded pictures; (2) identification of how damaging each area was by obtaining the ratio of the bounding box to the picture size (included in the evaluation methods) and (3) generating a predicted repair cost based on the calculated severity level after the image has been processed.

The YOLOv8 deep learning model finds several types of vehicle damage such as dents, scratches, and cracks within an uploaded picture through the use of bounding boxes, which are positioned around the affected areas of the vehicle. The visual accuracy of the model can be evaluated through the alignment of the bounding box created by the model with the damaged portion of the vehicle in the uploaded picture.

When evaluating the performance of the severity estimation aspect of the system, the ratio of the estimated damaged area to the total area of the image is compared. The damage ratio used in the system is calculated using the coordinates of the bounding boxes; once this is determined, the severity levels of minor, moderate, and critical are assigned to the estimated damage. The cost estimate calculation is based on the severity level of the identified damage but is determined through established rules or mappings. While there is no dynamic pricing used in the vehicle damage estimation, the system provides an approximate estimate that is more than adequate for practical applications in the real world when performing vehicle damage inspections.

This will also increase the reliability of the system as well as reduce the chance that images of vehicle damage will be misused in insurance claims.

The Damage Detection Module creates bounding boxes for visible areas of damage on vehicle images as shown in the Figure 5.5. The YOLOv8 processing model identifies where there is damage or scratches, cracks on the vehicle's surface after entering an uploaded image into the Damage Detection Software. The data shows that the Damage Detection System works well at detecting clearly visible damage areas that are large enough for the model to identify. The model has a high accuracy rating for detecting major dent, structural and body damages under "normal" lighting conditions. The accuracy rating drops somewhat with smaller scratches present and/or poor lighting conditions; however, the system is still able to accurately locate large damaged areas.

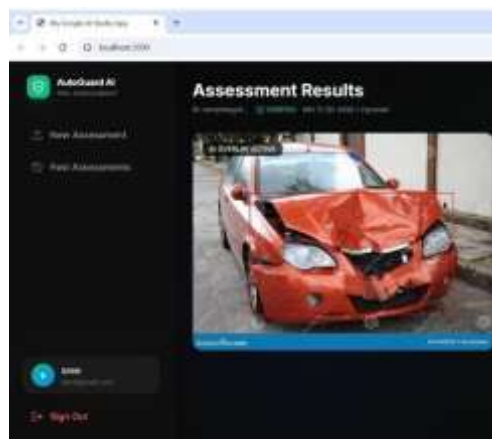


Figure 5.5: Detected Damages Using YOLOv8 Bounding Boxes

The bounding boxes indicate the marked damaged areas make it easy to see if the results agree with what users see. This indicates that the Deep Learning-based Damage Detection Model works well in practical applications. After determining where areas of damage exist, the Damage Detection System calculates the damaged area using the coordinates from the bounding boxes; then the Severity Estimation Module compares the total area of damage to the total area of the image to determine the damage ratio. The damage ratio is mapped to assigned severity categories. The results show that the larger areas of damage indicated by the bounding boxes will result in higher severity; conversely, smaller areas of damage will have lower severity values. The Severity Score is normalized between 0-100 to promote consistency when evaluating vehicle images. The numeric value of the severity score promotes increased clarity and faster decision making for inspection and repair planning.

The process of classifying severity ensures that the damage detection and assessment system not only identifies damage, but it also provides users with a meaningful report of the seriousness of the damage that has been detected as shown in the Figure 5.6. This is beneficial to the overall utility of the damage detection and assessment system in the workflows of any vehicle inspection and/or insurance processing.

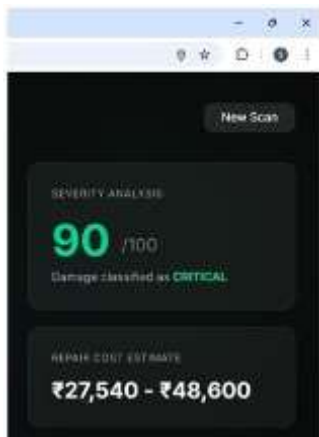


Figure 5.6: Severity Score Generated Based on Damage Analysis

Based on the severity score that was generated in the previous module, the system calculates an approximate range of cost estimates for repairs. The cost estimate is calculated using a rule-based, or heuristic, method where each severity level is assigned an approximate cost range). The output of the energy evaluation module indicates the amount of money that will be needed for repairs based on the level of severity assigned to the damage. For example, critical damage requires more money to repair than minor damage. As a result, this cost estimation will allow the users to make an educated decision about the expected cost to repair their vehicles, without requiring them to wait for an in-person insurance inspection to occur.

The cost estimate output will also be displayed clearly on the system interface as shown in the Figure 5.7, which will enhance user interaction and usability.

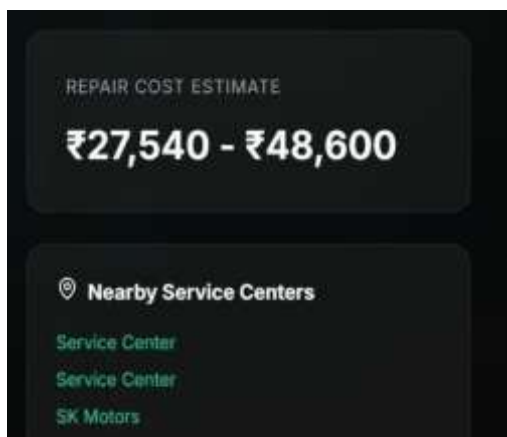


Figure 5.7: Repair Cost Estimation Based on Damage Severity

The tampering detection module assists the system in providing trust and reliability. Each image that is uploaded into the system generates a hash code, which is placed in the system's database. When a new image is uploaded, the hash code of the new image is compared to the previously stored hashes.

Upon finding a matching hash, the system detects/image matches as identical as shown in the Figure 5.8. The results also confirm that multiple uploads of the same image can be detected by the system, preventing fraudulent behaviour where an image of damaged property is uploaded repeatedly. At the moment, the system strictly detects only exact duplicates; however, this provides a simple way to be able to identify

fraud at a very basic level in a vehicle damage-assessing program. The incorporation of detected damage with detection of tampering has enhanced the security of the system as well as the trust in the output produced by the analyse program.



Figure 5.8: Duplicate Image Detection Using Image Hashing

The system's output includes detected damaged areas, degree of severity, estimated cost to repair the vehicle, and detected tampering. The results are given via a user-friendly display showing the area of damage detected within the original vehicle image and giving a structured way to report output values that were calculated.

The summary output from the analysis allows users to quickly assess the condition of the vehicle without hovering over the vehicle image and examining it closely. The continuity of the results produced by the analysis for different test images verifies that the system will deliver consistent and reliable results based on its programming and circuitry. Since each individual module of this system is independent, components within this system are able to operate independently while functioning as a total system.

The integration of damage detection, degree of severity, and predicted cost demonstrates the application of this proposed system within an actual vehicle inspection environment.

The web-based dashboard that has been generated by using this system provides the user with a more interactive interface in which to upload images of their vehicles and view the resulting analysis information. The original image of the vehicle will also be presented with highlighted area's of damage within the vehicle, a measurement of the severity of the damage, and a computed cost estimate for the repair of the damaged area highlighted on the vehicle image.

Users can download comprehensive PDF reports from the dashboard that contain all analyses done on their vehicles. In addition to providing a way to document an assessment, these reports also facilitate the submission of insurance claims resulting from the inspection of the vehicle. The user-friendly graphical interface of the dashboard allows for easy navigation and increases accessibility of the application to both tech-savvy users and others.

The dashboard improves the overall usability of the application by presenting complex outputs generated during the assessment in a simple and easy-to-understand manner.

The application processes each uploaded image of a vehicle rapidly, with very quick turnaround on the results of those images being processed in relation to the time taken to receive

the output. The YOLOv8 object detection model allows for rapid detection of vehicle damage from images; thus making the application ideal for near real-time utilization. Upon submission of an uploaded image, the application immediately starts analyzing that image and displays the results asynchronously; therefore, no discernable lag between submitted image and available output

The real-time capability of the application increases its practicality for use in the vehicle inspection center or by insurance agency. No longer will a user have to wait for processing of uploaded images before they can determine whether or not damage exists on a vehicle. Continuous monitoring of uploaded images can also lead to identifying vehicle damage sooner and increasing efficient workflow within the organization.

Evaluation of the system shows reliable detection of damage, accurate estimation of severity of damages, and consistent cost estimation for damages across all uploaded images. Modular design of the application ensures that all functions of each module operate independently of one another, while still maintaining the efficiency of the other modules. The implementation of destructive and non-destructive methods of detecting, estimating severity of damage to a vehicle, and estimating costs associated with repairing damage allows the system to be operate (limited human interaction) in a manner that produces high levels of accuracy and efficiency.

This output includes all results from the inspection of a vehicle's damaged parts, broken up into distinct categories (identified areas of damage, classification of damage severity level, estimate of reparation costs, and current condition of the vehicle). At its core, this proposal offers an automated approach to determining both whether a vehicle had damaged parts and their severity of damage. These processes will enhance the efficiency, accuracy, and reliability of all inspections performed on damaged vehicles in the future, thereby enhancing the overall quality of service being provided.

Image Condition	Detection Quality	Severity	Cost Range	Tampering
Clear dent	High	Critical	Rs.40k- Rs.80k	No
Minor scratch	Medium	Low	Rs.5k- Rs.10k	No
Blurred image	Low	Incorrect	Variable	No
Duplicate upload	High	Same	Same	Yes

Table 1. Sample System Outputs

Damage Severity	Severity Score
Minor	0 – 30
Moderate	31 – 60
Critical	Above 60

Table 2. Severity Score

VI. CONCLUSION

Vehicle damage assessment has become an important aspect of insurance processing and vehicle inspection process as a result of both the rapid growth in the number of vehicles being used on the roads and the rising number of accidents that involve motor vehicles. Manual inspection methods typically take longer than expected, are inconsistently applied and rely on subjective judgment of individuals, resulting in inaccurate assessments and delay in making decisions.

This study presented an automated vehicle damage detection and assessment of damage severity system utilizing deep learning techniques through image processing techniques. The use of the YOLOv8 model for the detection of damaged areas of vehicles (e.g., dents, scratches, and cracks) from photos of different sides of vehicles has been implemented in the new technology to evaluate the extent of damage on vehicles. Once the damage area(s) on the vehicle have been established, the system calculates the ratio of damage and assigns a level of severity; calculates the cost of repairs based on a rules-driven approach and provides evidence of tampering if applicable; assistance in producing damage report documentation automatically.

Through the evaluation of available photographs submitted with claims, the system has shown to be capable of accurately identify visible vehicle damage, classify the level of severity for damaged vehicles in a consistently reliable manner, and generate realistic estimates of repair costs. Therefore, the use of the proposed automated vehicle damage detection system has reduced the amount of time and energy spent performing damage assessments manually, thus enhancing the reliability and credibility of the results obtained from the analysis using this system.

Future areas of research should look at expanding the capabilities of the proposed vehicle damage detection system to accommodate real-time analysis of video footage for continuous monitoring purposes. Further research will determine what type of advanced segmentation models (e.g., Mask R-CNN) can be used to improve the accuracy of damage feature boundary identification in determining vehicle damage severity levels, as well as using machine learning algorithms to generate accurate estimates of repair costs using historical repair data. Additional future research opportunities may include implementing the vehicle damage detection system on cloud-based platforms to improve the scalability, accuracy, and real-world applicability of the system.

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