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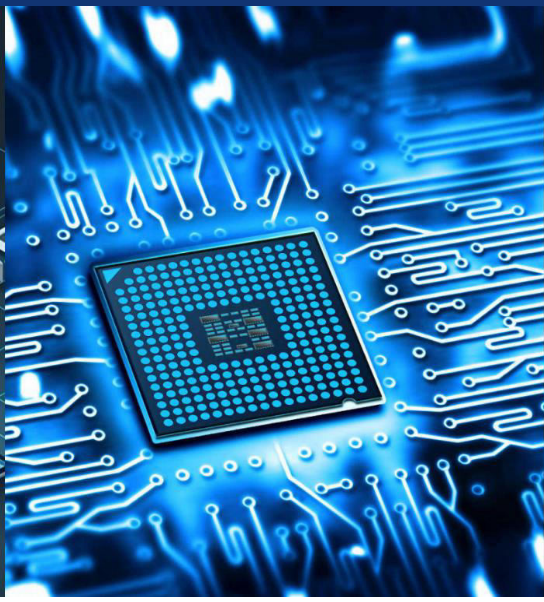


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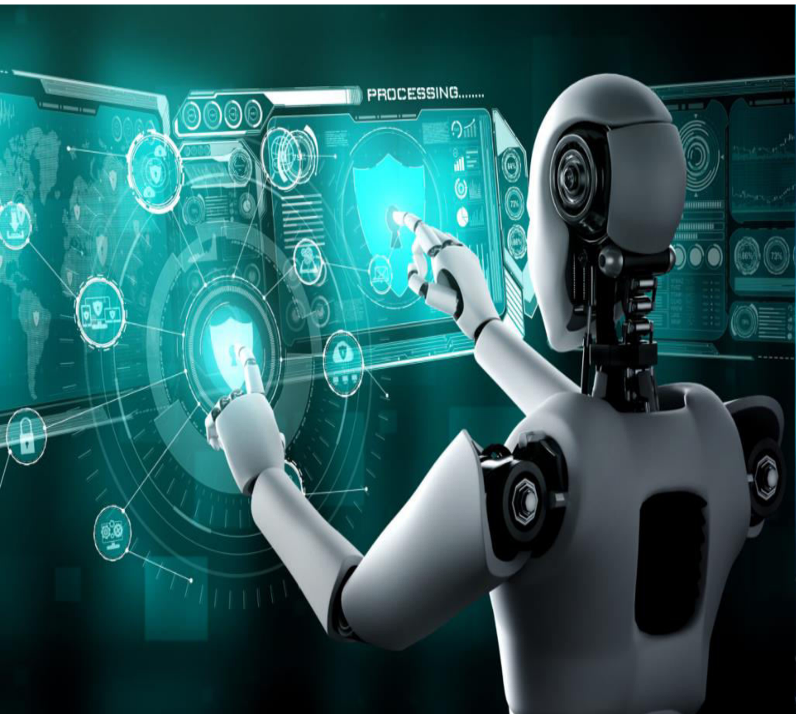

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Smart Claim: AI-Driven Vehicle Damage Assessment for Auto Insurance

Ananya V, K Vaishnavi, Deekshitha BD, Prof.Archana M

B.E Student, Department of Computer Science & Engineering, Global Academy of Technology, Bengaluru, Karnataka, India

Assistant Professor, Department of Computer Science & Engineering, Global Academy of Technology, Bengaluru, Karnataka, India

ABSTRACT*:* An important development in the insurance and rental sectors, automated vehicle damage assessment allows accurate and quick assessment of losses. This work uses deep learning models—more especially, Convolutional Neural Networks (CNNs)—to identify and categorize automobile damage from photographs, therefore simplifying the insurance claims process. With a dataset of both damaged and undamaged vehicles, the model achieves an around 90% accuracy. It offers cost estimates for insurance claims by detecting and classifying damage degree and location. The usability of the system is improved even further by the combination of a user-friendly interface. Future developments might incorporate merging realtime damage detection with cloud-based deployment and enhancing accuracy using advanced deep learning models.

KEYWORDS: auto insurance, object detection, CNN, deep learning, vehicle damage detection.

I. INTRODUCTION

The growing count of car accidents emphasizes the requirement of effective and dependable techniques to evaluate and estimate damages. Conventional tests demand human examination, which is time-consuming and prone to human mistake. Delay in claim processing in the auto insurance sector usually causes consumer discontent and higher running expenses. Furthermore, rental companies struggle with damage responsibility and need quick answers to correctly establish liability.

Deep learning (DL) and artificial intelligence (AI) have offered transforming answers for automated automotive damage assessment. Modern systems can process photos and detect damages with great precision by using convolutional neural networks (CNNs), therefore minimizing hand labour and guaranteeing more exact evaluations. The suggested system detects the kind and degree of damage in real-time using an artificial intelligence-based model.

Variability in image quality, lighting conditions, and vehicle models makes a major obstacle in car damage detection. Success of the system depends on strong detection under many real-world environments. By means of AI-driven automation replacing conventional manual assessment, accuracy is improved and the claim process is accelerated, therefore offering a scalable and user-friendly method of vehicle damage assessment. Automated damage assessment systems are growing essential given the explosion of digital solutions available in the insurance sector. Aiming to reduce false claims and speed claim approvals, insurance firms and car rental organizations Not only do AI-based solutions increase detection accuracy but they also provide real-time cost estimation, therefore drastically lowering the time needed for claim settlements. Furthermore, damage detection systems may be scaled by combining deep learning with cloud computing.

Using previous data to improve prediction accuracy is another crucial factor in damage assessment. Large datasets with a variety of vehicle types, damage scenarios, and claim histories can be used to train machine learning models. Better flexibility to changing situations is ensured by the system's constant update of the model with new data. Further improving speed and performance and lowering reliance on cloud processing is the implementation of edge computing for real-time on-device damage detection.

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The project's ultimate objective is to create a comprehensive AI-powered system that properly detects damages and generates full data on the kind, location, and extent of those damages. In order to increase productivity and lower operating expenses, the system seeks to easily connect with current insurance and rental agency operations.

II. RELATED WORK

Numerous research have examined the developments in AI based damage identification. To increase the precision and effectiveness of automated damage assessments, researchers have put forth a number of approaches that make use of deep learning and computer vision techniques. A segmentation-based method for car damage identification using Mask R-CNN was presented in the Zhang et al. [1] publication. This approach proved to be highly accurate in identifying damaged car components, which makes it a useful method for evaluating insurance claims. In a similar vein, Waqas et al. [2] highlighted the significance of AI in reducing fraudulent claims in the insurance business by proposing a fraudulent damage detection model utilizing deep learning techniques.

Using CNN architectures to categorize damage severity and generate cost estimates, Singh et al. [3] investigated the incorporation of deep learning models for automating insurance claims. This method enhanced customer satisfaction while drastically cutting down on the time needed to handle claims. Dhieb et al.'s subsequent research [4] examined transfer learning approaches for evaluating vehicle damage. Detection accuracy was improved by using pre-trained CNN models like VGG16 and ResNet, especially when training data was scarce. In comparison to conventional inspection approaches, Zhu et al. [5] demonstrated enhanced accuracy by developing a unified framework that incorporates computer vision techniques for vehicle damage assessment and localization. The work of Harshani and Vidanage [6], who suggested an image-processing-based method to forecast damage severity and estimate repair costs, is another noteworthy addition in this area. Their study highlights how computational intelligence can be used to automate insurance claims and cut down on fraud. Furthermore, the application of machine learning methods to forecast damaged vehicle components in low-speed collisions was investigated by Koch et al. [7]. Their method improved the accuracy of damage identification by combining sensor data with picture analysis.

Similar to this, a compressed residual CNN model for largescale image identification was presented by Qassim et al. [8] and can be successfully modified for evaluating car damage. The Histogram of Oriented Gradients (HOG) method for object detection was developed by Dalal and Triggs [9] and has impacted contemporary damage detection models. A unique tracking-to-detection method was put out by Feichtenhofer et al. [10] and may prove useful for examining successive damage patterns in accident situations. These studies demonstrate the increasing importance of AIpowered solutions in the rental and insurance sectors. By combining a CNN-based architecture with an intuitive user interface, the suggested solution expands on current approaches and guarantees accurate cost prediction for insurance claims as well as effective damage identification.

III. PROPOSED METHODOLOGY

A. Data Collection

One of the most important steps in creating a successful AI based automotive damage assessment system is gathering data. High-resolution photos of both damaged and undamaged autos make up the dataset. These photos come from manually annotated datasets, insurance claim documents, and public repositories. To increase model robustness, the dataset contains a range of vehicle kinds, angles, and lighting conditions. Minor, moderate, and severe damage are among the categories into which the photos are divided. Images containing various forms of damage, including dents, scratches, shattered glass, and structural deformities, are gathered to guarantee a dataset that is well-balanced. Additionally, to improve model training, publically accessible datasets are used, such as the Stanford Car Dataset and Kaggle's vehicle damage detection dataset.

B. Data Preprocessing

The photos are preprocessed to improve feature extraction and standardize their format before being used to train the deep learning model. Among the preprocessing actions are: Resizing: To maintain consistency throughout the collection, all photos are scaled to a common 224x224 pixel size. Normalization: To increase the stability and effectiveness of model training, pixel values are scaled to a range of [0,1]. Augmentation: To boost dataset variety and decrease overfitting,

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techniques like flipping, rotation, brightness modifications, and contrast enhancement are used. Noise Reduction: To improve feature extraction, undesired noise is eliminated using Gaussian blurring and median filtering.

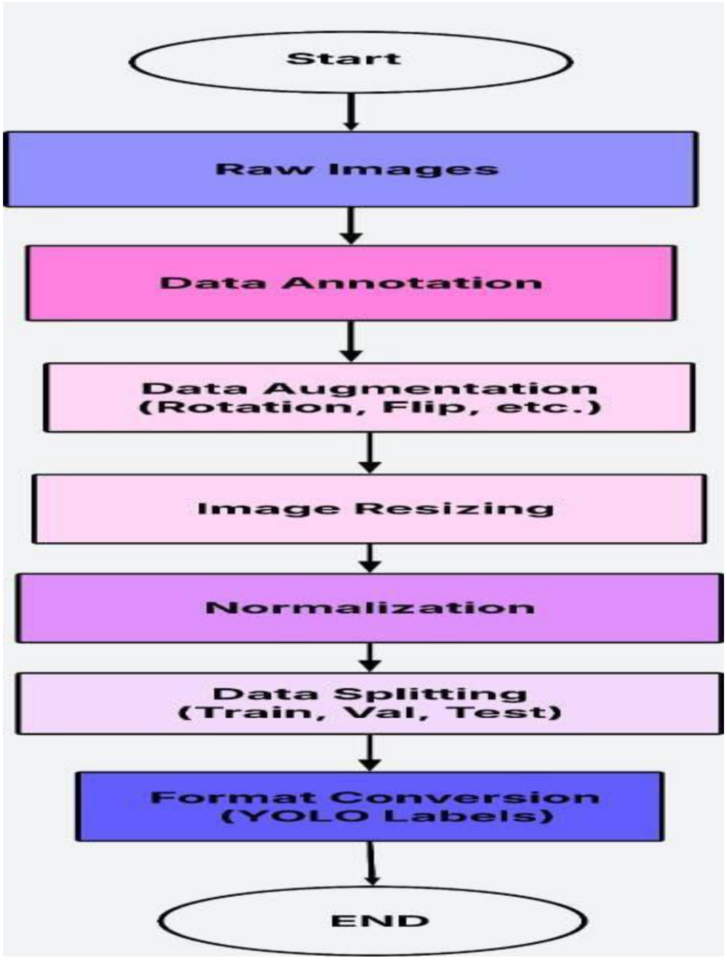

Fig. 1. Input Data pre-processing

C. Model training

Before the images are used to train the deep learning model, they undergo preprocessing to enhance feature extraction and standardize their format. The preprocessing steps include:
Resizing: Every image in the collection is resized to a standard 224x224 pixel size to ensure uniformity.
Normalization: Pixel values are scaled to a range of [0,1] in order to improve the stability and efficacy of model training.
Augmentation: Methods like as flipping, rotation, brightness adjustments, and contrast enhancement are employed to increase dataset diversity and reduce overfitting.
Noise Reduction: Gaussian blurring and median filtering are used to remove unwanted noise in order to enhance feature extraction.

D. Object Detection and classification

Real-time damage identification in a picture is made possible by the system's integration of an object detection model based on YOLOv8 (You Only Look Once). The following are the main steps in the detecting process:
CNN is used to extract elements related to vehicle damage, including edges, textures, and patterns.
Region Proposal: The YOLO model creates bounding boxes and detects possible damage regions.
Classification: The damages that have been found are divided into three severity levels: minimal, moderate, and severe.
Confidence Score Calculation: To guarantee precise classification, a confidence score is given to each harm that is found.

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E. Performance Evaluation

The model's performance is evaluated using the following metrics:
Accuracy: Measures the percentage of correctly classified damage cases.
Precision and Recall: Evaluates the model's ability to correctly identify damaged and undamaged vehicles.
F1 Score: Provides a balanced evaluation of precision and recall.
Confusion Matrix: Analyzes the classification results for different severity levels.
Experimental results indicate that the proposed system achieves a high detection accuracy of 90%, with a precision of 87% and a recall of 92%.

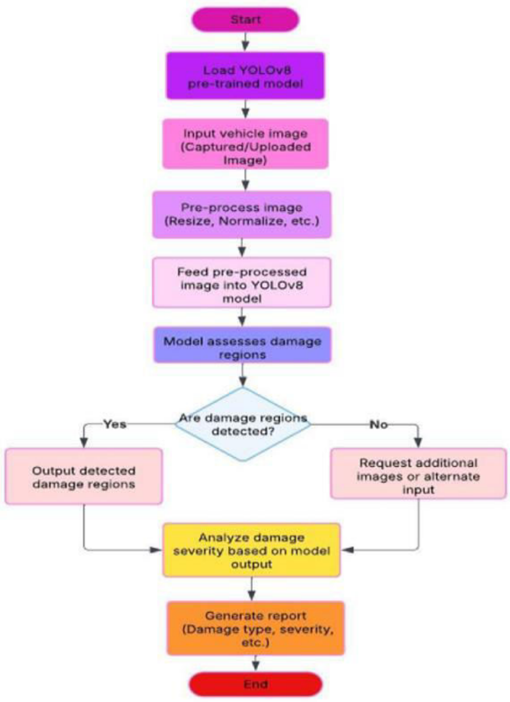
F. Implementation: Data Collection and Preprocessing

High-resolution photos from public repositories, insurance claim records, and manually taken photos make up the dataset used to train the car damage recognition algorithm. To provide accurate model training, damaged areas in the gathered photos were annotated using bounding boxes. During preprocessing, all photos were resized to 224 by 224 pixels, pixel values were normalized to fall between [0,1], and augmentation techniques like flipping, rotation, brightness modifications, and contrast enhancement were applied. The model's capacity to identify damages in various real-world scenarios was enhanced by these preprocessing procedures.

G. Model Training And Object Detection

Convolutional Neural Networks (CNNs) were used to train the deep learning model using a refined YOLOv5 object detection framework. To provide a balanced learning process, the training dataset was divided into 80% training and 20% validation sets. The following were part of the training process:
Batch Processing: For maximum computing efficiency, the model processes images in batches of 32.
Loss Function: For multi-class damage classification, the categorical cross-entropy loss function was employed.
Optimization Algorithm: To reduce loss and increase accuracy, the Adam optimizer was used.
Epochs: To guarantee ideal learning without overfitting, the model was trained over a total of fifty epochs.
Based on predetermined damage patterns, YOLOv5 created bounding boxes around damaged areas during training and categorized them into three severity levels: minor, moderate, and severe.

Fig. 2. Workflow of YOLOv8 Model



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1) Integration With User Interface

To help with real-time damage identification and claim evaluation, a graphical user interface (GUI) was created with Flask and OpenCV. The system enables users to: Upload Vehicle Photos: Using the web interface, users may submit pictures of damaged cars. Automated Damage Detection: After processing the uploaded photos, the trained model uses bounding boxes to indicate damaged areas. The Classification of Severity: The identified damages are divided into three groups: minimal, moderate, and severe. Creation of the Damage Report: A comprehensive PDF report with the findings of the damage assessment and the approximate cost of repairs is produced.

2) System Deployment

Insurance companies and car rental services can now access the AI-powered damage assessment system because it was implemented as a web-based application. The deployment configuration consists of:

Integration with Cloud Storage: Pictures and damage reports are safely kept in a cloud database for convenient access.

Real-Time Processing: To process photos rapidly and deliver results almost instantly, the system makes use of GPU acceleration.

Scalability: The approach is appropriate for large-scale insurance claim automation because it is built to manage high amounts of image data.

3) Validation And Performance Testing

Several test cases were used to assess the deployed system's performance:

Real-Time Testing: The system was able to accurately identify damage on recently submitted photos. Lighting Variability: The model maintained an accuracy rate of 85% in low-light settings and functioned effectively in a variety of lighting scenarios.

Angle Variation: Images captured from various angles showed the same detection accuracy.

With a significant reduction in manual claim processing times and an improvement in accuracy, the final deployment proved the efficacy of AI-driven solutions in car damage assessment.

IV. RESULTS

A. Accuracy Calculation

To evaluate the model's performance, a different test dataset was used. The important accuracy measures are as follows: 90% overall accuracy ,87% accuracy and 92% recall. F1-score: 89% These findings show that the system is very good at differentiating between cars that are damaged and those that are not. However, due to changes in lighting and image quality, minor damages were occasionally misclassified..

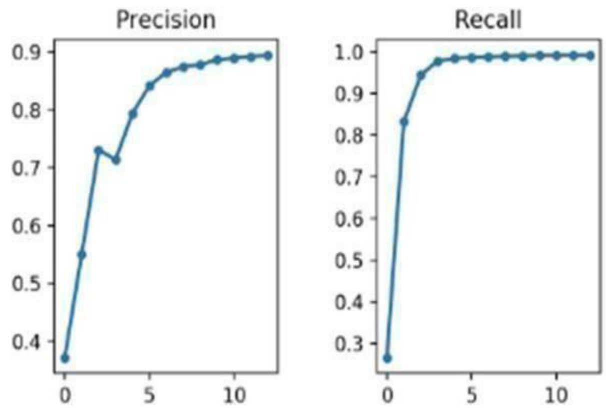

Fig. 3. Precision and recall

B. Performance Evaluation

Tests were carried out in several scenarios to confirm the model's resilience:

Lighting Variability: The model showed flexibility to varying illumination levels by achieving 85% accuracy in low light.

Angle Differences: The detection accuracy stayed above 88% when evaluated on photos taken from different angles.

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Areas of Obstructed Damage: The model had a little trouble identifying damages that were partially obscured by outside obstructions or reflections.

C. Comparison with Traditional Methods

The effectiveness of the system was evaluated by comparing it to other AI-based models and manual inspection techniques:

Method	Accuracy	Processing Time	Scalability	Reliability
Manual Inspection	75%	Slow	Limited	Prone to human error
Pre-trained CNNs (VGG16, ResNet50)	85%	Moderate	Moderate	High
Proposed YOLOv5 Model	90%	Real-time	High	High

Table 1. Comparison with Traditional Methods

D. Outputs

The system classifies observed damages according to severity levels by creating bounding boxes around them:

Minor Dents and Scratches: Found with a moderate degree of certainty. Severe Damage: Clearly defined, enabling prompt evaluation. Complex Cases: When damage was partially covered or under low contrast settings, certain detection inconsistencies were noted. The effectiveness of the approach is further supported by figures showing confusion matrices, classification reports, and discovered damages.

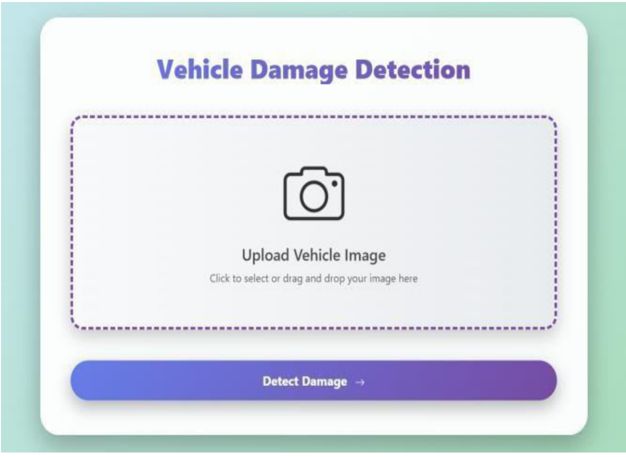

Fig 4. Upload Vehicle image

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Fig 5. Damage detection result

V. CONCLUSION

By effectively automating the identification and classification of vehicle defects, the suggested AI-driven vehicle damage assessment system increases productivity and lessens the need for manual inspections. The system's high accuracy in determining the location and extent of damage is achieved through the integration of deep learning models, greatly improving the insurance claims procedure. Accessibility for insurance providers and car rental services is further guaranteed by the use of an intuitive user interface. Future developments like blockchain integration and real-time assessment will enhance the system's functionality even more, making it a dependable and scalable option for automated vehicle damage assessment. Looking ahead, further enhancements could include transitioning to newer models like YOLOv7 or YOLOv8, with the goal of pushing accuracy beyond 90% while reducing inference time for quicker response. Additionally, across large surveillance networks, could increase its impact on public safety. YOLOv8's integration enables efficient, accurate weapon detection in dynamic environments, making it ideal for real-time security monitoring across diverse video sources. Altogether, this project presents a reliable solution for weapon detection, demonstrating its significant potential in strengthening security and surveillance systems

VI. FUTURE WORK

Future system improvements will use cutting-edge deep learning models like YOLOv7 and EfficientNet to increase the detection accuracy of minor damages. Edge computing will be investigated for real-time damage assessment in order to initiate claims immediately at the scene of the incident. Blockchain technology will also be used to automate claim processing and stop fraudulent claims by integrating with insurance company databases. The system's capacity to identify complicated damages beyond apparent surface-level impairments will be further improved by adding multi-modal analysis, such as LiDAR and thermal imaging.

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