Car Damage Assessment Using Deep Learning and Image Processing Techniques

G. Srikar
22BCE9946
Department of SCOPE
VIT-AP University
srikar.22bce9946@vitapstudent.ac.in

M. Narasimha Rao
22BCE9812
Department of SCOPE
VIT-AP University
narasimha.22bce9812@vitapstudent.ac.in

R. Veera Venkata Naga Rahul Reddy
22BCE8855
Department of SCOPE
VIT-AP University
rahul.22bce8855@vitapstudent.ac.in

***Abstract*—In recent years, the rapid growth of artificial intelligence and machine learning techniques has enabled automation in various domains, and car damage assessment is no exception. In this we introduce a novel approach for assessing car damages using a combination of deep learning techniques and image processing methods. Specifically, our goal is to classify vehicle damage into three severity levels: minor, moderate, and severe. To achieve this, we utilize transfer learning with a well-established Convolutional Neural Network (CNN) architecture called InceptionV3. Additionally, we apply various image processing techniques, such as edge and contours detection to enhance critical features and assist the deep learning model in making more accurate predictions. The dataset used for training and evaluation comprises a limited number of 1,600 labeled images, yet our method achieves a promising accuracy of 70% on the test data. Our results suggest that deep learning, when combined with traditional image processing techniques, can significantly enhance the accuracy and efficiency of car damage assessment, ultimately benefiting the automotive, insurance, and repair industries.**

***Index Terms*—Car Damage Assessment, Deep Learning, Image Classification, Digital Image Processing, Edge Detection, Contour Analysis, Convolution Neural Network, Transfer Learning, InceptionV3, ImageNet**

I. Introduction

Vehicle damage assessment is a critical aspect of the automobile insurance and repair industry. Traditionally, the evaluation of vehicle damage relies on human inspection, which is subjective, time-consuming, and prone to inconsistencies. The rise of computer vision and deep learning enables automated and scalable solutions for this problem. Our work focuses on building a model to predict the severity of car damage using both convolutional neural networks (CNNs) and classical image processing techniques. With the increasing number of vehicles and claims, the automation of damage analysis becomes essential for timely and objective evaluations. This project also bridges the gap between visual feature extraction and contextual understanding of damage patterns using deep learning.

With the help of image processing techniques we can localize the damage by using edge detection and contour analysis, and this helps the model to train and understand the pattern of the damage. We build a model that predicts damage severity in three classes: minor, moderate, and severe from car images. We aim to provide not just classification but also extract features using Image processing techniques to correctly classify the images.

II. Literature Review

Vehicle damage detection and assessment have seen significant advancements through the application of deep learning and computer vision. Several studies have employed convolutional neural networks (CNNs) and transfer learning for detecting and classifying car damage.

Phyu Mar Kyu and Kuntpong Woraratpanya [1] applied pretrained VGG16 and VGG19 models for car damage detection and severity assessment. They achieved 95.22% accuracy in damage detection and only 54.8% accuracy in severity classification using VGG16, indicating the challenges of severity assessment despite strong performance in classification tasks.

Similarly, Jason Elroy Martis et al. [2] developed a dent severity prediction system using transfer learning and background elimination. Their model achieved an overall accuracy of 96.34% for dent severity classification, demonstrating the value of fine-tuning neural networks on preprocessed image data. However, their system was focused specifically on dents rather than generalized damage.

In a more comprehensive setup, Pérez-Zarate et al. [3] introduced an ensemble of YOLOv5 detectors for real-time damage assessment in insurance settings. Despite improvements in detection metrics and scalability, their severity prediction hovered around 50–60%, showing a recurring limitation across most systems.

Other studies have explored broader detection and classification frameworks. Zhang et al. [4] and Gupta et al. [5] utilized CNNs and segmentation networks for localizing damage. However, these models often required extensive labeled datasets and struggled in unseen environments. Kumar [6] proposed a rule-based method but lacked the robustness and adaptability of deep learning approaches.

Our work builds upon these foundations by integrating deep learning with traditional image processing techniques to address the limitations observed in previous approaches.

III. Dataset Description

We utilized the publicly available *Car Damage Severity Dataset* [9] sourced from Kaggle, which is specifically curated for severity classification tasks in vehicle damage assessment.

The dataset is organized into two main directories:

- `train/` – contains 1300 labeled images
- `test/` – contains 300 labeled images

Each of these directories is further divided into three subfolders, corresponding to the severity levels of damage:

- **Minor:** Includes images with small scratches, surface dents, and other light damages
- **Moderate:** Represents broken lights, damaged bumpers, or partially deformed panels
- **Severe:** Depicts vehicles with significant structural deformation or extensive damage

This well-structured format allows for direct mapping between each image and its class label based on its directory, making it suitable for supervised deep learning classification models. Sample images are shown in fig 1

Fig. 1. Examples of car damage severity levels. From left to right: Minor (e.g., small dent or scratch), Moderate (e.g., broken windshield), and Severe (e.g., extensive structural damage).

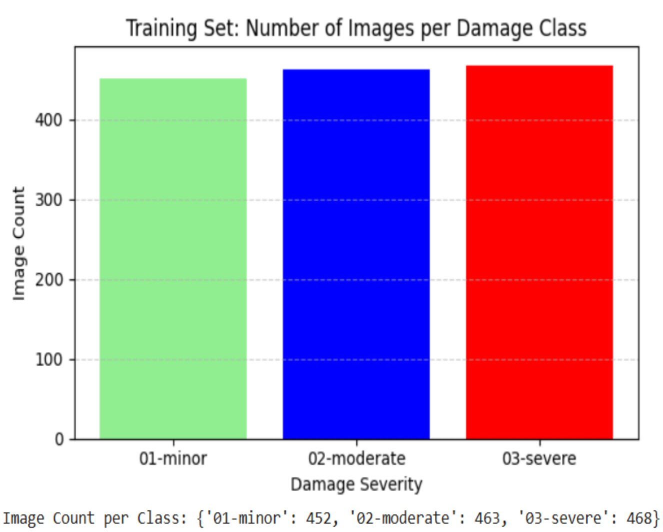

Fig. 2. Training Set: Number of Images per Damage Class

IV. Methodology

A. Preprocessing and Data Augmentation

To standardize the input format and enhance the model's performance and generalization, we applied the following preprocessing steps:

- **Resizing:** All images were resized to `224x224` pixels.
- **Normalization:** Pixel values were normalized to bring them to a common scale, which accelerates model convergence.

Given the relatively limited dataset size (1600 images) and slight imbalance between classes, we used a variety of data augmentation techniques to improve generalization and reduce overfitting:

- Horizontal and vertical flipping
- Random rotations and zooming
- Brightness and contrast adjustments
- Translation and cropping

B. Image Processing Techniques

Before diving into deep learning models, we applied image preprocessing using Digital Image Processing (DIP) techniques. This helped enhance features like cracks, dents, or broken regions. Digital Image Processing (DIP) refers to the use of computer algorithms to perform image enhancement, feature extraction, and segmentation. In our work, DIP acts as the first stage to filter out noise and highlight damage-related regions for analysis. Techniques such as thresholding, edge detection, and contour analysis are applied to isolate meaningful parts of car images that may indicate damage. Canny edge detection and Sobel operators are instrumental in identifying contours, discontinuities, and cracks that suggest impact or wear. Sample images are shown in fig 3

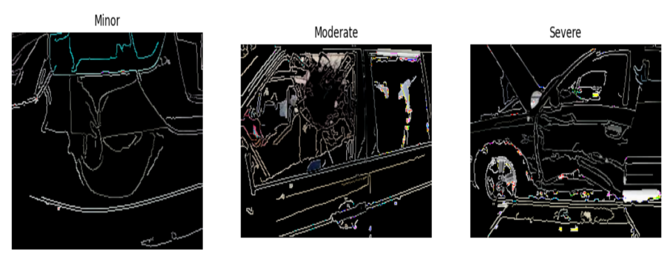

Fig. 3. Showing damage localized images after applying Image processing

C. Initial CNN

Our project began with basic Convolutional Neural Networks (CNNs) comprising 3 to 5 layers, including convolutional, pooling, and dense layers. These networks initially achieved a high training accuracy of around 85%, but only about 40% on the test set—clearly indicating overfitting. To address this, we applied data augmentation techniques such as flipping, rotation, zooming, and shifting. While this helped increase variance in training data and slightly improved the results, the overall testing accuracy still hovered around 50%. This revealed that simple CNNs lacked the generalization capability required for handling the diversity and complexity of damage patterns in our dataset.

D. Deep Learning Exploration: ResNet and Inception

To improve accuracy, we explored transfer learning with pre-trained models, starting with ResNet[10]. Despite its success in many vision tasks, ResNet failed to perform well on our dataset, achieving testing accuracy close to 50%. One major challenge was the inability to focus on localized damage areas, especially when the damage was subtle or not centered. We attempted traditional Digital Image Processing (DIP) techniques like edge detection and contour extraction to help localize the damage, but these methods lacked robustness for diverse lighting and angles. As a more sophisticated solution, we transitioned to the InceptionV3[11] architecture, known for its multi-path processing through inception modules. These modules apply multiple filter sizes in parallel, enabling the network to capture both small details like scratches and large damage like broken doors or shattered windshields. This approach significantly improved the model's ability to learn diverse features, pushing accuracy up to 60%(shown in fig 4).

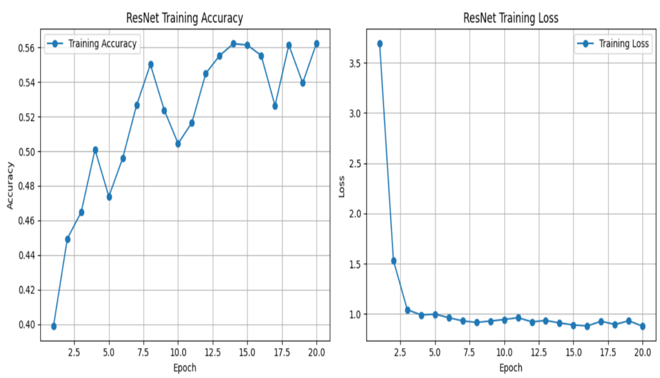

Fig. 4. Training and Validation Accuracy/Loss Curves of Resnet Model

E. Transfer Learning with Inception and Final Model Optimization

For small and diverse datasets like ours, transfer learning is highly effective because it allows the model to reuse learned features from large-scale datasets such as ImageNet. According to widely accepted practices in transfer learning, when working with limited and diverse data from original trained data of the model, it is beneficial to train the initial layers of the pre-trained model. This helps the network adapt its low- and mid-level features (such as edges, textures, and simple shapes) to the target dataset, which in our case includes various types of car damage.

Following this approach, we fine-tuned InceptionV3[11] by unfreezing the first 200 (according to tensorflow layer count) layers. This configuration struck the right balance between leveraging existing knowledge and adapting to our data. We also applied L2 regularization and dropout to reduce overfitting, which further improved generalization. With this setup, our model achieved its best performance—80% training accuracy (shown in fig 5) and 70% testing accuracy.

We also tested other configurations by freezing other set of initial layers and also tried the first 30 layers to be frozen and training the remaining ones, which gave decent results. However, training the initial layers of 200 proved to be more effective for our dataset. This strategy was key to overcoming the challenges posed by limited sample size and varied damage categories.

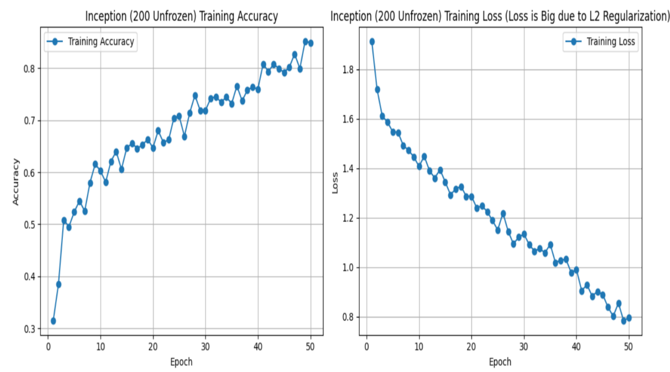

Fig. 5. Training and Validation Accuracy/Loss Curves of InceptionV3 on training initial 200 layers Model

V. Results and Observations

The proposed model was trained on a labeled dataset comprising car damage images categorized into three classes: minor, moderate, and severe. Utilizing InceptionV3[11] with transfer learning, fine-tuning of the initial layers, and image processing, the model achieved a training accuracy of 80% and a testing accuracy of 70%. This indicates that the model was able to generalize reasonably well to unseen data, despite the inherent challenges in accurately distinguishing between different levels of damage severity.

To qualitatively assess the model's performance, several test images were evaluated, Sample images are shown in fig 6, and the predicted severity class was recorded. In most cases, the model successfully identified and classified the type of damage present. Visual samples of test images are presented below along with their predicted severity levels, providing insight into the behavior of the model and its ability to interpret various types of damage. And the entire methodology is developed in Google colab develepment environment.

A. Confusion Matrix

The confusion matrix below provides a detailed analysis of the model's performance on the test dataset. It reflects how well the model distinguishes between the three damage severity classes: Minor, Moderate, and Severe.

Predicted Actual	Minor	Moderate	Severe
Minor	62	16	4
Moderate	12	45	18
Severe	3	21	67

The confusion matrix shows that most misclassifications occur between neighboring classes, such as Moderate being confused with Minor and Severe. This indicates that the model has learned meaningful patterns but struggles with visually

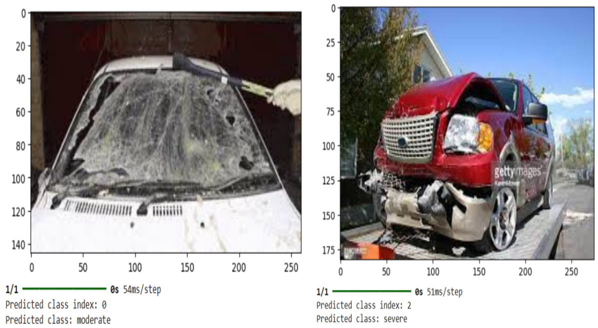

Fig. 6. Sample test images with predicted damage severity labels, indices are 0-moderate, 1-minor, 2-severe

similar damage levels—a common challenge in real-world scenarios.

VI. Applications

Our model has a wide range of applications in the **automotive**, **insurance**, and **repair** industries. By automating the car damage detection process, it offers several benefits such as increased workflow efficiency, reduced human error, and improved assessment accuracy.

Key Use Cases

- **Insurance Claim Automation** Insurance companies can leverage the model to automatically evaluate vehicle damage during claims processing. This reduces the need for manual inspections, speeds up claim approvals, and minimizes operational costs.
- **Rental Car Inspection** Car rental companies can use the system to perform automated pre-rental and post-rental inspections. This ensures accurate tracking of vehicle condition and prevents disputes over damages.
- **Surveillance in Parking Lots** Integrating the model with parking management systems enables real-time damage detection. It helps identify accidents or vandalism incidents, leading to quicker responses and better security in parking areas.
- **Automated Fleet Monitoring Systems** Fleet operators can deploy the system to continuously monitor the condition of their vehicles. This facilitates proactive maintenance and minimizes downtime.
- **Damage Assessment Kiosks in Service Stations** Service stations can install self-service kiosks equipped with the model, allowing customers to quickly assess vehicle damage without needing a technician.

VII. Conclusion

We proposed a hybrid approach for car damage assessment that integrates transfer learning with InceptionV3 and image processing techniques. Our best model achieved 70% accuracy in the tests despite the relatively small size of the data set and the variety of damage portions that are difficult to extract. Our confusion matrix tells that the miss classifications are between neighboring classes only, this suggests that our model learned meaningful patterns, by incorporating methods such as Canny edge detection and contour analysis, we provided damaged details and improved model focus on damaged areas. This achieved significant performance in terms of accuracy and damage extraction in comparison to the solutions that exist so far in the assessment of the severity of a car. The combination of deep learning with classical techniques helped mitigate the shortcomings of relying solely on one method.

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