**ABSTRACT**

**IEEE BASE PAPER ABSTRACT:**

Vehicle damage localization and severity estimation is essential to post-accident assessments, with a traditional process taking an average of seven days and requiring substantial work from both customers and dealers. Towards improving this process, we propose an end-to-end system which inputs a set of user-acquired photographs of a vehicle after an accident and outputs a damage assessment report including the set of damaged parts and the type and size of the damage for each part. The system is composed of three deep learning modules: a model to identify whether a vehicle is present in the image, a model to localize the vehicle parts in the image, and a model to localize the damage in the image. We demonstrate the effectiveness of each module by evaluating them on labeled datasets containing images of vehicles after an accident, some collected by the OE (Original Equipment) Insured Fleet and some acquired by users of the OEM (Original Equipment Manufacturer) mobile application. We also describe how the modules fit together with a post-processing step to aggregate outputs between the different modules across multiple user-acquired views of the accident. Our approach demonstrates the potential for an accurate and automated vehicle damage estimation system to support a substantially more efficient vehicle damage assessment process.

**OUR PROPOSED PROJECT ABSTRACT:**

This project presents an advanced system for Automated Vehicle Damage Localization and Severity Estimation using deep learning, developed to automate the traditionally manual process of assessing vehicle damage. Built using Python for the backend and HTML, CSS, and JavaScript for the frontend, the system operates on the Flask web framework, offering a user-friendly, web-based interface. At the core of this system is the YoloV8 model, a state-of-the-art object detection algorithm capable of identifying and categorizing vehicle damage with high precision. The system achieves an accuracy of 91%, making it an effective solution for tasks like insurance claims processing, vehicle repair evaluation, and accident analysis.

The system supports three modes of operation: image-based, video-based, and webcam-based predictions, making it versatile for various practical applications. In the image-based mode, users upload images of vehicles, and the model analyzes the image to detect, localize, and classify different types of damage. The video-based mode extends this capability to moving images, enabling real-time damage detection in videos. Finally, the webcam-based mode provides a live stream for instant damage detection, making the system adaptable to dynamic environments like car repair shops or roadside assistance services.

The dataset used for training and validation comprises 778 labeled images, with 485 images for training and 293 for validation. The dataset includes eight specific damage categories: damaged door, damaged window, damaged headlight, damaged mirror, dent, damaged hood, damaged bumper, and damaged windshield. By detecting and localizing these damages, the system can accurately estimate the severity and nature of the vehicle’s condition, streamlining workflows for professionals in the automotive and insurance sectors.

This automated system represents a significant technological leap in vehicle damage assessment. Its ability to accurately detect and classify vehicle damages in real-time minimizes human error, speeds up processing, and improves the overall reliability of damage assessments. The flexibility provided by the three different prediction modes—image, video, and webcam—ensures that the system can be applied in a wide range of scenarios, from individual use to professional environments, offering valuable efficiency and accuracy in vehicle damage evaluation.