

Original Article

# Evaluation of Mechanical Damage Characterization, Automotive Panel Deformation and Repair Cost Estimation using Deep Learning Techniques

N.V. Sailaja<sup>1</sup>, CH V K N S N Moorthy<sup>2</sup>, Singam Vamshi Krishna<sup>1</sup>, T Varshitha<sup>1</sup>, Shaik Mahimood Pasha<sup>1</sup>, Jangamari Sandeep Kumar<sup>1</sup>

<sup>1</sup>Department of Computer Science and Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India.

<sup>2</sup>Department of Mechanical Engineering, Vasavi College of Engineering, Hyderabad, India.

<sup>2</sup>Corresponding Author : [krishna.turbo@gmail.com](mailto:krishna.turbo@gmail.com)

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**Abstract** - In the automobile insurance sector, there is a significant requirement to improve the efficiency and accuracy of the process of damage analysis following vehicle accidents. Conventional approaches require the manual inspection of the damaged areas of the vehicle, which is time-consuming and susceptible to human error. These factors may lead to delays in the processing of the claim and the evaluation of the damage. There are no self-service facilities where policyholders can upload images and videos to aid in the process of the insurance claim. To improve upon these disadvantages of the traditional process, AI-based computer vision systems are highly appropriate and can efficiently use video and image analysis techniques to improve the accuracy of the process of damage analysis. These systems accurately measure the degree of damage, which accelerates the process of claims and minimizes the reliance on human verifications. AI-based damage detection includes estimation of the cost of repair and handling of claims and enhances the overall policyholder experience. One of the significant innovations of the AI-based system is the inclusion of deep learning methodologies to improve the accuracy of the process of estimating the costs of repairs of the damaged areas of the motor vehicle. These systems analyze damage data with higher precision, providing insurers with authoritative estimates that enable equitable and timely payment of claims. The proposed work aims to allow insurers to make decisions on whether to repair or replace vehicle parts depending on vehicle type and other variables. In addition, the development of self-service tools also facilitates policyholders in uploading images and videos directly, enabling an inspection-free claims process. Overall, the integration of AI-based solutions in vehicle insurance provides a faster, accurate, and effective claims experience.

**Keywords** - Cost Estimation, Deep Learning, Repair vs Replacement, Object Detection, Vehicle Damage Detection, VGG16.

## 1. Introduction

In the Vehicle Insurance Industry, conventional methods used to evaluate automobile damage require the manual inspection of the damaged areas of the vehicle, which is time-consuming and also prone to human error and subjective judgment. These can lead to delayed processing of claims and differences in damage estimates. These factors may lead to delays in the processing of the claim and the evaluation of the damage. There are no self-service facilities where policyholders can upload images and videos to aid in the process of the insurance claim. In order to overcome these challenges, next-generation artificial intelligence-based computer vision technologies are becoming more widely accepted. With the application of real-time image and video analysis, such advanced systems can accurately assess the level of automobile damage, thus reducing the need for

physical examination. AI automation significantly improves the methodology of assessing the repair cost to allow fair and efficient resolution of claims and prevention of operational inefficiencies. This enables the provision of a better, more transparent, efficient, and hassle-free service to the insured. AI-driven solutions significantly enhance the accuracy of damage detection, facilitating informed decision-making on repair or replacement. Moreover, the use of self-service technology enables policyholders to directly upload images or videos of damaged vehicles using a mobile application. This removes the necessity of physical inspection, thereby making the process of claims simpler and more convenient to the customer. An uninterrupted, consistent, and less laborious claims process can be offered through the implementation of an AI-driven automated process. The implementation of AI-based damage assessment systems is considered an important



innovation in the automobile insurance industry, as the process is faster, more precise, and cost-reducing.

### *Novelty*

The application of artificial intelligence in assessing motor vehicle damage improves performance while at the same time serving as a precautionary measure to prevent fraudulent claims, considering its capacity to identify discrepancies in images or videos uploaded. Insurance companies can apply an artificial intelligence model, which incorporates historical data and repair cost databases to offer accurate predictions. AI technologies similarly enable the provision of real-time estimates, which means that small damage claims can be settled within a reasonable time. This innovation further reaches workshops and repair shops through the provision of detailed damage reports, ensuring the use of the components that are required to be repaired or replaced. Finally, AI-based automation provokes an integrated platform under which insurers, policyholders, and repair all stores can benefit from a faster, accurate, and transparent claims process.

#### **1.1. Objective**

The objective of this study was to assess the technical feasibility and practical applicability of an autonomous system capable of detecting damage from video input and estimating corresponding auto insurance claims, along with the repair vs. replacement decision, using advanced computer vision and deep learning methods.

The specific objectives include:

- ✓ To assess the technical feasibility and practical applicability of an autonomous system for vehicle damage detection through video input.
- ✓ To detect vehicle damage using advanced computer vision and deep learning methods.
- ✓ To estimate corresponding auto insurance claims based on the detected damage.
- ✓ To support decision-making regarding the repair versus replacement of damaged vehicle parts.
- ✓ To evaluate the effectiveness of advanced computer vision and deep learning methods in vehicle damage assessment.

#### **1.2. Vehicle Damage Detection and Claims Assessment**

Assessment of motor vehicle damage in insurance claims is a variable and time-consuming procedure in manual processing. Manual processing relies on human adjusters, subject to human discretion and less readily available in remote or high-traffic regions. Computer vision and deep learning present an opportunity to automate and make the process standardized from real-time multimedia input.

#### **1.3. Artificial Intelligence in Vehicle Assessment**

Recent breakthroughs on Convolutional Neural Networks (CNNs), object detection structures, and transfer learning have

further boosted automatic visual interpretation considerably. Through the use of ambient input, like video recorded by mobile phones, these artificial intelligence systems have the potential to extract and interpret pertinent damage information without dedicated sensors. Such a feature can potentially make smart systems, not just detect damage, but also estimate its severity and relate this to estimated repair costs.

## **2. Related Work**

With many difficulties being found that are attached with vehicle damage detection, costing, and the decision-making process whether to repair or replace or not, accuracy of detection, speed in processing, dealing with occlusions, and the real environment have emerged as a major topic for research. More so, the problems become even clearer while elaborating on the deployment of automated assessment of vehicle damages within the area of insurance claims, specifically. For this objective, researchers have developed a number of highly advanced computer vision and artificial intelligence models that are capable of assisting this process in the most optimal manner.

Recent developments in computer vision and deep learning have transformed the automation of vehicle damage evaluation and insurance claims processing. The technologies offer scalable, precise, and rapid solutions that minimize human involvement, reduce processing time, and improve the customer experience. The domain of research has developed a number of methods, including damage detection, classification, cost estimation, and fraud prevention.

Early research in this area has concentrated on utilizing object detection approaches for damage localization and identification. Ruitenbeek and Bhulai used YOLOv3 and FSSD models through transfer learning for damage detection on the exterior of vehicles. Even though good results were obtained, the authors found that there was a problem with dealing with glare, reflection, and small objects, highlighting the need for good-quality images and pre-processing. To bridge the gap for image quality, Hoang et al. [2] presented a new dataset called VehiDE, with over 13,000 images and a synthetic dataset with over 1 million images, facilitating a standardized evaluation for damage segmentation and classification.

Mask R-CNN has become a robust architecture for fine-grained damage localization and segmentation. Totare et al. [3] applied this architecture to segment damaged areas and classify severity with transfer learning. Their methodology showed superior accuracy and scalability, but still posed an open question of integrating price prediction. Taking the work in this direction forward, Dhieb et al. [4] and Qaddour and Siddiq [5] used Inception-ResNetV2 and Mask R-CNN for total vehicle damage examination and achieved noticeable accuracy improvement as well as a reduction in processing time. Their approaches also established a foundation for real-time implementations within insurance processes.

Considering mobile and light implementations are needed, Widjojo et al. [6] introduced a MobileNetV2 and Mask R-CNN pipeline, which obtains a high F1-score of 91% while being real-time responsive. They pointed towards possible extensions in fraud detection as well as in real-time feedback systems.

Fernando et al. [7] followed a multi-modal strategy where they combined Convolutional Neural Networks (CNN) with Natural Language Processing (NLP) as well as multilingual voice assistants with the motive to automate the processing of claims completely and to enhance customer engagement.

Semantic segmentation methods were further developed by Mallios et al. [8], who proposed metadata-driven deep learning for damage classification and cost estimation. Their use of structured insurance data has been valuable in matching machine-generated predictions with actual repair practices.

Mandara and Ankalkoti [9] also proposed a framework for claims processing using a combination of classical image processing and machine learning classifiers, with a focus on minimizing human bias and errors, all through a machine learning-based approach, as presented in the reference.

Transfer learning and ensemble methods have also been prominent. Parhizkar and Amirfakhrian [10] proposed a dual-path CNN, using ResNet50 to boost the performance of damage dataset classification, even compared to traditional segmentation methods, as presented in the reference. Kyu and Woraratpanya [11] also employed a combination of VGG16 and VGG19 networks for multi-class damage classification, achieving an accuracy rate of 95.22.

Patil et al. [12] in their research on ensemble Convolutional Neural Networks (CNNs) reported an accuracy rate of 89.5%, highlighting the significance of datasets. Elbhrawy et al. [13] proposed a Cost Estimation System (CES) that incorporates object detection using YOLO and Transformers, which enabled intelligent claim estimation. The proposed approach not only mechanized damage analysis but also resolved the major issue associated with insurance fraud detection.

Extending the functional pipeline, Imaam et al. [14] proposed a comprehensive machine learning framework that incorporated damage detection, repair cost estimation, and customer churn modeling, which could be readily integrated with existing insurance systems. Lee et al. [15], meanwhile, presented the TQVCD, a dataset that resolved viewpoint dependency, thereby enhancing performance in three-quarter view classification and damage severity analysis.

Mohammed et al. [16] designed a dual Mask R-CNN architecture for simultaneous damage detection and repair cost estimation. Their method attained an accuracy of 98.5%. Sree

et al. [17] designed a Deep CNN framework that not only detects damage but also assesses the level of damage and prevents fraudulent claims. This is an essential feature of any insurance solution. Several researchers have worked on developing web-based full-stack applications.

Bhoite et al. [18] and Sneha et al. [19] used CNN and OpenCV on responsive platforms to enable the identification of damage, along with real-time solutions for insurance customers and insurance inspectors.

In the field of repair cost estimation, Narra Suma and Savitha [20] implemented MobileNetV2 to estimate the costs of repairs based on image features and obtained an accuracy of 87.35%, thus proving the possibility of using lightweight networks.

Kadokia et al. [21] presented a system based on images and implemented a large-scale system with the use of VGG16, ResNet50, and XGBoost to obtain the severity and cost of the accident, thus providing a view of the automated process of accident assessment. Likewise, Warungse et al. [22] used ResNet to classify damage types and severity levels with high reliability.

Agarwal et al. [23] used a combination of CNN and R-CNN for damage severity assessment and detection. However, they found that internal damage was not addressed. Khinde et al. [24] developed a Flask-based CNN for classifying external damage. Future work includes using Vision Transformers and increasing the size of the datasets.

This set of studies collectively illustrates the potential of deep learning and computer vision to transform the car damage assessment process into an efficient, precise, and scalable process. The current line of research continues to tackle issues related to generalization, internal damage, fraud, and the application of these techniques in the insurance infrastructure. These studies all point towards the increasing capability of AI and deep learning methods to transform damage detection and the insurance claims process in terms of accuracy, efficiency, and customer satisfaction.

Most studies suggest that CNN, Mask R-CNN, and ensemble models should be used to attain improved performance, and also acknowledge the importance of developing large datasets to extend applicability. In addition, there is emphasis on automating the process of damage detection and cost estimation, which expedites the process of making claims and reduces its vulnerability to human error.

### 2.1. Research Gaps

Table 1 shows the key contributions of the existing works and corresponding research gaps, mentioning clearly the methods used by the researchers.

**Table 1. Summary of the existing work along with the research gaps**

Ref. No.	Authors	Method / Model Used	Key Contribution	Limitations / Gaps
[1]	Ruitenbeek & Bhulai	YOLOv3, FSSD	Damage detection using transfer learning	Sensitive to glare, reflections, and small objects
[2]	Hoang et al.	VehiDE Dataset	Large dataset (real + synthetic) for evaluation	Still depends on image quality
[3]	Totare et al.	Mask R-CNN	Fine-grained damage segmentation & severity classification	No cost estimation integration
[4]	Dhieb et al.	Inception-ResNetV2	Improved accuracy & faster processing	Limited real-world deployment discussion
[5]	Qaddour & Siddiqa	Mask R-CNN	Real-time vehicle damage assessment	Integration with pricing is unclear
[6]	Widjojo et al.	MobileNetV2 + Mask R-CNN	Lightweight, real-time (91% F1-score)	Needs extension for fraud detection
[7]	Fernando et al.	CNN + NLP + Voice Assistants	Multi-modal automated claims processing	System complexity
[8]	Mallios et al.	Metadata-driven DL	Combines structured data for cost estimation	Limited scalability discussion
[9]	Mandara & Ankalkoti	ML + Image Processing	Reduced human bias in claims	Lower accuracy vs deep learning
[10]	Parhizkar & Amirfakhrian	Dual-path CNN (ResNet50)	Improved classification performance	Dataset dependency
[11]	Kyu & Woraratpanya	VGG16 + VGG19	Multi-class classification (95.22%)	Heavy models
[12]	Patil et al.	Ensemble CNN	Improved accuracy (89.5%)	Requires large datasets
[13]	Elbhrawy et al.	YOLO + Transformers	Damage detection + fraud-aware cost estimation	Computational complexity
[14]	Imaam et al.	ML Framework	Integrated detection, cost, and churn prediction	System integration challenges
[15]	Lee et al.	TQVCD Dataset	Solves viewpoint dependency	Limited adoption
[16]	Mohammed et al.	Dual Mask R-CNN	Simultaneous detection + cost estimation (98.5%)	Real-world validation needed
[17]	Sree et al.	Deep CNN	Damage detection + fraud prevention	Internal damage not addressed
[18]	Bhoite et al.	CNN + OpenCV	Web-based real-time system	Limited scalability
[19]	Sneha et al.	CNN + OpenCV	User-friendly insurance platform	Accuracy limitations
[20]	Narra Suma & Savitha	MobileNetV2	Cost estimation (87.35%)	Moderate accuracy

[21]	Kadokia et al.	VGG16, ResNet50, XGBoost	Severity + cost estimation	High computational cost
[22]	Warungse et al.	ResNet	Reliable damage classification	Limited scope
[23]	Agarwal et al.	CNN + R-CNN	Damage detection & severity	Internal damage ignored
[24]	Khinde et al.	CNN (Flask-based)	Web-based damage classification	Needs larger datasets

### 3. Proposed Methodology

The proposed system for autonomous car insurance claims is founded on a systematic AI-based approach, such as vehicle damage detection, repair or replacement estimation, and claims handling. The process utilizes computer vision, machine learning, and deep learning. aids in simplifying the claims process, eliminates the need for manual inspection, and ensures maximum accuracy. The process is split into different stages, like image acquisition, preprocessing, damage and part detection, cost estimation, and claims verification.

#### 3.1. Existing Systems

##### 3.1.1. Manual Inspection-Based Systems

Conventional insurance claim settlement practices rely on physical inspection by adjusters, who inspect crashed cars and estimate the repair expenses required. The process is special in the sense that it involves a long process, inconsistency, and high costs, as different adjusters would arrive at different estimates of the same damage. Insurance organizations have to employ many people, thereby incurring administrative expenses. Additionally, the absence of standardized verification procedures puts the system at risk of fraud claims, leading to economic loss and controversies.

##### 3.1.2. Semi-Automated Systems

Semi-automatic systems allow policyholders to upload videos of damaged vehicles via mobile apps, minimizing the need for manual or on-site inspection. Nevertheless, the systems are based on human verification, thus reducing their overall efficiency. They operate on basic rule-based systems, which fail to detect trivial or subtle damages. Furthermore, the lack of AI-based fraud detection makes them susceptible to fabricated or manipulated claims, leading to a decline in the reputation of claims and increased processing times. Although an improvement over manual systems, semi-automatic systems can be improved based on automation as well as precision.

#### 3.2. Proposed System: AI-Based Vehicle Damage Detection and Insurance Claim Estimation

The proposed Enhanced Deep Learning Algorithms for Vehicle Damage Detection and Insurance Claim Estimation utilizes computer vision and deep learning methods fueled by Artificial Intelligence (AI) to enable computerized vehicle damage examination. The system analyzes images and videos

provided by policyholders to determine damages, provide an estimate of the cost, and decide whether to repair or replace. Some of the notable features of the proposed system are:

- Automated Damage Detection uses YOLO, VGG16, and Mask R-CNN to accurately detect and tag car damage and identify the exact damaged area.
- True Cost Estimation for Repairs or Replacement – Applies machine learning algorithms to predict repair costs and replacement costs from damage severity and past claims.
- AI-Based Claim Processing – Includes fraud detection algorithms to verify claim validity and predict approval outcomes.
- Accessible Self-Service Platform – Facilitates policyholders to file photos and videos through a mobile app, making face-to-face interviews unnecessary.
- Accelerated Claim Approvals and Real-Time Analysis – Allows for rapid and precise assessment of damages, hence significantly shortening claim processing time.

The system processes the uploaded policyholders' videos with the use of computer vision and deep learning to recognize and classify damage. The technology eliminates the need for physical checks, hence speeding up the process of claims handling. It includes estimation of repair costs and whether or not it is cost-effective to fix or replace the damaged vehicle or property. The system makes educated decisions based on historical claims information. The system also involves verification of the extent of damage against the policy of cover and streamlines the process of approval of claims. The system also seeks to reduce human interaction, reduce claim handling duration, and enhance the accuracy of claims settlements.

#### 3.3. Data Collection

The initial process of the research is collecting data in the form of video clips of the car. The video of the crashed car has been retrieved. The policyholder will record a video of the crashed car and post it via the mobile app. The dataset utilized in car damage detection within this research is out of a total of 11,685 labeled images, which are accessed from the Roboflow platform. It is split into an 87% set of images for training, a 9% set of images for validation, and a 4% set of images for testing. The data set utilized for vehicle parts segmentation in this research includes a total of 3291 annotated images specifically tailored to train and test the model's capability to

recognize and segment the different components of vehicles. Collected and organized through the Roboflow platform, the data set is separated into three sets: 2,796 images (85%) are used for training, 328 images (10%) for validation, and 167 images (5%) for testing. This dataset contains various types of damage captured under various conditions, making it ideal for training deep learning models to effectively detect and segment vehicle damage.

### 3.4. Experimental Setup

The System development involved frontend and backend environment configuration and a model training pipeline. On the frontend, Visual Studio Code (VSCode) was used alongside Expo Go for mobile application development, with Appwrite backend services and Appwrite Cloud Database used for data retrieval and storage. A Flask server was used for the integration of the trained model and backend functionality management.

For local development, 16 GB RAM, 512 GB SSD, and an 8 GB NVIDIA GeForce RTX 3070 GPU were made available to the system, thus making it feasible for the efficient processing of application-level tasks. To support the model training process, Google Colab was used, with a T4 GPU runtime environment that offered 15 GB of GPU RAM, 12.7 GB of system storage, and 112.6 GB of disk storage.

The deep learning model was implemented using the Detectron2 library. The configuration was based on the Mask R-CNN architecture, with a ResNet-50 backbone and a Feature Pyramid Network (FPN), on the COCO Dataset. The model was then fine-tuned on a custom dataset, with certain parameters being a batch size of 2 images, a base learning rate of 0.005, and a maximum of 3000 iterations.

The Region of Interest (RoI) head was adjusted to predict a single category (damage), and the RoI batch size assigned per image was set to 128. Evaluations were carried out after every 400 iterations. Prior to starting each training session, any pre-existing output directories were deleted to maintain the integrity of clean logs and results. This configuration provided a solid and streamlined workflow for training the model.

### 3.5. Pre-Processing

After the video footage has been captured, preprocessing takes place before the video footage enters the models for analysis. The steps under preprocessing are carried out to optimize video footage to the maximum extent possible for detection operations.

- Video to frame: Upon entry of the video, a few frames are selected through CV2.
- Frame enhancement: The frames are enhanced to enhance object detection.
- Noise reduction: It is a method of removing noise from frames through different means.

#### 3.5.1. Object Detection

Object detection is carried out using computer vision, and YOLO5 is implemented YOLO5 for object detection. It validates if the object in the picture is a car.

### 3.6. System Architecture

The system architecture is designed in the form of a multi-layer pipeline, where policyholders input images/videos and deep learning algorithms browse through these to determine the type of damage, estimate repair costs, and predict claim settlement outcomes. The architecture, as shown in Figure 1, consists of the following key components:

#### 3.6.1. Data Input Layer

The process starts with the data acquisition step, in which the policyholder takes pictures or videos of the damaged car through a mobile app or web interface. Such inputs are stored in a secure manner by cloud platforms like AWS S3 or Firebase. Both real-time and batch uploads are supported by the system, so that immediate feedback is provided for real-time uploads and scheduled processing for batch uploads, providing an integrated user experience.

#### 3.6.2. Preprocessing Layer

Pre-processing is applied to the data before providing the images and the video frames to the deep models. Some of the pre-processing tasks are removal of noise, enhancement of contrast, resizing, and cropping. These are done to standardize the input and prepare it for model inference. Object-centric pre-processing, like background suppression, isolates the vehicle and makes the damaged areas clearer.

#### 3.6.3. Damage Assessment Layer

In the damage assessment layer, sophisticated computer vision is employed along with deep learning. YOLO (You Only Look Once), VGG16, and Detectron2 using Mask R-CNN are utilized for object detection and segmentation of damaged vehicle components. These models detect the major components of the vehicle and damage localization through the use of bounding boxes or masks.

Computer vision is important for facilitating the system to recognize and understand visual information. It supports feature extraction like edge detection, contour detection, and region segmentation, all of which are critical in identifying and classifying damage. In addition, Convolutional Neural Networks (CNNs) such as VGG16 and Detectron2 are employed to determine whether the input is a car, based on visual data patterns. Severity is automatically graded by merging model outputs with custom logic.

#### 3.6.4. Cost Estimation and Decision Layer

After damage identification and categorization, machine learning algorithms like XGBoost and Random Forest are utilized to estimate the cost of repair. The machine learning models are trained on historical data with fields like vehicle

make, type of damage, part replaced, and cost. In case the severity is beyond a specified threshold (e.g., 80%), the system suggests replacing the vehicle. Otherwise, it provides a cost breakdown of repairs needed.

3.6.5. Insurance Claim Processing Layer

Once it has estimated the cost of damage, the system verifies if the damages found are covered under the insurance policy. This is managed through an automated policy validation module. At the same time, a fraud detection model screens through historic trends to detect any indication of exaggerating a claim or image tampering. Referring to

previous fraudulent attempts, the system flags suspicious inputs for manual checks.

3.6.6. Decision Layer and User Notification

Finally, the system assesses whether to authorize, reject, or advance the claim based on the entirety of the gathered data. The outcome, accompanied by a detailed report that encompasses damage specifics and projected costs, is conveyed to the user via the mobile application. This notably reduces the duration of the claim approval process, thereby enhancing customer satisfaction and lowering operational costs.

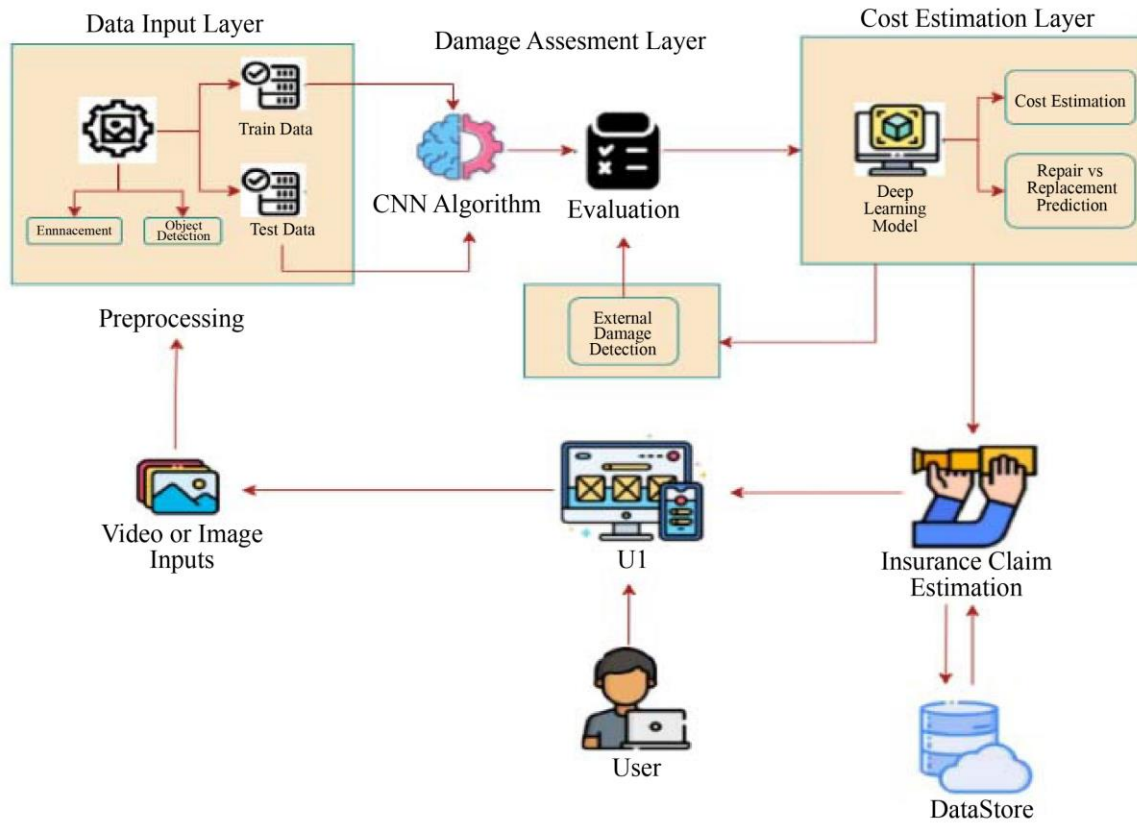


Fig. 1 Architecture diagram

3.7. Damage Detection and Parts Identification

In the damage assessment layer, computer vision techniques are combined with deep learning models to identify and inspect auto damage effectively. Typical architectures such as YOLO (You Only Look Once), VGG16, and Detectron2 with Mask R-CNN are applied in object detection and segmentation processes. They help identify the various parts of the vehicle and annotate them appropriately. The damaged regions are labeled using bounding boxes, and therefore, the impact area localization is straightforward. Furthermore, the system assesses and labels the damage severity from visual features and model outputs. This automated process significantly enhances the efficiency and

accuracy of car inspection, and it helps streamline insurance claim processing and minimize human error in damage assessment.

Algorithm:

- **Input:** Video frame or webcam input containing vehicles.
  - **Output:** Frames with tracked objects, bounding boxes, damage segmentation, severity classification, and part identification.
1. Capture a frame from the video or webcam input.
  2. Run object detection using the YOLO model to detect vehicles.

3. Extract the Bounding Box (BBox) for each detected car.
4. Classify objects using the VGG16 model to confirm if the detected object is a car.
5. Apply Detectron2 Mask R-CNN to segment damaged regions in detected vehicles.
6. Extract damage features (size, depth, texture) from the segmentation mask and classify the damage into the corresponding car parts.
7. Overlay bounding boxes, severity labels, part labels, and track lines on the frame.
8. Repeat steps 2–7 until all frames in the video are processed.
9. Save the annotated frames and return results to the mobile application.
10. Return: Processed frames with tracking IDs, bounding boxes, segmentation masks, and parts classification.

### 3.7.1. Object Detection (Vehicle Detection)

The Ultralytics object detection model is real-time. It is also called a single-stage detector, in which it predicts bounding boxes and classes in a single forward pass through the network. YOLOv5 has been proven to be efficient and fast, and can be used in applications requiring accurate and quick object detection, and can handle auto-learning bounding boxes. It is a PyTorch-optimized model that supports multiple scales to balance performance against computational expense.

### 3.7.2. Object Classification (Vehicle Verification)

VGG16 is a Convolutional Neural Network designed by the Visual Geometry Group at Oxford University. VGG16 is built using 16 layers, with most convolutional layers and fully connected layers. Some of the most widely used models in image classification, such as VGG16, have an uncomplicated, regular look as well as a shape that has small 3x3 filters in all its convolutional layers.

### 3.7.3. Damage Segmentation and Severity Estimation

Detectron2 is a robust and efficient object detection library created by Facebook AI Research (FAIR). It is founded on PyTorch and utilizes cutting-edge techniques for a range of tasks, such as object detection, instance segmentation, keypoint detection, and panoptic segmentation. Detectron2 architecture is very easy to customize and is very modular, making it ready for research and use.

### 3.8. Cost Estimation and Repair Vs Replacement

Leveraging the output from the damage segmentation module, this algorithm focuses on providing an accurate cost estimate for vehicle repairs. Using the identified damaged parts, severity score, and vehicle brand, the system queries a historical database of repair costs to derive pricing benchmarks. If the damage severity exceeds a set threshold (e.g., 80%), the system suggests part replacement over repair. Otherwise, it recommends repair as a cost-effective option. A predictive model synthesizes this data to generate a comprehensive repair estimate, including labor and part costs.

The result is compiled into a clear summary report, which is then sent to the user via the mobile app, offering transparency and informed decision-making.

#### Algorithm:

- **Input:** Segmented damage regions and detected vehicle details.
- **Output:** Estimated repair cost and recommendation (Repair vs. Replace).
  1. Extract damage region information from the Detectron2 segmentation output and identify the damaged parts.
  2. Retrieve historical repair cost data based on vehicle brand and part type.
  3. Input damage severity, part type, and vehicle brand into the model.
  4. Identify the repair vs replacement:
  5. If damage severity > 80%, recommend replacement.
  6. Otherwise, recommend repair.
  7. Predict the cost for the damaged parts.
  8. Generate a repair cost summary report.
  9. Send the report to the mobile app for user review.
  10. Return: Estimated cost and repair vs. replacement decision

### 3.9. Claims Assessment

The final algorithm orchestrates the insurance decision-making process based on the evaluated damage and estimated costs. It begins by collecting all relevant claim inputs, such as repair costs, damage severity, vehicle details, and user claim history. This information is securely transmitted to the insurance company's server for review. Advanced analytics or rule-based systems are applied to verify document authenticity, cross-check repair estimates, and detect potential fraud. Based on these evaluations, the insurer makes a final decision to approve, reject, or request additional information. The decision is relayed back to the mobile application along with the reasoning and next steps. Users can then monitor their claim progress and outcomes directly from their dashboard, completing a streamlined and transparent claims journey.

#### Algorithm:

- **Input:** Vehicle damage assessment and estimated repair cost.
- **Output:** Final claim approval decision from the insurance company.
  1. Collect claim details (damage severity, repair cost, vehicle info, past claims).
  2. Send the claim request to the insurance company for verification.
  3. The company reviews the claim (checks documents, verifies costs, detects fraud).
  4. The company makes a final decision (Approve, Reject, or Request More Info).

5. Send the final decision to the user via the mobile app.
6. Allow users to track claim status in the app.
7. Return: Final claim decision with reasons and next steps.

#### 4. Results

The Advanced Deep Learning Techniques for Automotive Damage Detection and Insurance Claim Estimation were applied on a test to see how well they work, especially in strengthening the accuracy of damage detection and segmentation features. These sophisticated approaches employ deep models of learning to exactly find the damaged portions, find different damage levels, and enhance segmentation precision. Evaluation was carried out on the basis of evaluating the ability to reduce classification error, provide appropriate detection of damaged car parts, and provide more accurate damage localization. The findings showed that these methods would significantly enhance test accuracy, which ultimately optimizes the process of insurance claim estimation and reduces human intervention.

##### 4.1. Add a Car

The first step is user car integration, which involves capturing relevant details such as model, make, registration number, and photos from various angles. The information is useful for vehicle identification and assessment of any damage in subsequent stages. Check in the database.

##### 4.2. Check in Database

In the next phase of the claims process, the system locates the vehicle by pulling the license plate number and checking it against the database. The vehicle is indicated if it is located, and the user is allowed to continue the claim process. It provides a guarantee that only registered vehicles can trigger a damage assessment and claim filing.

##### 4.3. Upload a Video

The self-service solution enables policyholders to upload a video through a mobile application. It extracts frames, detects vehicles, segments damaged regions, classifies severity, identifies damaged parts, and creates reports for efficient insurance claim processing.

Before uploading the Video, the video will be mapped with:

1. Car Brand
2. Car Model
3. Car Number

##### 4.4. Damage and Parts Identification Results

This algorithm is applied to analyze video frames to find and inspect car damage. The algorithm captures the frames and locates vehicles employing the YOLO model and identifies the bounding boxes of recognized automobiles. To perform proper identification, objects are then classified as a

vehicle employing the VGG16 model. Then, Detectron2's Mask R-CNN is utilized to outline damaged areas of identified automobiles. The damaged segments are evaluated based on parameters such as size, depth, and texture to determine the severity and the damaged car parts.

Bounding boxes, part labels, severity indicators, and tracking lines are superimposed on top of the frames for easy inspection. The aforementioned operation is done for every video frame to support continuous tracking and assessment. The labeled frames are saved and forwarded to a mobile application for convenience. Real-time identification of vehicle damage with accurate classification is supported by the aforementioned approach.

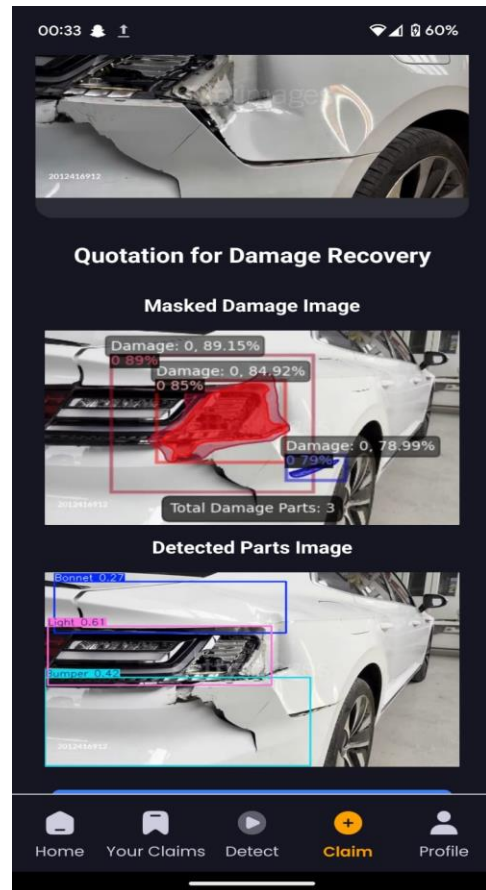


Fig. 2 Damage results from UI

The suggested system demonstrates an overall accuracy of 95.22%, which indicates its high reliability in vehicle damage detection and identification of the damaged parts. Such accuracy is a factor of the model's high performance at various stages, ranging from vehicle detection to damage localization, severity classification, and component labeling. The use of sophisticated deep learning models, including YOLOv5 for object detection, VGG16 for verification as a car, and Detectron2 for segmentation, contributes to high performance. The high accuracy ensures that the system can

effectively assist with insurance claim estimates by reducing errors, reducing the need for manual checking, and accelerating the entire process with precise results.

#### 4.4.1. Damage and Parts Identification Results

The system employs YOLOv5 as the vehicle detection algorithm, identifying bounding boxes for cars in each person frame. The objects are recognized on detection by VGG16 to confirm their identity as vehicles. In the course of damage assessment, Detectron2 Mask R-CNN detects damaged regions by finding irregularities in shape, texture, and structure. Segmentation mask helps in finding salient damage characteristics like size, depth, and texture variation. According to these established characteristics, the system determines the level of damage as minor, moderate, or severe. The severity level classification aids in the appropriate evaluation of insurance claims by determining the extent of repairs required. Lastly, the labeled frames, severity tags, and segmentation masks are established, thereby providing a full and computer-aided process of damage assessment.

#### Model Results

##### a) Object Detection (Vehicle Detection)

YOLOv5 is used for detecting vehicles in all frames of the given image or video. It places bounding boxes over the vehicles and allows them to be recognized in a variety of situations, such as changing light, angles, and backgrounds. The process is efficient and is particularly well-suited for real-time detection.

##### b) Object Classification (Vehicle Verification)

Once an object is detected by YOLOv5, VGG16 confirms whether the detected object is a vehicle or not. This filters out only accurate vehicle detection to pass through for damage evaluation to minimize errors and false alarms.

##### c) Damage Segmentation and Severity Estimation

Detectron2, one version of the Mask R-CNN model, was used to calculate the regions of the identified affected vehicle. It is a textural, geometrical, and structural abnormality to accurately identify damage. The system produces annotated results that include sketched damage areas along with severity labels, which are for downstream claim estimation.

#### Dataset Used

The data set used within this study for vehicle damage detection is a set of 11,685 annotated images that have been acquired through the Roboflow platform. The data set is split into three subsets in a strategic fashion: a training set of 10,224 images (87%), a validation set of 974 images (8%), and a test set of 487 images (4%). The division is favorable for rigorous training as well as fair testing of the performance of the model. The data set covers a wide variety of damage types taken under different conditions, therefore being suitable for training deep learning models to effectively detect and segment car damage.

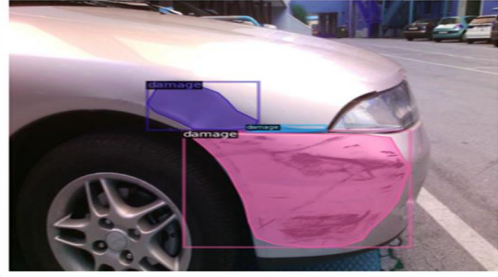


Fig. 3 Damage segmentations



Fig. 4 Damage identified

#### 4.4.2. Parts Identification

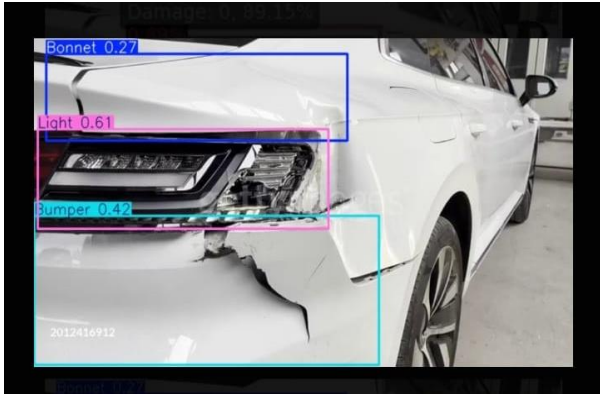
The system employs Detectron2 to execute accurate car part detection using advanced segmentation and classification operations. After the damage points have been identified, the model checks their position, shape, and structural attributes to correctly identify them in relation to car components such as the bumper, door, fender, or hood. All parts detected are assigned their respective label to avoid confusion during damage estimation. Such segmentation, besides identifying damage, also correctly assigns damage to a specific vehicle component. All detected components are marked accordingly, giving clean visual and text labels to assist in damage estimation.

#### How Parts Are Labeled

Through image processing, the model provides segmentation masks that label different parts of the vehicle. The segmented parts are then mapped to pre-defined labels for different auto components. Labeling is achieved through:

- **Bounding Boxes & Masks:** Each detected part is enclosed within a bounding box, and a segmentation mask is applied to highlight its exact shape.
- **Classification Scores:** The model assigns a confidence score to each detected part, ensuring accurate classification.
- **Overlaid Labels:** The name of the detected part (e.g., “Front Bumper” or “Door”) is overlaid on the image for clarity.

Through automating the identification of parts, the system reduces human inspection inaccuracy, simplifies insurance claim processing, and generates accurate repair or replacement estimates. Labeled results are also archived for future validation to facilitate claim validation and fraud detection.



**Fig. 5 Parts identification results**

**Model Results**

The model is able to do effective identification of parts from frames of video through the detection of vehicles and the segmentation of individual parts through instance segmentation with deep learning. Since the video is processed frame by frame, the model detects vehicles and generates accurate masks to distinguish individual parts, such as bumpers, fenders, headlights, hoods, and doors. The detected parts are given a corresponding class name so that the vehicle structure can be distinguished easily. The overall identification allows the system to determine which individual parts are in the frame and to distinguish them effectively, even in the event of occlusion or changing views.

Through the use of Mask R-CNN, the model not only detects but also tracks these parts across successive frames by assigning them individual IDs. This tracking feature ensures continuity and prevents redundant labeling, thus ensuring consistency in the analysis throughout the sequence of the video. The high-resolution output comprises bounding boxes, part labels, and mask overlays, which serve as the basis for additional damage analysis and insurance automation. Accurate part identification is essential for subsequent damage localization and cost estimation in the automated claims process.

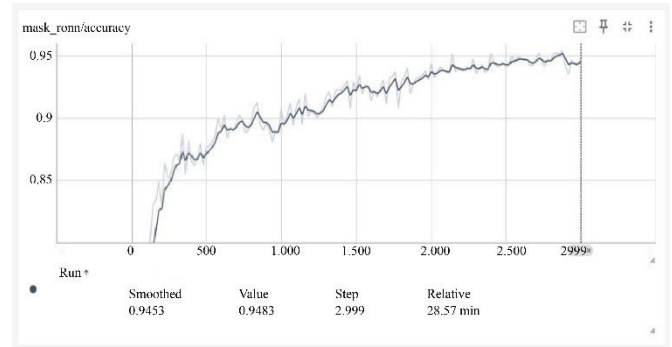


**Fig. 6 Parts identification by model**

**Dataset Used**

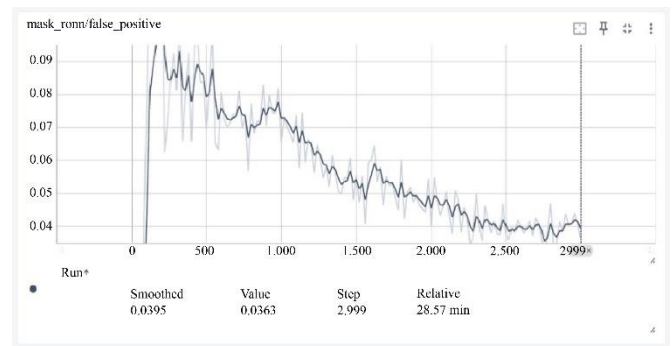
The data set utilized for vehicle parts segmentation in this research includes a total of 3291 annotated images specifically tailored to train and test the model's capability to recognize and segment the different components of vehicles. Collected and organized through the Roboflow platform, the data set is separated into three sets: 2,796 images (85%) are used for training, 328 images (10%) for validation, and 167 images (5%) for testing. Every image is also annotated with a thorough description of car components like bumpers, headlights, doors, hoods, and fenders, making it possible for the model to learn part-level differences with high accuracy. This balanced and curated dataset is crucial in making the parts detection model more robust and generalizable across different vehicle models and orientations.

**4.5. Accuracy of the Model**



**Fig. 7 Detectron2 with masked RCNN accuracy graph**

In Figure 7, the graph represents the performance accuracy of the Mask R-CNN model employed in the Vehicle Damage Detection System. It represents a consistent increase in accuracy with each training step, which reflects proper learning by the model. The accuracy reached a plateau at approximately 94.45%, and the last raw accuracy is approximated at 94.83% by step 2999. The model's overall accuracy is 95.22. The steep initial increase reflects quick learning in the early steps, followed by slow convergence, which again reflects the model's proper learning abilities. This performance level reflects the model's high competence in detecting and segmenting vehicle damage accurately.



**Fig. 8 False positives of the detectron2 model**

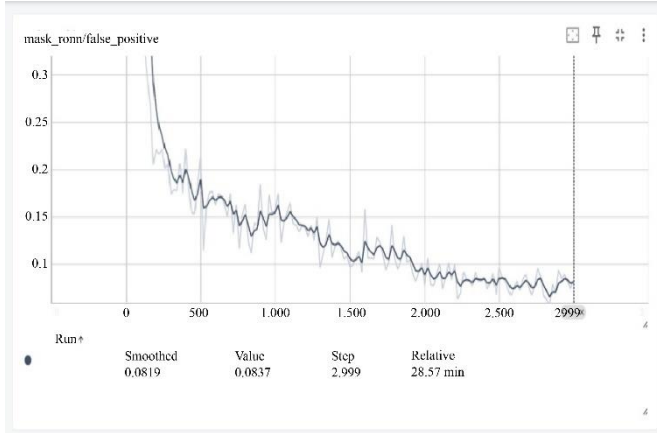


Fig. 9 False negatives of the detectron2 model

In Figures 8 and 9, the two curves show the false negative and false positive patterns throughout the Mask R-CNN model's training process in the Vehicle Damage Detection System. The false negative rate starts high but then levels out, finally converging to a smoothed rate of 0.0819, which indicates that the model increasingly shows a lesser tendency to miss actual damaged regions with time. Similarly, the false positive rate also shows a declining trend, with the final low smoothed rate of 0.0395 indicating that the model increasingly does a better job of not marking non-damaged entities as damaged. Both of these metrics show consistent improvement for the model from 2999 training steps. The overall decline in false predictions shows that the model is increasingly becoming reliable in its damage detection feature.

#### 4.6. Comparison with Existing Models

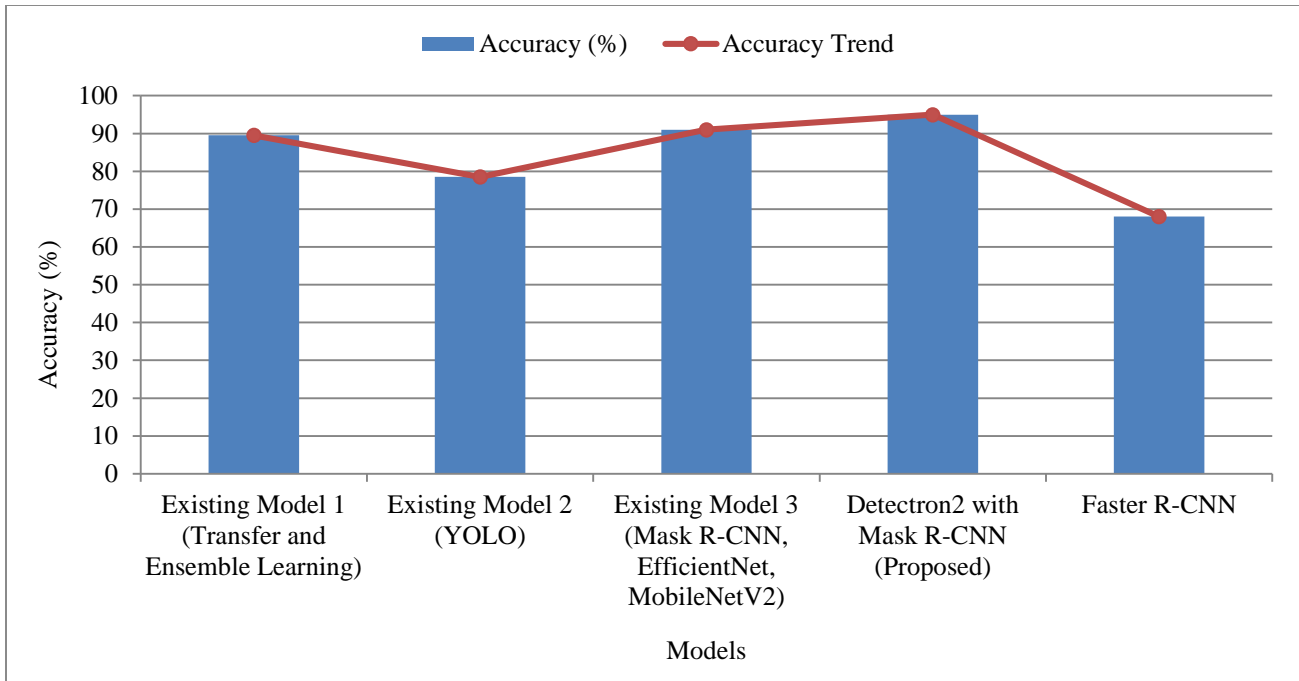


Fig. 10 Accuracy comparison of detectron2 with masked R-CNN and other existing models for vehicle damage detection

As shown in Figure 10, the bar chart illustrates a comparative analysis of the levels of accuracy exhibited by five various models employed in the identification of vehicle damage. The three models previously set have accuracy levels of approximately 89.5%, 78.5%, and 68.5%, a moderate level of competency in the identification of vehicle damage. The advanced model, such as Detectron2 with Mask R-CNN, exhibits far better performance, recording accuracy levels of approximately 95.2%. Notably, Detectron2 with Mask R-CNN outperforms any other model, exhibiting the highest accuracy and affirming its higher level of competency in effectively detecting and analyzing vehicle damage. The improved performance of Detectron2 by using Mask R-CNN is in its instance segmentation capability, which detects

damage at the pixel level as opposed to providing only outlines of bounding boxes. This feature greatly improves the precision of detecting the damaged areas on a vehicle.

Additionally, the fact that the model is rooted in a stable Detectron2 architecture by Facebook AI Research provides it with strengths like efficient training processes, scalability, and high generalization to varying conditions like varying lighting, angles, and damage types. Its high precision and accuracy make it highly suitable for real-world applications like automated damage assessment and insurance claim handling, making it one of the top-performing models in the comparative study, as shown in Table 2:

**Table 2. Car damage detection models: Accuracy and key findings**

Model	Accuracy	Findings
Transfer and Ensemble Learning	89.5	Achieved 89.5% accuracy but faced limitations due to dataset unavailability and manual annotation affecting scalability.
YOLO	78.5	Achieved 78.5% accuracy, but recall (70.25%) and mAP (0.66) limitations indicated the need for improvements in precision and real-world adaptability
Masked RCNN, EfficientNet, MobileNetV2	91.0	Achieved 91% F1 score, but segmentation accuracy and overlapping masks remained as challenges.
Detectron2 with Mask RCNN (Proposed System)	95.22	Achieved the highest accuracy, showing better potential for precision and adaptability in car damage detection.
Faster RCNN	68.0	Lower accuracy compared to other models, indicating limitations in performance for car damage detection.

**4.7. Cost Estimation: Repair vs. Replacement**

The system assesses the level of damage by examining segmented images from Detectron2 and determining the damaged parts of the vehicle. It fetches repair cost histories based on vehicle brand and type of part, so it is accurate in cost estimation. With input of damage severity, type of part, and vehicle brand into the model, the system decides whether to repair or replace a damaged part. If the severity is more than 80%, replacement is advised; otherwise, repair is advised. The system then estimates the cost of repair and creates a detailed cost report. This report is forwarded to the mobile application for user inspection, enabling decision-making. By comparing repair cost, part condition, and damage severity, the system maximizes the insurance claims process for efficient and accurate vehicle restoration.

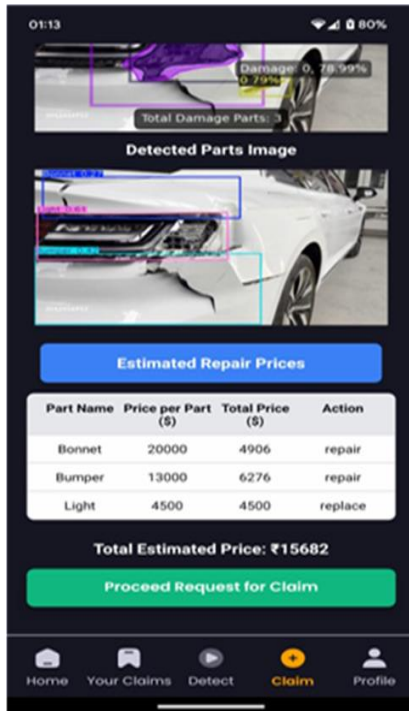
**4.8. Claims Processing**

The system handles damage estimates and car repair costs in order to authorize insurance claims. It starts with gathering necessary claim information, which involves damage degree, repair charges, vehicle characteristics, and claims history. All this information is submitted to the insurance company to verify, wherein the company looks into documents, confirms repair costs, and makes fraud checks. Upon this assessment, the company then concludes—accepting, denying, or requiring further information. This decision is conveyed to the user through the mobile application, whereby they may also monitor claim status in real-time. With efficient claim validation and approval, the system delivers an open, speedy, and correct insurance claims process for insured parties.

**5. Conclusion**

This article presents an advanced and state-of-the-art artificial intelligence-based system for vehicle damage detection and estimation of insurance claims. The system utilizes cutting-edge computer vision and deep learning techniques to overcome the limitations of the traditional manual and semi-automatic methods. The framework utilizes pre-trained models for object detection using YOLOv5, vehicle classification using VGG16, and segmentation using Detectron2 for the detection of damaged vehicle parts, assessment of damage extent, and prediction of repair costs using machine learning regression algorithms such as Random Forest and XGBoost.

All the tools are designed to work cohesively with each other using a unified backend framework to ensure correctness, efficiency, and scalability with minimal human intervention and maximum consistency. Additionally, access to self-service stations provides policyholders with the option to directly upload images and videos, thus simplifying the submission of claims without inspections. With all of these, the application of AI-based systems in the motor vehicle insurance industry ensures an efficient, accurate, and timely claims processing system.



**Fig. 11 Estimated repair cost**

The architectural design for the system begins by preprocessing video input through OpenCV to obtain individual frames. YOLOv5 is then used to detect possible vehicles, while VGG16 is used to confirm through verification if the detected objects are actually automobiles. Validated frames are then passed to Detectron2, which is trained on COCO-formatted datasets annotated through Roboflow, to perform instance segmentation and identify damaged parts such as bumpers, doors, hoods, among others, and assess the severity of the damage (classified as minor, moderate, or severe). Through the results obtained from this segmentation, structured data is passed to regression models that are tasked with submitting cost estimates for repair or replacement operations. The modularity of the system also eases its maintenance, extension, and integration into any platform.

The provided solution is better than the traditional one in terms of precision, speed, and reliability. It also saves time spent on claim processing, removes any inconsistency that may appear because of human judgment, and reduces costs, while also significantly improving the end-user experience through fast and unambiguous results. The existence of available open data and platforms is a step towards easy extension or modification of the system for a wide range of practical applications. The practical application of models and the improvement of the automated pipeline also show the relevance of this system to commercial environments within the motor and insurance industries. Data security and user data privacy for user-uploaded data, such as images, videos, and insurance claim documents, are collected and then stored on cloud storage services such as AWS S3 and Firebase, providing greater data security and reliability through data encryption. However, there is a limitation in terms of providing support for a wide range of mobile devices, as the

application's performance is based on the availability of RAM and connectivity.

Looking ahead, there are some promising directions for future developments. The system may be made to accommodate multi-perspective damage inspection on 360-degree photos for end-to-end car inspection. OCR techniques may be applied to enable automatic document verification and number plate reading. Lightweight deployment on mobile devices, such as TensorFlow Lite or ONNX, would enable real-time online audits. Fraud detection software can also be enhanced by using anomaly detection methods and metadata analysis of uploaded documents and videos. In addition, by growing the dataset size with more real-life conditions in different environmental conditions, the model's stability can be improved further. Integration with APIs of insurance companies can also enable end-to-end approvals of claims, making the system more practical and usable.

In conclusion, this study has provided a strong foundation for intelligent and computerized systems in damage detection and the estimation of insurance claims. This study has also significantly contributed to the digital innovation of vehicle inspection and insurance practices through the use of deep learning and computer vision approaches, thus improving their intelligence and reliability.

### Conflicts of Interest

The author(s) declare that there is no conflict of interest regarding the publication of this paper.

### Funding Statement

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