Vehicle Damage Assessment System

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ABSTRACT

The automotive industry's continuous growth has necessitated more efficient and accurate methods for assessing vehicle damage and estimating repair costs. This project introduces an Integrated Vehicle Damage Assessment System (IVDAS) that combines advanced computer vision techniques, machine learning algorithms and repair cost databases to create a comprehensive solution.

It addresses the limitations of traditional manual approaches by automating the process of evaluating vehicle damage and generating accurate repair cost estimates. The system utilizes an array of high resolution images capturing the extent of damage from various angles and lighting conditions. Through the application of CNN's and deep learning, it extracts intricate details from the images facilitating precise identification and classification of damage types such as dents, scratches, paint damage and structural issues.

Beyond damage assessment, it also incorporates a sophisticated cost estimation component. By interfacing with a comprehensive database of repair costs for different types of damages and vehicle models, the system calculates an approximate repair cost based on the identified damage severity. This integration streamlines the assessment process and provides users with accurate cost projections, assisting insurance companies, repair shops and vehicle owners in making informed decisions. The trained model can be integrated into a user friendly software interface, enabling users to input images and promptly receive detailed damage assessments along with cost estimates.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

In the ever-evolving landscape of automotive technology and safety, the Vehicle Damage Assessment System stands out as a ground-breaking solution poised to transform the way vehicle damages are evaluated and assessed. This innovative project represents a fusion of cutting-edge artificial intelligence (AI) algorithms, computer vision, and advanced data analytics to streamline and enhance the vehicle inspection process, offering a more efficient and accurate means of assessing damages.

As automotive industries strive for heightened safety standards and optimal performance, the need for robust systems to evaluate vehicle damages has become increasingly critical. The Vehicle Damage Assessment System addresses this demand by leveraging state-of-the-art machine learning techniques to automate and expedite the assessment of damages incurred by vehicles. This not only reduces the burden on human inspectors but also significantly improves the accuracy and reliability of the assessment process.

At its core, the system employs computer vision algorithms capable of analysing images and videos of damaged vehicles. These algorithms are trained on vast datasets encompassing various types of damages, from minor dents to severe structural issues. The deep learning models within the system learn to recognize patterns and anomalies in the visual data, enabling them to accurately identify and categorize different types of Damages with a high degree of precision.

CHAPTER 2

LITERATURE SURVEY

This topic discusses the work done by various authors, students, and researchers in brief around discussion, which is Vehicle Damage Assessment System Prediction using Machine Learning. The purpose of this section is to critically summarize the current knowledge in the field of Vehicle Damage Assessment System.

Table 2.1: Survey on Vehicle Damage Assessment

Sl.No.	PAPER	AUTHORS	YEAR	METHODOLOGY
[1]	Convolutional Neural Networks for vehicle damage detection	R.E van Ruitenbeek, S.Bhulai	2022	The authors compared different models and backbones, including YOLOv3, SSD MobileNet, and Faster R-CNN, to evaluate their performance.
[2]	Automatic damaged vehicle estimator using enhanced deep learning algorithm	Jihad Qaddour, Syeda Ayesha Siddiqa	2023	The methodology involves employing Mask R-CNN with VGG-16, VGG-19, and Inception- ResNetV2 as backbone models are used.

[3]	A Unified Framework of Intelligent Vehicle Damage Assessment based on Computer Vision Technology	Xianglei Zhua , Sen Liub, Peng Zhang,	2019	The paper proposes a unified framework for intelligent vehicle damage assessment using various computer vision algorithms, including RetinaNet, Mask R-CNN, and Inception, to improve accuracy and reduce computational complexity.
[4]	Vehicle Damage Severity Estimation for Insurance Operations Using In-The-Wild Mobile Images	Niall McLaughlin	2023	The research highlighted the challenges of damage detection, classifying damages into categories like Broken Light or Dent. The approach used instance segmentation to measure damage independently on each body panel.
[5]	Evaluation of deep learning algorithms for semantic segmentation of car parts	Kitsuchart Pasupa ,Phongsatho rn Kittiworapa nya, Napasin Hongngern, Kuntpong Woraratpan y	2021	The authors evaluated the performance of each model in terms of mean average precision (mAP) and robustness against real- world weather and lighting conditions.

[6]	Vehicle-Damage-Detection Segmentation Algorithm Based on Improved Mask RCNN	QINGHUI ZHANG, XIANING CHANG, SHANFEN G BIAN	2022	Different weights were introduced in the loss function for different- scale targets to improve the masking accuracy.
[7]	Integration of image segmentation and fuzzy theory to improve the accuracy of damage detection areas in traffic accidents	Majid Amirfakhrian and Mahboub Parhizkar	2021	Categorizing the image of the car using image segmentation. Identifying the damaged areas using car vision techniques.
[8]	Research on Intelligent Vehicle Damage Assessment System Based on Computer Vision	Zhu Qianqian, Guo Weiming, Shen Ying and Zhao Zihao	2020	By incorporating deep learning algorithms for damage recognition, the system can effectively identify various types of vehicle appearance damage. The primary objective of this system is to enhance the efficiency of insurance claim settlements and mitigate traffic congestion resulting from small-scale cases.

[9]	Deep Learning based car Damage Classification and detection	Mahavir Dwivedi,Satya Samal,Omkar SN	2019	The study also explored different pre-trained models like VGG19 and InceptionV3, with a focus on techniques to enhance accuracy and training speed, such as determining optimal learning rates. Additionally, the implementation of YOLOv3 for damage detection highlighted its speed and accuracy benefits, while MobileNets were investigated for their suitability in lightweight neural networks for mobile applications.
[10]	Damage Assessment of a vehicle and Insurance Reclaim.	Vaibhav Agarwal, Utsav Khandelwal, Shivam Kumar, Raja Kumar, Shilpa M	2022	Focuses on utilizing VGG19 over VGG16 for improved accuracy in assessing the severity of vehicle damage, incorporating transfer learning and L2 regularization to enhance model performance.
[11]	Car Damage Assessment for Insurance Companies	Mandara G S, Prashant Ankalkoti	2022	By employing a Convolutional Neural Network (CNN) model and the VGG16 algorithm, the system can swiftly detect the presence of a car in an image and analyze the extent of damage it has incurred.

2.2 LITERATURE SURVEY SUMMARY

Paper 1: Convolutional Neural Networks for vehicle damage detection

The study compares the mean Average Precision (mAP) performance of the Feature Pyramid Single Shot Detector (FSSD) and You Only Look Once version 3 (YOLOv3) models before and after unfreezing the base network. The evaluation of the best model trained on the y-axis dataset and tested on the x-axis dataset is presented. The research extends previous work by using a larger dataset, classifying and localizing damage on twelve categories, and evaluating different object detection models. Optimization of batch size and learning rate for mAP performance is discussed. Comparison of one-stage models with various backbones is made, focusing on damage detection in vehicles. The study includes practical evaluation in a light street setup for damage inspections. Various references to related works and methodologies in damage detection using deep learning are provided.

Paper 2: Automatic damaged vehicle estimator using enhanced deep learning algorithm

The study delves into the comparison of RoIAlign and RoIPool methods in object detection tasks, highlighting the advantages of RoIAlign in improving the accuracy of sample points' position calculation through bypassing quantization and utilizing bilinear interpolation. RoIAlign also facilitates the generation of fixed-size Regions of Interest (RoI) using average and maximum pooling techniques. In the realm of vehicle damage detection, the research leverages deep learning techniques, transfer learning, and Mask R-CNN for the identification of damages. Notably, the study found that Inception ResNetV2 outperformed VGG-16 and VGG-19 in both detection and severity classification tasks, showcasing its efficacy in this domain. Furthermore, the development of a web-based automatic claim estimator aimed at enhancing the efficiency of the claim estimation process.

Paper 3: A Unified Framework of Intelligent Vehicle Damage Assessment based on Computer Vision Technology

The paper introduces a unified framework for intelligent vehicle damage assessment, focusing on identifying vehicle parts, damage position, and damage type. It employs object detection technology in computer vision to accurately identify damaged positions. The algorithm utilizes RetinaNet for object detection and Mask R-CNN for image segmentation, achieving over 70% accuracy in identifying damage types and degrees. The method involves processing detected results to combine overlapping areas, enhancing accuracy. Additionally, the Inception classification network is modified for multi-label classification, enabling the classification of multiple damage types in the same area.
In the experiments, the algorithm is trained on a dataset containing over 300,000 annotated vehicle images, ensuring diversity and comprehensiveness in training samples. Data reduction and annotation methods are detailed, including the division of vehicle parts into 31 categories and damage types into 6 categories. The paper discusses the selection of models and training samples as crucial aspects of supervised learning. References to deep learning frameworks such as RetinaNet, Mask R-CNN, and Single Shot Multibox Detector are provided, highlighting the use of advanced techniques in the proposed algorithm for intelligent vehicle damage assessment.

Paper 4: Vehicle Damage Severity Estimation for Insurance Operations Using In-The-Wild Mobile Images

The research focused on refining instructional materials for annotators to ensure consistent labeling of image samples. By assessing inter-annotator consistency through IoU measurements, they aimed to improve annotation quality. The process involved providing large batches of images to annotators and incorporating active learning elements. For instance, annotators labeled vehicle damage in images, refining the process over time. The study also delved into automated vehicle insurance claims processing using computer vision and natural language processing. Dimitrios Mallios, with a background in computer engineering and artificial intelligence, made significant contributions to the field. The research highlighted the challenges of damage detection, classifying damages into categories like Broken Light or Dent. The approach used instance segmentation to measure damage independently on each body panel. Additionally, the study developed a car angle classifier and a parts and damage detector, utilizing segmentation models for accurate predictions. The authors emphasized the importance of refining the pipeline for granular damage prediction to enhance accuracy in insurance operations.

Paper 5: Evaluation of deep learning algorithms for semantic segmentation of car parts

Object Detection and Semantic Segmentation Evaluation: Five deep learning algorithms were tested for semantic segmentation of car parts, with HTC showing the best performance. The robustness of the models was tested in challenging real environments with various weather conditions and lighting. Mean Average Precision (mAP) was used to evaluate the algorithms' performance, and robustness was measured using mean performance under corruption (mPC) and relative performance under corruption (rPC) metrics.

Model Performance: Mask R-CNN, GCNet, PANet, CBNet, and HTC were evaluated for object detection and semantic segmentation. HTC with ResNet-50 was the best algorithm for instance segmentation, achieving a mean average precision of 55.2. Image segmentation was used to automatically identify car parts for damage evaluation and repair cost estimation. Different algorithms showed varying performance based on the size of the car parts.

Cascade Mask R-CNN with CBNet: A composite backbone combining assistant and lead backbones improved prediction accuracy for instance segmentation. The study provides insights into the effectiveness of deep learning algorithms in segmenting car parts for damage evaluation and repair cost estimation. The evaluation metrics used, such as mAP, mPC, and rPC, offer a comprehensive analysis of the algorithms' performance under different conditions. The findings can benefit developers of automated car damage evaluation systems in designing more efficient and accurate models for car part segmentation.

Paper 6: Vehicle-Damage-Detection Segmentation Algorithm Based on Improved Mask RCNN

The Vehicle-Damage-Detection Segmentation Algorithm is based on an improved Mask RCNN framework that enhances model regularization and generalization. This algorithm utilizes Mask RCNN for detecting and segmenting damaged areas in vehicle accidents. Experimental results demonstrate that the improved Mask RCNN shows a significant performance enhancement in car damage detection compared to the Mask RCNN algorithm. The model incorporates enhancements such as RoIAlign for precise sample point calculation and adjusts network layers for improved accuracy. The detection performance of the improved algorithm surpasses that of Mask RCNN in car damage detection accuracy. The model components include ResNet50, FPN, and improved network structures for robust feature extraction. Additionally, the algorithm introduces a balance coefficient λ to control the proportions of classification and regression losses in the Faster RCNN and Mask RCNN models.

Paper 7: Integration of image segmentation and fuzzy theory to improve the accuracy of damage detection areas in traffic accident

The study introduces a novel method for crash detection and diagnosis of damaged car parts through image processing and machine learning techniques. By combining the particle swarm optimization (PSO) algorithm with a voting classifier, the proposed method significantly enhances the accuracy of crash detection. The research addresses weaknesses in previous segmentation-based methods, such as inefficiency for large images, inability to process blurry images, weakness in different lighting modes, and noise sensitivity, by providing solutions to these challenges. The study evaluates the proposed method's performance for detecting damaged areas in traffic accidents using MATLAB programming language and compares it with existing methods. Additionally, the article discusses the application of the PSO algorithm for continuous optimization problems and the importance of parameter settings in achieving convergence. Overall, the research contributes to improving accident detection accuracy and highlights the significance of image processing and machine learning in this domain.

Paper 8: Research on Intelligent Vehicle Damage Assessment System Based on Computer Vision

The research is centered around the development of an Intelligent Vehicle Damage Assessment System that leverages smartphone technology for photography. This innovative system is designed to aid in the detection of front-end damage, assess the extent of damage, and provide anti-fraud services. By incorporating deep learning algorithms for damage recognition, the system can effectively identify various types of vehicle appearance damage. The primary objective of this system is to enhance the efficiency of insurance claim settlements and mitigate traffic congestion resulting from small-scale cases. Its multifaceted functions encompass accident investigation, image-based damage assessment, generation of damage results, and anti-fraud measures within the vehicle insurance domain. Through the integration of intelligent photography and ID recognition technologies, the system aims to operate seamlessly, ultimately streamlining the vehicle damage assessment process, enhancing accuracy, and optimizing insurance claim settlement procedures.

Paper 9: Deep Learning based car damage Classification and detection

The study delves into the realm of vehicle damage classification and detection through the lens of deep learning. The research aimed to streamline the vehicle insurance claims process by automating the identification of damages, leveraging the advancements in computer vision and Convolutional Neural Networks (CNNs). An extensive dataset of annotated images was manually collected to train and test various deep learning models. The Resnet34 model exhibited promising accuracy in class predictions, albeit with some misclassifications attributed to similarities between classes. To optimize the system for real-world applications, the inference model was fine-tuned to run efficiently on both laptops and handheld mobile phones, catering to the needs of insurance companies. Hardware specifications included the use of a Nvidia GTX 1080Ti for training, boasting 8GB of graphics card memory and 24GB of system RAM. The study also explored different pre-trained models like VGG19 and InceptionV3, with a focus on techniques to enhance accuracy and training speed, such as determining optimal learning rates. Additionally, the implementation of YOLOv3 for damage detection highlighted its speed and accuracy benefits, while MobileNets were investigated for their suitability in lightweight neural networks for mobile applications.

Paper 10: Damage Assessment of a vehicle and Insurance Reclaim.

The research focuses on utilizing VGG19 over VGG16 for improved accuracy in assessing the severity of vehicle damage, incorporating transfer learning and L2 regularization to enhance model performance. However, a notable challenge lies in the scarcity of publicly available datasets for car damage, hindering the development and training of effective models. The study emphasizes the importance of deep learning architectures in automating the process of vehicle damage detection, enabling faster and more efficient analysis compared to traditional manual methods.

Furthermore, the implementation of a CNN model aims to streamline the auto insurance claims process by leveraging image analysis and pattern recognition to identify and quantify damage in automobiles. This approach not only facilitates quicker assessment of damage but also seeks to reduce loss adjustment expenses and expedite the processing of insurance claims. The model segregates damaged parts into categories for repair or replacement based on the percentage of damage, providing a structured approach to handling claims efficiently.

Paper 11: Car Damage Assessment for Insurance Companies

In the realm of increasing vehicular accidents, the need for efficient car damage assessment is paramount. Insurance claims often hinge on accurate evaluations of vehicle damage, a process that can be time-consuming and resource-intensive. To address this challenge, a proposed system leverages machine learning and computer vision technologies to streamline the claiming process. By employing a Convolutional Neural Network (CNN) model and the VGG16 algorithm, the system can swiftly detect the presence of a car in an image and analyze the extent of damage it has incurred.

The system's methodology involves dataset preparation, damage level classification, and the utilization of a CNN model for image processing and segmentation. By categorizing damage levels into small, average, and severe, the system can provide detailed insights into the condition of the vehicle. Furthermore, the system's ability to predict the location of damage (front, rear, side) and assess its severity (minor, moderate, severe) enhances its utility for insurance companies seeking accurate and efficient car damage assessments.

CHAPTER 3

OBJECTIVE

- To detect the type of damage in the uploaded image of the vehicle with the help of YOLOV5 Object Detection Algorithm.
- To estimate the cost of damage repair with the help of confidence scores.
- Simple and intuitive user interface will make the program simple and intuitive to use. Users will be able to quickly upload pictures of damaged cars and get an estimate for the cost of repairs.

CHAPTER 4

PROBLEM DEFINITION

The contemporary automotive industry faces a pressing challenge in the manual and time-consuming nature of vehicle damage assessments. Traditional inspection methods rely heavily on human inspectors, leading to delays, inconsistencies, and subjective evaluations in identifying and categorizing damages. The complexity of modern vehicles, coupled with the increasing diversity of damages, exacerbates these challenges, impeding operational efficiency and decision-making processes.

The Vehicle Damage Assessment System addresses this problem by leveraging cutting-edge AI, computer vision, and machine learning technologies. The current problem lies in the inadequacies of manual inspection methods, hindering the industry's ability to adapt to the complexities of modern vehicles and the growing demand for streamlined processes. As the automotive landscape evolves, the need for a robust, realtime, and adaptable solution for damage assessment becomes evident, and the Vehicle Damage Assessment System aims to fill this crucial gap in the industry.

CHAPTER 5

SYSTEM REQUIREMENTS SPECIFICATION

Software Requirements:

- Python
- Numpy
- Pandas
- sklearn
- VSCode
- Flask Server

Hardware requirements:

- Processor: Intel(R) Core(R) or AMD Ryzen
- CPU Hard disk: 500GB HDD
- RAM: 4GB RAM
- GPU: 8 GB or above

CHAPTER 6

SYSTEM DESIGN

Various Modules of Developing:

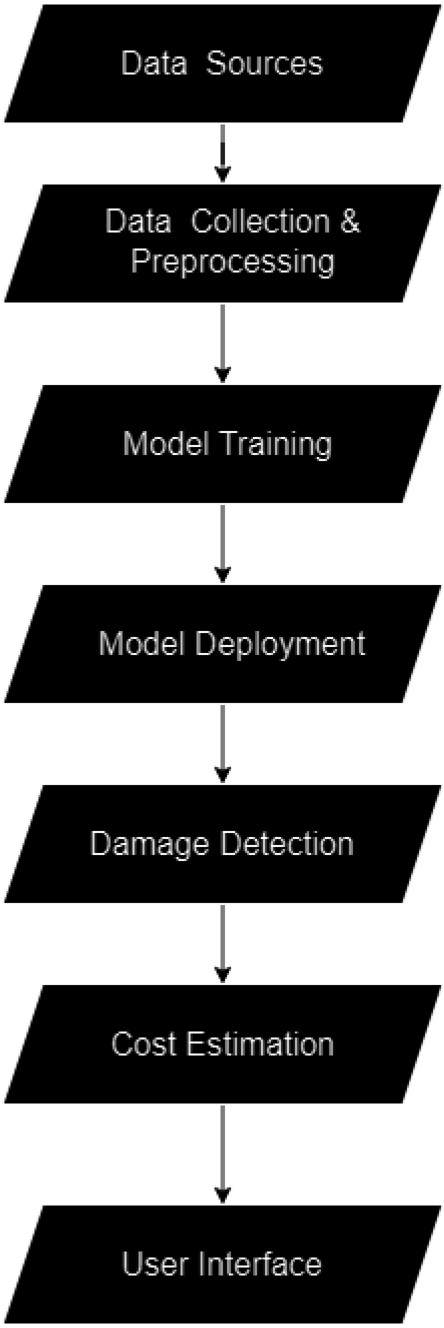

Fig 6.1: System design

USE CASE DIAGRAM

The user can upload any damaged car/bike image in our website, On uploading the image, YOLOV5 Object Detection model analyses the image and detects the type of damages if any, along with that the user can even obtain the cost estimate for that particular damage repair.

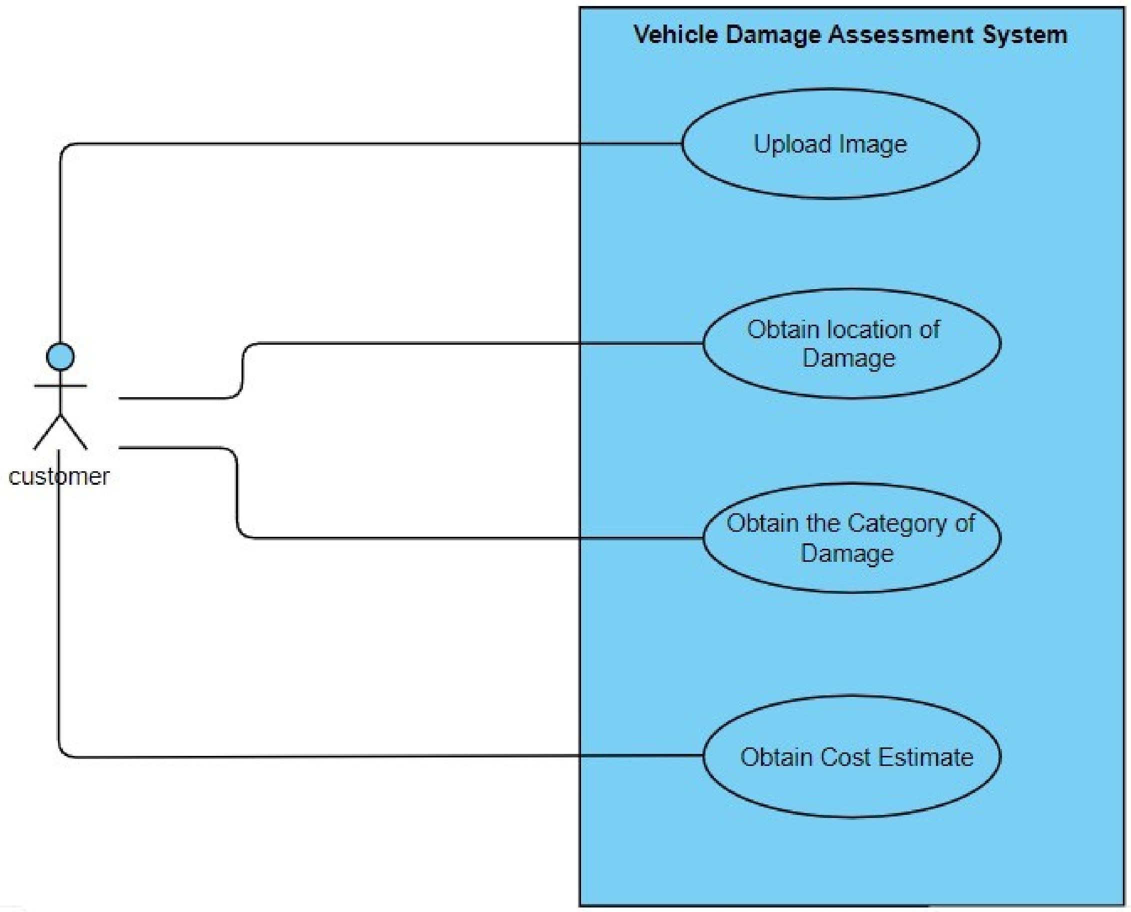

Fig 6.2: Use Case Diagram

CHAPTER 7

IMPLEMENTATION

Mask R-CNN: Mask R-CNN is a powerful instance segmentation model that extends the Faster R-CNN architecture by adding a branch for predicting segmentation masks alongside the existing branches for object detection. This model achieves state-of-the-art performance in various computer vision tasks, including object detection, instance segmentation, and semantic segmentation.

Mask R-CNN consists of two main stages: a region proposal network (RPN) and a mask prediction network. The RPN generates candidate object bounding boxes, similar to Faster R-CNN, while the mask prediction network produces segmentation masks for each candidate box.

But when we compared Mask R-CNN with YOLOV5, we found YOLOV5 more accurate when it comes to detecting damages in the vehicle image. Hence we chose YOLOV5 over Mask R-CNN for training our dataset.

YOLOv5: YOLOv5 (You Only Look Once version 5) is a fast object detection algorithm that processes images in one pass through a neural network, dividing them into grids to predict bounding boxes and class probabilities for objects, offering a balance between speed and accuracy.

YOLOv5 is an efficient object detection system that quickly analyzes images, dividing them into grids to simultaneously predict bounding boxes and class probabilities for objects. It employs a neural network architecture with an EfficientNet backbone, trained on labeled datasets, and is widely used for real-time object detection in various applications.

```
git clone https://github.com/ultralytics/yolov5  # clone

cd yolov5

pip install -r requirements.txt  # install

python train.py --img 416 --batch 4 --epochs 200 --data "C:\Users\Admin\Downloads\custom_data.yaml" --cfg models/yolov5s.yaml --weights yolov5s.pt --name
custom_experiment --device 0
```

Fig 7.1: YOLOV5 Training Code

The provided code begins by cloning the YOLOv5 repository from GitHub using the git clone command, ensuring that the necessary source code is available locally for training. Next, it navigates into the cloned repository directory. Once inside the repository, it proceeds to install the required Python packages listed in the requirements.txt file, ensuring that all dependencies necessary for running the YOLOv5 training script are installed. After setting up the environment, the code moves on to train the YOLOv5 model using the python train.py command. Several parameters are specified for training, including the input image size, batch size, number of epochs, paths to the dataset configuration file and model configuration file, path to the pre-trained weights file, experiment name, and GPU device index.

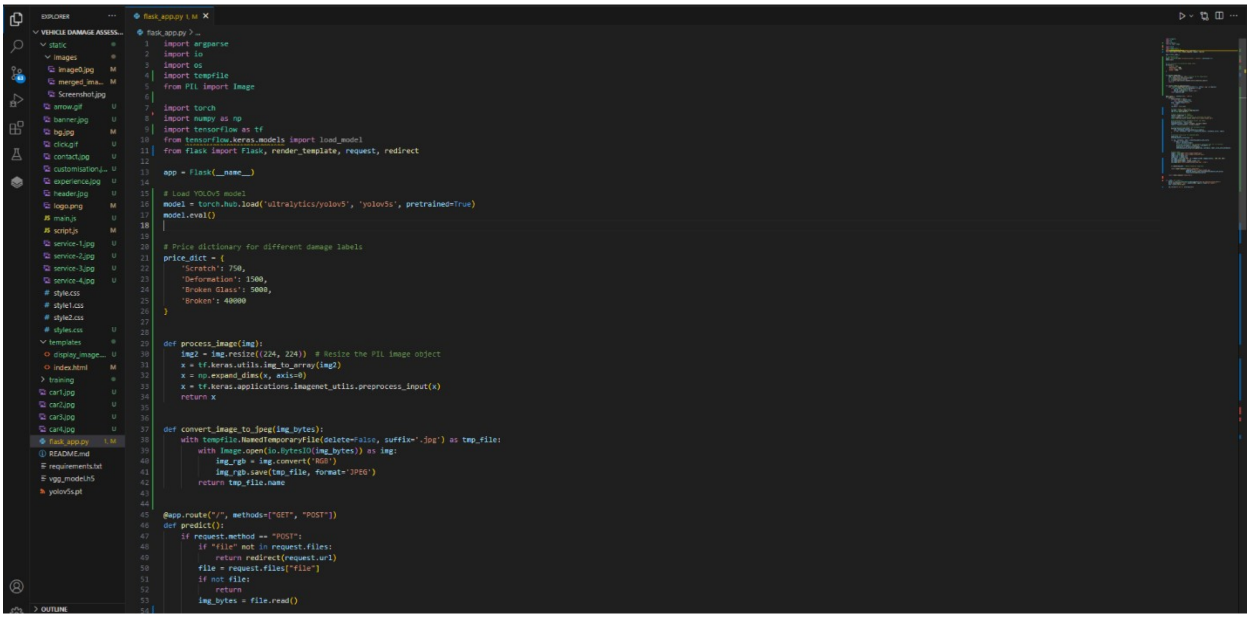

Figure 7.2:Flask Code

The provided code is a Python Flask web application that utilizes the YOLOv5 model for object detection. It loads the YOLOv5 model, defines a Flask route for handling image uploads, and processes the uploaded image to perform object detection.

The detected objects, confidence scores, and labels are extracted from the model's predictions. However, the code snippet lacks an explanation of how the detected objects, confidence scores, and labels are further utilized, particularly in the context of associating them with damage types and prices.

Figure 7.3:Flask Code

This code calculates the total price for detected labels based on a predefined price dictionary. It then merges the detected objects with the original image, removes the temporary image file, and renders a template to display the original image, detected objects with their corresponding prices, and the total price. Finally, it runs the Flask app on the specified port.

Output: This code is a Flask web application that performs object detection using the YOLOv5 model. When the application is run, it starts a web server on the specified port (default is 5000). The user can access the application through a web browser.

When the user uploads an image through the web interface, the `predict` function is triggered. This function:

1. Reads the uploaded image file.
2. Converts the image to JPEG format and saves it as a temporary file.
3. Performs object detection on the image using the YOLOv5 model.

4. Extracts detected objects, confidence scores, and labels from the model's predictions.
5. Calculates the total price for detected labels based on a predefined price dictionary.
6. Merges the detected objects with the original image.
7. Removes the temporary image file.
8. Renders a template to display the original image, detected objects with their corresponding prices, and the total price.

CHAPTER 8

RESULTS

We successfully trained a YOLOv5 model on a collected car damage dataset to detect various types of vehicle damages. We Trained the model on 200 epochs on a batch size of 4 and image size of 416 x 416. The trained model demonstrated robust performance in detecting damages. Qualitative results showcase the model's ability to accurately localize damages within images, with bounding boxes effectively outlining the affected areas. Furthermore, leveraging the detected damages, we also predict repair costs. Our system showed promising results in estimating repair costs for 4 different types and severity levels of damages. These findings underscore the potential utility of our approach in automating vehicle damage assessment processes, offering practical benefits for insurance claim processing and auto repair services.

Fig 8.1:Car Damage Output

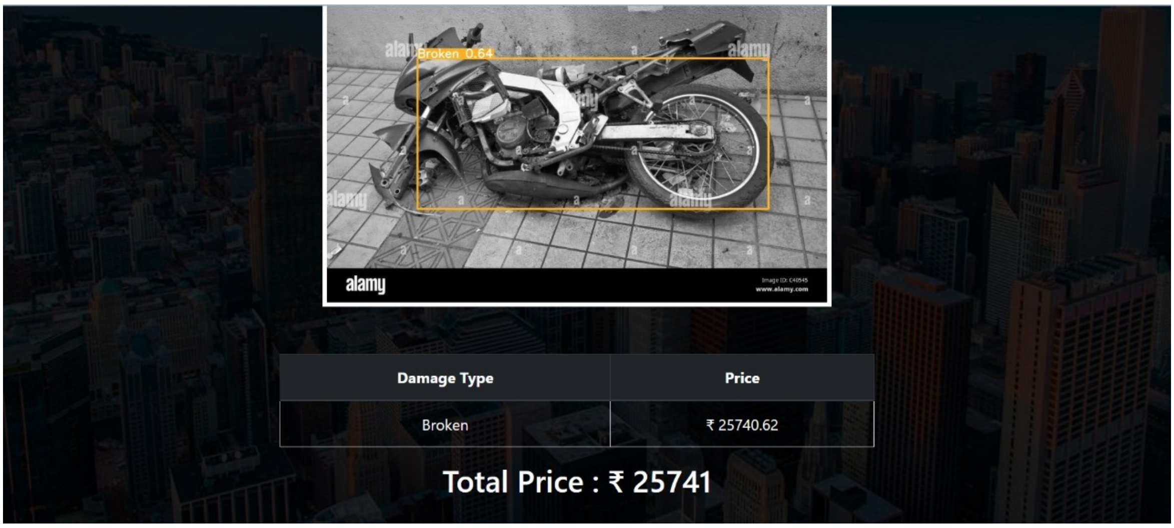

Fig.8.2:Bike Damage Output

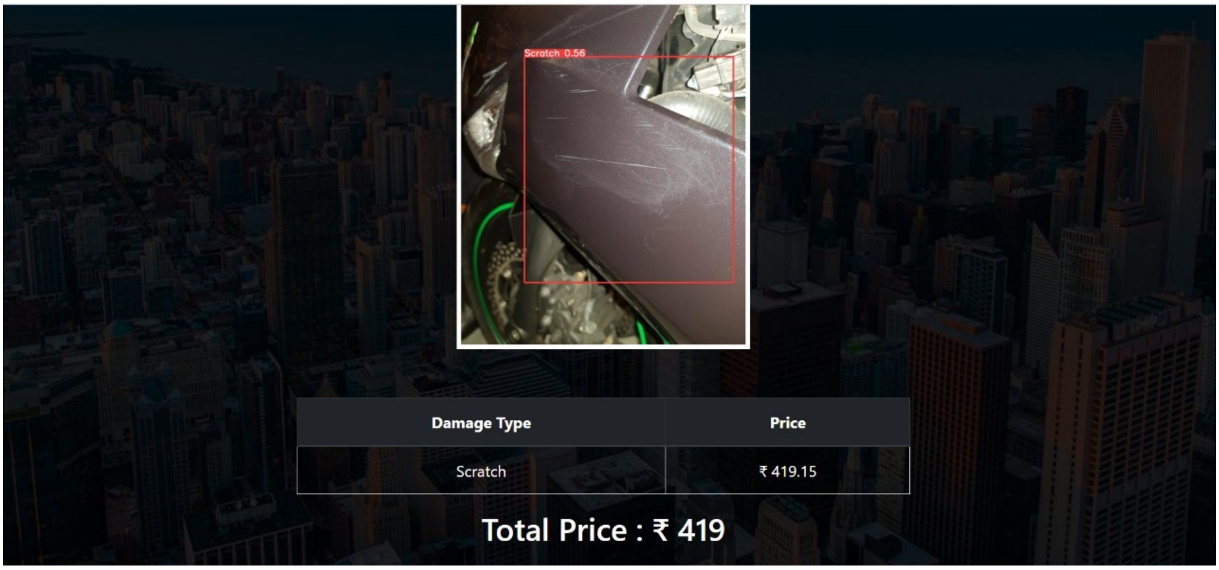

Fig 8.3: Bike Damage Output

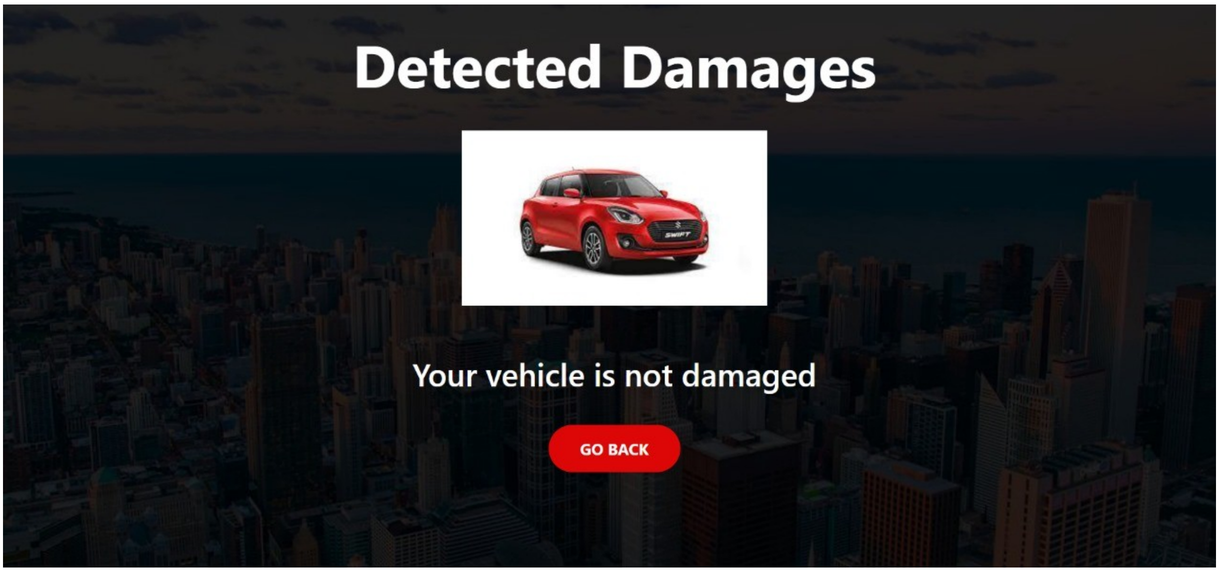

Fig 8.4: Car Undamaged Output

CHAPTER 9

CONCLUSION

Vehicle Damage Assessment System(VDAS) stands as a beacon of innovation in the automotive industry, offering a transformative solution to the longstanding challenges associated with manual vehicle damage assessments. By harnessing the power of artificial intelligence, computer vision, and machine learning, this system not only addresses the inefficiencies and subjectivity inherent in traditional inspection methods but also propels the industry into a new era of efficiency, accuracy, and adaptability.

The real-time capabilities of the Vehicle Damage Assessment System mark a significant departure from the delays characteristic of manual assessments, allowing for prompt decision-making in critical scenarios such as insurance claims and resale evaluations. Its adaptability across various industry applications ensures that it is not merely a standalone solution but an integrated tool capable of enhancing workflows in insurance, repair services, and fleet management.

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