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Car Damage Assessment to Automate Insurance Claim

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Abstract - *Car Damage inspection is an integral step in claim sanctioning and often the process of damage inspection is delayed and inaccurate leading to claim leakages. Our challenge is to develop a web application integrated with a deep learning model that takes user input as images of the damaged cars and analyzes the damage to generate a cost report that would be used by the company to sanction the first payout. The model uses MASK R-CNN algorithm with Faster R-CNN to detect and localise the damaged areas. The system is also integrated with a security module that would detect and store the car license plate, body type and logo details for verification.*

Key Words: Deep Learning, MASK R-CNN, Faster R-CNN

1.INTRODUCTION

Today the increase of automobile industries is directly related to the increased traffic on the roads. Owning a car is not just a luxury anymore but a necessity in day-to-day life. With the increase in the number of cars on the road there is an increase in the number of daily accidents and hence, there is an increase in the number of insurance claims filed. Car damage may vary from a minor scratch to a huge body dent that needs to be identified and analysed to claim the insurance amount. Today deep learning and image processing holds application in various fields. Car damage analysis can be carried out through image processing and deep learning automating the insurance claim process.

Claiming car insurance is a tedious process and there is a delay in filing the initial insurance claim and sanctioning the first payout. With the growth of the automobile industry and the rate of car accidents increasing daily, insurance companies waste millions of dollars in the form of claim leakage.

Claim leakage is the difference between the amount that the company spent and the amount they should have actually spent. This could occur due to inefficient claim processing, improper payments, human error such as lack of quality inspection or improper customer service or even claim fraud. Claim leakage can only be discovered through audit of closed claim files. These issues can be tackled by automating the car damage analysis phase and fastening the insurance claim process with the help of deep learning techniques.

Capturing and uploading photos through mobile devices have become very convenient today. The knowledge of car damage assessment can be formulated in a computer vision problem where the user can upload images of the damaged car which can be analyzed with the help of image processing and deep learning techniques. This would eliminate the need for manual inspection of the damage eliminating delay and human error.

Our aim is to create a system that would detect damaged parts of a car through images and generate a cost analysis report which can be used by the company to sanction the insurance amount. The task would be to create an end-to-end system that would detect and classify type of damage through images and implement a car number plate, body type and logo detection system to verify car details.

2. LITERATURE REVIEW

2.1 MASK R-CNN

Mask RCNN is a deep neural network aimed to solve instance segmentation problem in machine learning or computer vision. In other words, it can separate different objects in an image or a video. You give it an image, it gives you the object bounding boxes, classes and masks.

There are two stages of Mask RCNN. First, it generates proposals about the regions where there might be an object based on the input image. Second, it predicts the class of the object, refines the bounding box and generates a mask in pixel level of the object based on the first stage proposal. Both stages are connected to the backbone structure [1].

2.2 Car Damage Assessment using CNN

The project involved developing and training a CNN model with 10 convolutional layers and 3 pooling layers with Relu as the activation function at each layer and the final layer being a Fully Connected Layer. The dataset used in training the model was obtained through web scraping. The model performed well on high quality images but gave inaccurate results on blurred images. The main disadvantage was the lack of widely available labelled dataset [2].

2.3 Automatic Car Damage Assessment through videos

Wei Zhang, Yuan Cheng, Xin Guo, Qingpei Guo, Jian Wang, Qing Wang, Chen Jiang, Meng Wang, Furong Xu, Wei Chu proposed a method to detect and analyze car damage through user input videos. The approach involved 2 modules Damage recognition and localisation and component recognition and localisation to segment the damage and components at pixel level to get accurate results. The model required high quality videos as input to generate accurate results [3].

2.4 Recognition of Car Manufacturers using Faster R-CNN and Perspective Transformation

Israfil Ansari, Yeunghak Lee, Yunju Jeong, Jaechang Shim proposed a method to detect car logos from CCTV footages. The approach involved performing perspective transformation on CCTV footages to get a clear view of the logos and then detecting and localizing the car logos through faster RCNN [4].

2.5 Vehicle Logo Detection and Classification using Discriminative Pixel-patches Sparse Coding

Yi Ouyang developed a system to detect and classify vehicle logos with the help of sparse coding. The method localised the car logos by detecting the number plate with the help of 3-channel pixel regression technique then performing multi-class structural linear SVM for logo classification [5].

2.6 Vehicle Type classification With Deep Learning

The paper researches various algorithms to classify the car body type from images as SUV, sedan, pick-up truck. Dataset used was the stanford dataset with 224 images and achieved an accuracy of 76 percent when arithmetic mean computation was on a hierarchical tree on ResNet 34 architecture [6].

3. PROPOSED SYSTEM

3.1 Car Verification Module

The Car Verification module implements a license plate detection system that detects and localises the license plate in the image by edge detection and with the help of EASYOCR extracts the license number; which will then be verified with the database. If the car details are registered the user would be navigated to the damage detection phase else, he/she would be prompted with a message to register their car.

3.2 Damage Detection Module

To find the damaged parts of the vehicle, we use a custom trained MaskRCNN model using transfer learning on the COCO dataset model. Our model covers 5 types of damages : Scratch, Bumper Dent, Door Dent, Glass Broken and Smash.

3.2.1 Object Detection:

Object localization is done to identify the location of damaged parts in an image and draw a bounding box around each detected object. For object detection, MaskRCNN uses FasterRCNN which combines object localization and classification for generating bounding box and class for each object. In FasterRCNN, an image is inputted to CNN to get a convolutional features map. Region Proposal Networks (RPN) are used on feature map to predict regions proposals to be used by RoI Pooling for predicting class and bounding box of object.

3.2.2 Instance Segmentation:

Along with bounding box generation and classification, Mask RCNN also predicts segmentation masks in pixel-to-pixel manner using Fully Convolutional Network (FCN) on each Region of Interest (RoI). Binary segmentation is performed in each bounding box to separate the object as foreground from background.

4. DESIGN

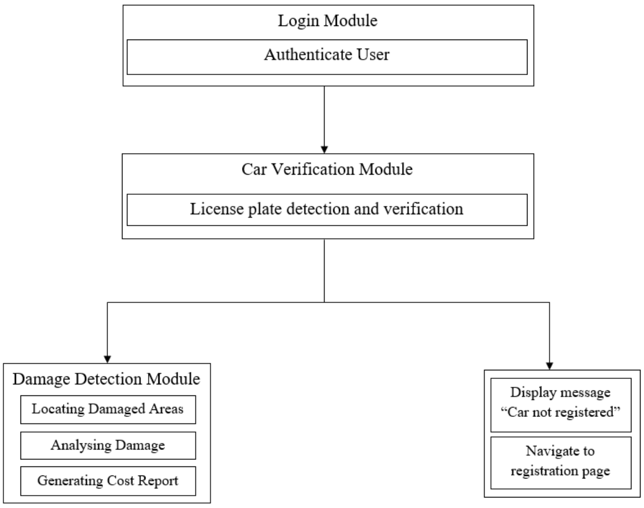

Fig. 1. Block diagram of proposed system.

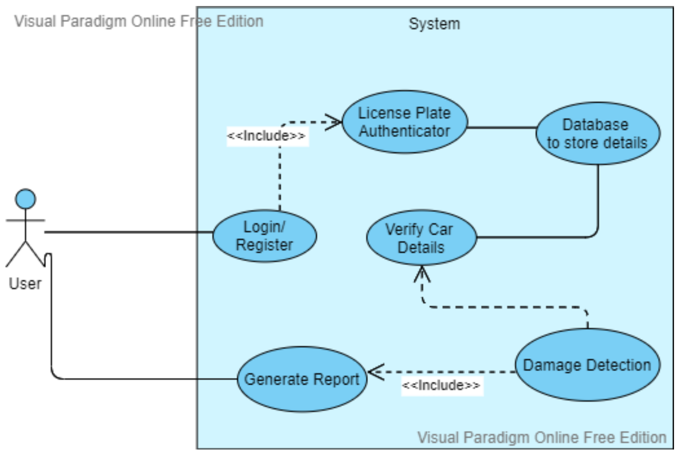

Fig. 2. Overall System UML Use Case

5. IMPLEMENTATION

The data-set required for training the Damage Detection Module was taken from kaggle which had 100 images in the training folder and 25 images in the test folder. The images were annotated manually to make it available for training; damages were classified into 7 different classes i.e., Door Dent, Bumper Dent, Body Scratch, Broken Windshield, Broken Glass, Broken Lights and Smash. The Mask RCNN model was configured to train on user data by changing its parameters and loading the pre-trained coco dataset weights. The model was trained for 10 epochs with 10 steps each epoch and the training weights were monitored on the basis of loss at the end of each epoch. The weights of each epoch were stored in the logs folder and the weights with minimum loss were used.

Fig. 3. License Plate Detector

Fig. 4. Damage Localization

Fig. 5. Damage Localization

Fig -6: Mask Generation and Damage Detection

6. RESULTS

The accuracy of the trained model solely depended on the training parameters and the availability of labelled dataset. The loss of the model after training for 10 epochs with step size of 100 was 0.064 on training dataset and 4.32 on validation dataset. The model metrics can be improved by training over a larger dataset for more epochs.

7. CONCLUSIONS

Our system proposes an approach to the problem of detecting and classifying damaged parts of car images and ultimately developing an end-to-end system that generates a cost report for the damaged car. Detection is achieved using Image Processing and Deep Learning and Transfer Learning techniques.

As future scope, the accuracy of our system in recognizing the number plate and damaged parts can be improved.

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