Car Damage Detection and Cost Evaluation Using MASK R-CNN

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Car damage detection and Cost Evaluation using MASK R-CNN

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Abstract. Detecting the damage on a car is an image-based processing method with enormous scope for automation. This concept of automated detection of the extent of exterior damage on a car and subsequent quantification of the damage severity would benefit car insurers, car rentals and repair services. In this paper, we propose employing Convolution Neural Networks to build a Mask R-CNN model that can detect the area of damage on a car. The dataset used consists of images of damaged vehicles with a single class named scratch. The images are precisely annotated with the area of damage. The model is trained using the base weights of mrcnn coco dataset. The images are processed for 21 epochs. After processing, the final result is visualized using a color splash technique, wherein the area of damage is highlighted. This model would help in reducing the cost of processing insurance claims and lead to greater customer satisfaction. Car dealers can eliminate the manual process of damage assessment and the labor cost accompanied by it. Accuracy and transparency in pricing cars and their potential repairs will be made more prevalent. Fraudulent vehicle insurance claims can also be diminished. On implementing our model, we achieved an overall loss of 0.3888.

Keywords: Car Damage Detection, Mask R-CNN, Transfer Learning.

1 Introduction

With the increasing level of vehicle owners worldwide, there has been a steady growth in the number of accidents and insurance claims. On the other hand, there has not been a steady rise in the number of adjusters dealing with these cases. This will increase the processing time for the claims. Claims process time impacts customer retention, quality of the business services, and loss of loyal customers. It also takes a lot of time to differentiate fraudulent claims from genuine ones. Insurance companies require damage fixers for about 72.22% of minor instances. This calls for a higher cost in risk examination. The individual involved in an accident faces a long waiting time to inform the damages and their costs. They are often thrown at an outrageous fixed price, leading to dissatisfaction with the insurance company [1]. On the other hand, in-car rentals and repair services, used car evaluation is very random. The time taken to evaluate damages or subsequent repairs is massive and involves tedious labor. The potential cost of repair requires more transparency too. J. Kurebwa. et al. (2019) [2] suggested an intelligent damage assessment system to deal with the predicaments above. It can identify damage to all passenger cars. Damage range includes exterior parts, while environment range encompasses rain, snow, dark, bright light, etc. It aims to enhance vehicle owners' compensation circumstances and successfully restricts vehicle insurance companies' cost dissipation. Several detection and extraction models have been developed to improve deep learning techniques that consist of classification, segmentation, and extraction. J.D Dorathi. (2018) [3] proposed an algorithm that acquires road segments precisely by utilizing customized operators developed by exploiting road segments' properties.

Similarly, we suggest building a custom Mask R-CNN model that can detect the area of damage on a car. When an image is uploaded to the user interface, Mask RCNN will be applied with a damaged car image dataset, thereby determining the level of damage. To detect and classify damages according to the location of damage and its severity, the model will be trained using Transfer Learning. The system will recognize damage in all types of vehicles like cars, trucks, bikes, etc. It detects damage of all kinds and locations such as bumper dent, scratch, door dent, shattered glass, headlamp, tail lamp, scrapes, etc. Severity is tiered as minor, moderate, and severe. These details will be displayed to the user in an interactive form. This proposed system will be more specific to a single-vehicle than a vehicle type by considering attributes like the make, model, and manufacture year, thereby providing a more accurate cost of potential repair/recovery. Insurance companies can use the automated model for processing claims quickly. Car rentals and repair services can rule out manually assessing the damage. It decreases discrepancies and increases transparency on the cost of repairs.

The whole system consists of two parts: an automated system to detect the location of damage and cost estimation based on the severity of damage in collaboration with other attributes. In this paper, we choose to implement the damage detection module of our proposed system. We used a small dataset collected from the internet that consists of a single damage classification: scratches. We suggest using Mask R-CNN for its efficiency in segmentation and its excellent performance and accuracy in small target detection.

2 Related Works

Computer vision's prime mission is to detect objects and establish the object class in an image or video. The recognition of damages on a vehicle and the extraction of damaged parts' features entails deep learning techniques blended with computer vision and object recognition. Several systems have already been implemented with different styles with image datasets and robust computer hardware availability.

One such technique is the Scale Invariant Feature Transform (SIFT), an object detector and descriptor algorithm that distinguishes and describes the local features in images. W.A. Rukshala. et al. (2017) [4] proposed a system that predicts only minor damages on the vehicle's exterior. They suggested a scenario where a damaged image is uploaded, and the appropriate damage is identified by drawing out local features using SIFT (Scale Invariant Feature Extraction). A dictionary of codewords is created using Bag of Visual words algorithm. The extracted features are used to train the SVM, with a training set of data containing different vehicle types. CNNs are well known for being able to conduct fruitfully for functions, expressly object detection, recognition, and classification, with remarkable performance. J.D.Dorathi. (2020) [5] used a multiclass SVM classifier to effectively extract road regions from given satellite images by implementing a bio-inspired Improved Cuckoo Search algorithm. Jayawardena. et al. (2013) [6] proposed a method where 3D CAD models are utilized to recognize potential damage on a vehicle using a library of unimpaired 3D CAD models of vehicles as a basic premise of data. Kyu. et al. (2020) [7] applied deep learning algorithms VGG16 and VGG19 for car damage assessment on CNN models and executed transfer learning in pre-trained VGG models. D. Malathi. et al. (2017) [8] used a revised algorithm for hand-written character recognition using a Deep Belief Network trained with a simple RBM and three stacked RBM layers.

You Only Look Once (YOLO) is an object detection algorithm that extracts convolutional features by splitting the input image into prospective bounding boxes. It procures its name from its ability to envision class probabilities and encompass them within bounding boxes in a one-stage network framework. Dwivedi. et al. (2020) [9] used CNN models trained on an ImageNet dataset by implementing the YOLO object detector. YOLO being a state-of-the-art real-time object detector, can be modified to discover and train damage zones. Li. et al. (2018) [10] proposed using the same to initiate vigorous features to identify damage present in images efficiently. Local and global deep features are extracted using the VGG model.

Mask R-CNN presents instance segmentation and displays precise pixel numbers with bounding boxes and segmentation masks and the object's locality recognized in a discrete color. N. Dhieb. et al. (2019) [11] presented an innovative framework that can detect, locate and identify damage severity on vehicles using CNN, transfer learning, and Mask R-CNN techniques. The Inception-Resnet pre-trained model is used as a feature extractor to determine the severity level of impairment, localize and visualize them on the vehicle's image. Rahman. et al. (2020) [12] propounded a system alike with the type of damage being an additional attribute. It covered harm such as broken lights and glass, watch gouge, etc. K. Patil. et al. (2017) [13] considered damage type an essential attribute in their Mask RCNN model. They explored numerous approaches and established that implementing transfer learning from large CNNs trained on ImageNet proved to be a very efficient approach. Similarly, Zhang. et al. (2020) [14] proposed an improved Mask RCNN algorithm to segment vehicle damages by enhancing the model's network structure and modifying its internal structure. This produces a better detection speed and brings out great performance benefits.

3 Proposed Methods

3.1 Mask R-CNN

We propose to use Mask R-CNN to process the annotated dataset of damaged cars to detect the location of the damage on the car by generating a mask on the area. Mask RCNN is a deep neural network that solves instance segmentation problems in computer vision and machine learning that separates objects in an image or a video. Since this technique involves instance segmentation, each pixel of individual objects in the image is located instead of bounding boxes. It produces object bounding boxes, classes and masks in an image. Mask R-CNN extends Faster R-CNN by adding a parallel branch for speculating segmentation. It comprises of the following four components (Fig. 1)

Fig. 1. The architecture of Mask R-CNN

Backbone model: The Resnet 101 architecture is utilized to bring out characteristic traits from the images present in MASK R-CNN, close to ConvNet used in Faster RCNN. The ResNet 101 is a network that has been trained with the help of the dataset ImageNet. This pre-trained network can allocate almost a thousand items. These characteristic features are used as inputs for the next layer.

Region Proposal Network (RPN): The previous layer generates feature maps that pass through the Region Proposal Network. The purpose of this network is to identify if multiple objects are present within a region. It determines if the object exists in that particular region at that instant. The model predicts regions of feature maps that contain certain objects.

Region of Interest (ROI): The output of the RPN consists of regions of different shapes. To transform all the regions to the same shape, a pooling layer is applied. Bypassing the regions through an FCN layer, class label and bounding boxes are predicted.

Segmentation Mask: When ROIs are received based on IoU values, a mask branch is built on the present architecture. The segmentation mask is reverted to 28 X 28 for each region that contains an object and is also scaled up for inference.

4 Transfer Learning

Transfer learning is a concept used to solve problems of intimate nature with finer performance and speed. This technique is functional for small labeled datasets. A pre-trained model is used to extract features for the targeted task. Training the model is accelerated since it is not prepared from scratch, thereby saving processing time and memory space. Transfer learning diminishes the requirement for more data since a small dataset is adequate to create a module. In our proposed system, we will be using a relatively small dataset. Using a pre-trained model, we will be trained on an immense and diverse dataset called Microsoft COCO database to train our custom dataset. The weights of the pre-trained model are not modified during the process. The new model is trained on top of the shortened model's output after the final layer is removed. This will avoid overfitting and help our model learn more general features. It has been observed that Transfer learning executes the best amidst deep learning system used to train CNN [15].

5 Dataset Description

The dataset consists of 49 train images and 6 test images collected from the internet [Table 1]. The images' damage is annotated using VGG Image Annotator (VIA) and exported as json file (Fig. 2).

Table 1. Dataset Description.

Classes	Train Size	Test Size
Scratches	49	6

The damage has been marked under a single class called scratch. This will help to increase the accuracy of masking the area of damage while training the images. The json file consists of the x and y coordinates of the precise location of damage. The trained and test dataset are stored in two different folders while the json file and the annotations are present in the train folder itself. The custom dataset was trained using Mask R-CNN implementation code. A code for the finding the masks present in the image with backbone model, region proposal network, region of interest and segmentation mask was first implemented. Functions are imported to find the global minima where the loss is minimum. Training data are then parallelly processed.

Fig. 2. Sample images from a dataset with annotations of scratches using VIA.

To train our model, weights used for a pre-trained model specifically for Mask-RCNN trained on the MS Coco dataset were obtained. These weights were trained for 21 epochs to make the weights customized to our type of model. The initial data to be trained on analyzing the dataset shows the damage present on the car in the image. It also loads the mask generated from the manual annotations and accurately marks the x and y coordinates' damage. The damage is then accentuated using a color splash where the customized weights are loaded, and the mask is applied.

Fig. 3. Area of damage highlighted by the model for each image.

6 Result and Discussion

The customized weights have been originated by processing the images for 21 epochs. The overall loss obtained is 0.3888. With these weights, we test the model with the validation images. Taking a random image and customized weights, the output is

viewed. The output of the image consists of an object mask that precisely masks the damage.
Along with the mask, a class label at the top left corner and a bounding-box offset is displayed. The image takes two classes into consideration, “scratch” and “BG” for the background. Besides the class label, the accuracy of the object acquired by the model is exhibited. After each epoch, the overall loss decreased significantly.

Table 2. Experimental environment information table.

Attribute name	Attribute Value
TensorFlow Version	1.13.1
Keras Version	2.1.0
RAM	8.00GB
Processor	Intel(R) Core (TM) i5-7200U CPU @ 2.50GHz 2.7GHz
Graphics	Intel(R) HD Graphics 620
Operating System Version	64-bit Operating System, x64-based processor

Table 2 represents the system configurations used to set up the experimental environment. The model was implemented by using Google Colab as a project environment. Keras module version 2.1.0 and TensorFlow module version 1.13.1 were used.

Table 3. Experimental environment information table.

Parameter	Value
Learning_Rate	0.001
Learning _Momentum	0.9
Weight_Decay	0.0001
Detection_Min_Confidence	0.9
RPN_Train_Anchors_Per_Image	256
Train_ROIs_Per_Image	200
Steps_Per_Epoch	100
Num_Classes	2
Mask_Pool_Size	14
Pool_Size	7
Validation_Steps	50
Image_Resize_Mode	Square

Table 3 represents the different parameters set up in the environment to implement Mask R-CNN. Parameters include Mask Pool Size, Pool Size, GPU Count, Images per GPU, Learning Rate, etc.

Fig. 4. This image focuses on the result obtained in implementing the Mask R-CNN damage detection model. The model illustrates the area of damage by using a color splash technique.

Fig. 5. The Loss vs Epoch graph shows how increasing the number of epochs led to a significant decrease in loss. This in turn, increased the accuracy and efficiency of the model.

7 Conclusion and Future Work

In the work illustrated in this paper, we exemplify a method based on deep learning to detect scratches on vehicle bodies using Mask R-CNN and Transfer Learning. Our dataset was manually accumulated and annotated using VGG Image Annotator (VIA). Training the Mask R-CNN model involved using transfer learning based on a pre-trained model that was introduced on the Microsoft COCO dataset. We were successful in applying the Mask R-CNN framework to detect scratches on vehicles. Although a smaller dataset was utilized, we achieved a low loss of 0.3888 and a decent yet fast detection of damage. Besides, we do believe that a larger dataset with additional attributes such as different vehicle types, damages, severity, and locations of damage would lead to a more accurate detection that would suit contrasting scenarios. The model did find segmenting unapparent areas of damage difficult.

In future work, the dataset can be expanded to suit all types of vehicles like cars, trucks, bikes, etc. Different classes of damages and locations such as bumper dent, scratch, door dent, shattered glass, headlamp, tail lamp, scrapes, etc., can also be added. The severity of damage such as minor, moderate, and severe can be incorporated. We aspire to contrive a user interface that would allow the user to upload a stipulated image of a damaged car and acquire details regarding the damage along with the supposed cost of damage. This proposed system will be particular towards a single vehicle by taking attributes like the make, model and year of manufacture, thereby providing a more accurate cost of potential repair/recovery.

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