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RESEARCH PAPER

Deep Learning Based Car Damage Classification and Cost Estimation

Namam A. Mohammed, Moayad Y. Potrus, Abbas M. Ali

Department of software and informatics Engineering, College of Engineering Salahaddin University-Erbil, Kurdistan Region, Iraq

A B S T R A C T:
Due to the increasing number of people driving cars, the number of insurance claims has also increased. This process involves the manual assessment of the vehicle by an insurance company's service engineer, as well as the physical inspection by a licensed insurance company representative. An end-to-end solution has been proposed that would allow the customer and the insurance company to automate the process of recognizing the damaged area in the vehicles and estimating the cost of the damage. It would allow them to get a better understanding of the condition of the vehicle. For this purpose, A deep learning, Mask Region-based Convolutional Neural Network (Mask RCNN) model was utilized in this work to classify vehicle damages costs. Two Mask RCNN models were utilized, the first one was used to detect the sides of the vehicle, which will affect damage cost estimation and the second was used to find the area of the damage. The Experimental work shows that the proposed model gives reasonable results to estimate the cost of the damage. We achieve an accuracy of 98.5% with the combination of the two Mask RCNN models. And showed that Mask RCNN has a promising result to detect the area of the damage in the car.

KEY WORDS: Car Damage Detection, Mask RCNN, Deep Learning, Machine Learning, Cost of the Damage
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1. INTRODUCTION:

insurance has grown into a thriving business that is still reliant on human repair claim submissions. It requires a survey inspector to examine each car that has been reported as damaged and make an estimate of the damages as well as the claim amount that must be paid (Jason Yosinski et al., 2014).

Vehicle The internet insurance market is beginning to take shape. With its large premium scale and standardized products, automobile insurance has become an essential direction for insurance companies to gain clients. (statista.com.,2022).

Today, a lot of money is wasted in the car insurance industry due to claims leakage. This occurs when the amount of money that should have been paid for a claim is not received.

* **Corresponding Author:**
Namam A. Mohammed
E-mail: atot.namam@gmail.com
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Although various methods have been used to reduce the effects of claims leakage, they still introduce delays in the processing of the claims. An automated system is therefore needed to handle the entire claims process (B. Y. Lecun et al.,1998)(Krizhevsky A., et al., 2012). In this paper, we introduce a method that uses two mask RCNN to classify car damage types. It can perform this task by identifying common damage types such as crashes, dents, and scratches of bumpers, fenders, hoods, and trunks in addition to the broken head and taillight.

We created our dataset from the Copart website (https://www.copart.com), this website is an advertisement for displaying car images for selling, including damaged areas in the car, and since a huge of images displayed with their damages, we exploit these images to create a such dataset by manually annotating these images from the web. The task of classification is very challenging due to the existence of many inter-class similarities and the relatively small damage in the images. We experimented with various techniques such as training a Mask RCNN using the sides of the vehicles to recognize the front, back, left, and right of the car; this, in turn, will help more in fixing the cost, for example, the front of the vehicles is more costly than the back since the headlight and the engine is in the front of the vehicle.

2. Related Work

Several models have been created for detecting car damage. Due to its promising results, Deep Learning has been widely used in object detection. One of the most popular algorithms is CNN, which is a Convolutional Neural Network. This allows computers to perform various tasks such as visual object recognition and detection. Due to the immense amount of data that Deep Learning has been able to collect, its image classification capabilities are exceptional. However, training models using CNN is very complex to train models, they need computer resources and supervised methods. Autoencoders, on the other hand, can improve the performance of the model when training small samples. Convolutional Autoencoders (CAE) are also effective for images. One of the most common techniques used for training models is Transfer Learning. This method can be used to improve the performance of small models. Several CNN models are currently available on ImageNet. These models can be used for various applications such as image recognition and detection, these models as Alexnet, VGG-19, Resnet, and Inception.

Deep learning has been widely employed in different machine learning applications, such as computer vision tasks. (M. G. Soumalya Sarkar,2016) (D. Erhan et al., 2010).

Srimal Jayawardena (Srimal Jayawardena., 2013) proposed a complete car damage detection system based on photographs, even though they employed 3D CAD models and standard image processing technologies. Traditional approaches are readily superseded by the recent introduction of AI-based deep learning techniques.

Most current research employs Convolutional Neural Network (CNN)-based algorithms to classify a restricted number of automotive damage categories. (Kalpesh Patil et al., 2017); published a study in which they found that. To obtain damage categorization from photos of autos, the authors employed simple transfer learning and CNN assembly. In a separate technique, (Pei Li et al., 2018) employed the object identification model YOLO (Joseph Redmon et al., 2016) and discovered restricted damage classes on a car picture by fusing multiple backbones for the model.

In (Soumalya Sarkar et al., 2016), CNNs were used to examine structural damage. The researchers proposed a system called Structural Health Monitoring (SHM), in which damage is defined by the fractures that appear in a composite material. (Arun Mohan et al., 2018) address the topic of crack identification in-depth, but solely using image processing approaches, whereas the authors (Young-Jin Cha et al., 2017) utilize CNNs to detect crack-related damage. None of the prior initiatives have provided a complete end-to-end pipeline for automating the insurance claim process, (Ranjodh Singh et al., 2019). A method for detecting and recognizing minor automobile body damage in a completely automated manner (Sergei Gontscharova et al., 2014) sensor data, and PRNN classifier, have been used for this purpose, A greater percentage is associated with a bigger collection of training data.

A deep learning-based architecture for automatic and efficient automobile damage identification and localization is provided (Najmeddine Dhieb et al., 2020). The proposed method combines deep learning, instance segmentation, and transfer learning techniques for feature extraction and damage identification. Its purpose is to detect car damage automatically, find it, categorize it, and depict it by contouring the exact area of the damage, they obtained good results up to 96%. Investigate the use of Convolutional Neural Networks (CNNs) for detecting the level of damage using damaged automotive pictures.

In (C. T. Artan et al., 2020) employed transfer learning for examining the advantages of existing models of object recognition models for detecting and classifying damage based on the damage area and severity. With its basic yet successful design, Visual Geometry Group (VGG) (K. Simonyan et al., 2014), the 2014 runner-up, recognized the relevance of CNN's depth for its performance and became an influence for many following architects. (Huang et al., 2017) provide a precise and clear survey of new convolutional detection systems, characterizing how they going to lead ones to follow similar styles by defining flexible and unified deployments of the three meta-architectures (Faster RCNN, Region-based Fully Convolutional Network (R-FCN), and Single Shot Detector(SSD)) in TensorFlow, which they use to run experimental analysis that traces the accuracy/speed tradeoff curve for various detection systems, varying meta-architecture, feature extractor, image resolution, and so on. Their findings reveal that utilizing fewer suggestions for Faster R-CNN may greatly speed it up without sacrificing accuracy, putting it on par with its faster relatives, SSD and R-FCN, while SSD performance is less susceptible to feature extractor quality than Faster R-CNN and R-FCN. In a sequence of held-out tests, ((Malik et al., 2020) used a pre-trained CNN with a state-of-the-art YOLO (You Only Look Once) object detector to acquire a high accuracy score.

For automotive image modeling, several specialized research issues are investigated. one of them recognizing the automobile item in the backdrop photographs. In the last several years, many deep neural networks were suggested to identify a variety of things, and the field was rapidly developing. Objects that are generic R-CNN (He, K et al., 2016), Fast RCNN (Girshicket al., 2017). Redmon's colleagues framed object detection as a regression issue to separate bounding boxes using another popular technique, YOLO (Redmon et al., 2018).

Images of damaged automobiles were obtained from public sources, such as Google Images, using the COCO dataset and ImageNet. (Li & Li et al., 2021; Hashmat Shadab Malik et al., 2020)), these images were taken for general purposes showing damaged areas without classes of the damage.

This paper is divided into seven sections. The first two sections were an introduction and related work, and the next section, section 3 focuses on the Dataset description. While Section 4 presents the proposed algorithm to detect the damaged area and estimate the cost, while Section 5 explores the results of the study. Sections 6, and 7 present future work and the conclusion.

3. DATASET DESCRIPTION

We generated our dataset comprising of photos representing various types of automotive damage because there is no dataset for car damage classification containing damage classes separately like crashes, dents, and scratches of bumpers, fenders, hoods, and trunks, headlight, and taillight was broken are typically noticed types of damage. In addition to these types of damages, we gathered images are not containing any damage to prove and check the proposed classification process. The dataset's description is shown in Table I.

TABLE I: Description of our dataset.

Classes	Train Size	Test Size
Crash Bumper	186	49
Dent Bumper	155	39
Scratch Bumper	215	54
Crash Door	197	49
Dent Door	79	21
Scratch Door	186	46
Crash Fender	182	45
Dent Fender	123	42
Scratch Fender	96	34
Crash Hood	78	30
Dent Hood	89	43
Scratch Hood	90	43
Crash trunk	60	42
Dent trunk	56	23
Scratch trunk	43	21
Crash front	99	41
Dent front	98	34
Broken tail light	90	33
Broken headlight	85	32

images in the same class considered in the training process, for example in the table dent door is 79 which means that we considered 79 images in dent door class of damage. While the caption Test size means how many images are used for testing in the same class for example dent door class, we used only 21 images. In our work, we used 19 classes of damages. And these classes are unbalanced in the number of images, however, the balance and unbalance will not affect the classification if the mask RCNN is trained well.

It is well known that supplementing the dataset with affine altered images increases the classifier's generalization performance. As a result, we artificially increased the dataset. The Images append it with random rotations (between -20 and 20 degrees) and horizontal flip transformations about five times. Our work dataset was randomly divided into 80 percent and 20 percent for the classification studies, with 80 percent used for training and 20 percent utilized for testing; however, we can select a division for training or testing, since we were using the Python program the situation it is very easy.

4. The proposed Car-damage-detection Algorithm

This section clarifies the proposed system for estimating the cost of car damage. Figure 1 depicts the model of Mask RCNN, which is used for the automotive damage detection and classification system proposed in this paper.The image for the car's damaged region is chosen and gathered according to demand, and the data is annotated using the website https://www.robots.ox.ac.uk/~vgg/software/via/via.html labeling tool to create a format of a dataset in the JSON style, this dataset is subdivided into two sets these are training and testing set, as shown in Figure 1, The data is transmitted to two Mask RCNNs, one for side detection and the second to feature extraction, classification prediction, and segmentation masking, then the result of the two networks are analyzed to estimate the cost of the damage.

It is known that the cost of the front of the car is more than the back since the front contains the engine of the car in addition to some accessories that are costly such as a Headlight, bumper, hood, … etc. In this work, the total cost estimation can be expressed by eq.1

$$tc = fc + bc + lc + rc \qquad \text{...........(1)}$$

Where tc is the total, fc is the front side cost, bc is the back side cost, lc is the left side cost and rc is the right-side cost. The system can be implemented in one side estimation cost the cost weight will depend on the side detection of the mask RCNN1 this can be expressed by eq.2 and

$$\mathrm{e}\partial = detect(I)_{mask\ rcnn1} \qquad \text{......(2)}$$

$$c_e = f_\partial * detect(I)_{mask\ rcnn2} \qquad \text{........(3)}$$

Where ∂ is the side detection from the mask rcnn1 and f∂ is the factor which will be used for the sides and ce is cost estimation, this factor will be high for the front while for the side will be less than the back of the car.

4.1 Mask RCNN Algorithm

Mask RCNN is an enhanced model of Faster RCNN for feature extraction framework. It is containing two stages:

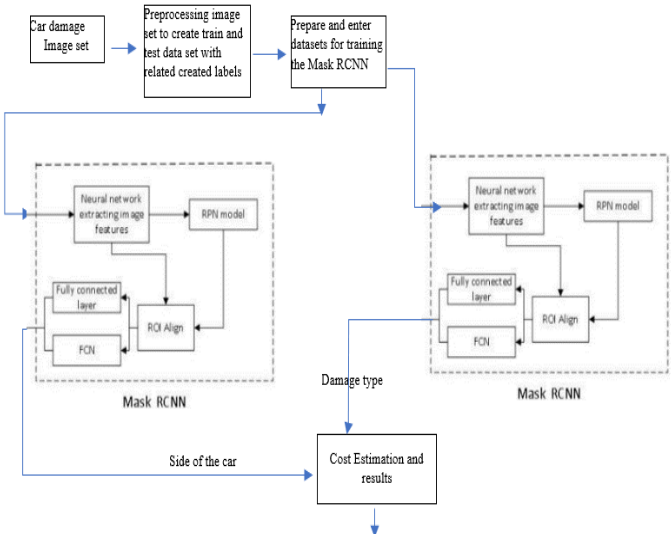

Figure 1: Detection of Car-damage and cost system framework

The first analyzes the image and creates the proposal, and the second assigns a classification to the proposal and generates a bounding box with the mask The block diagram of the network structure in Figure 2 depicts the Mask RCNN algorithm. The model flow is containing the following:

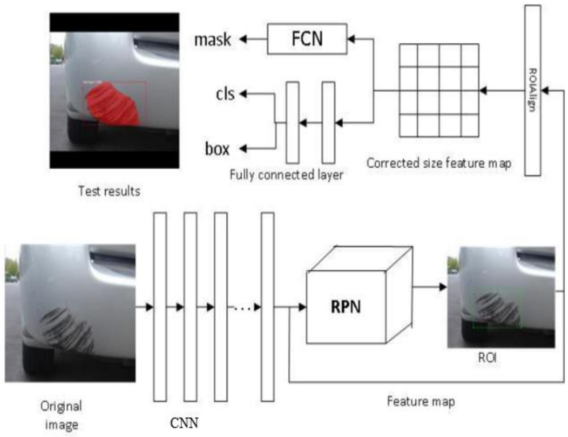

Figure 2: The framework model of Mask RCNN (Kalpesh Patil, Mandar Kulkarni,2017)

1. Enter the image of car damage to be handled into the network model that has been used to extract features and generate feature maps.

2. This feature map uses Region Proposal Network (RPN) to generate many candidate frames (the Region of Interest (ROI)), then the SoftMax classifier to perform binary foreground and background classification, as well as frame regression to obtain a more exact candidate frames of information location and non-maximum suppression to eliminate some of the unwanted ROI parts.

3. The feature map, is fed to the Align layer of RoI, with the last remaining ROI, which produces a fixed-size feature map for each ROI.

4. After that, the flow separates into two parts, the first one of which goes to the object classification represented by a fully connected layer and frame regression, and the second part is fed to the Full_Convolution_Network (FCN) for pixel segmentation.

4.2 Constructing the Dataset

This paper's principal research item is to build a dataset for images of damaged cars from web downloads specially from the Copart website (https://www.copart.com), this website is an advertisement website for selling cars showing all parts including damaged parts related to the displayed car, to check online the user if the car is suitable or not.

In addition, we use the Kaggle (COCO) dataset images for checking the proposed method for detecting the damages and estimating the cost. the experimental work gathered more than 2,000 cases of damaged car images divided into training sets and test sets.

The next two sections are the most important phases in obtaining a specialized dataset for identifying car scrapes in complicated situations. The following samples of car damage datasets have been used in the research work, shown in Figures 3 and 4.

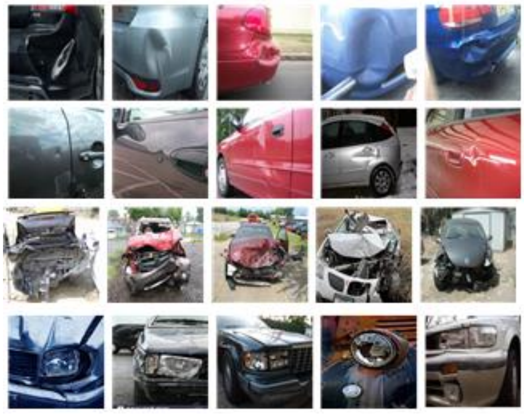

Figure 3: COCO dataset containing some dent

Figure 4: Sample images for car damage types. from Copart website indicates damage types of Bumper dent, Door dent, Headlamp broke, Tail-lamp broke, Scratch, Smash, and No damage

The collected images are labeled and separated into two sets, (training and testing) sets using the labeling program VGG Image Annotator (VIA). The following are the stages involved in this procedure. The folder "datasets" is built first, followed by separating it into two subfolders processing, "Train" and "Val," for keeping training and test samples, respectively. Each one contains photos that correlate to a JSON label information file of the same name. Figure 5 depicts the labeling damage position interface.

Figure 5. VIA labeled car-damage image

5. Experimental results and estimated cost of the damages

The proposed method has been checked to examine the enhancement of the proposed algorithm's detection performance on the data set related to car damage. The settings of the proposed algorithm have been done using some parameters clarified in Table 2, and Table 3. The detailed experimental work is done in the following steps,

TABLE 2: Experimental System setting

Attribute Name	Value
TensorFlow	1.13.0
Keras	2.2.5
RAM	16GB
Processor	Intel Core(TM) i7-11800H@ 2.30GHz 2.30 GHz
Graphics	Geforce RTX 3070
OS	Windows10

TABLE 3: Experimental Model setting

Attribute Name	Value
LEARNING_RATE LEARNING_MOMENTUM	10^{-3} 0.9
WEIGHT_DECAY	0.0001
DETECTION_MIN_CONFIDENE	0.8
STEPS_PER_EPOCH	100
NUM_CLASSES	19
MASK_POOL_SIZE	14
POOL_SIZE	7
VALIDATION_STEPS	50

5.1. Car damage detection experiment

The experiment is conducted to verify the accuracy of the proposed method to find the damage positions, two datasets have been used the first was COCO dataset in this case some images after labeled by the VIA website, Figure 6 shows some car damage detections and localization.

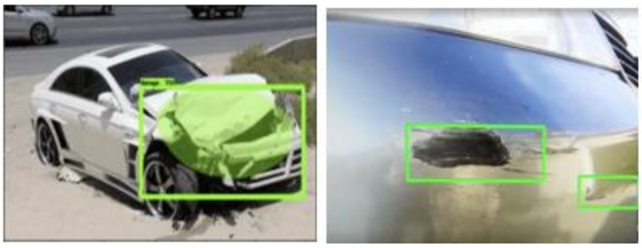

Figure 6. Mask RCCN car damage detection (COCO dataset)

New experimental work is conducted using the Copart dataset implementing the same model of mask RCNN the results are shown in Figure 7.

Figure 7. Mask RCCN car damage detection (Copart dataset)

detection accuracy performance for the proposed model based on the experimental work is more than 0.97 with confidence for the masks reach to 0.99 this indicated that can be used in more tests for calculation of damaged area and costs evaluation.

5.2. Cost estimation of the damaged area

Experimental work was conducted to estimate the cost of the damaged area, the dataset contains images taken from the Copart website of these cars' which already approved insurance claims. We have tried to create the dataset to include all the classes and parts used by an insurance inspector. We did not include the interior of a car as our focus is on identifying external damages. Each image was then annotated with details to help us understand more about it.

Annotating a car using a rectangle selection tool was performed to study its various details, such as its make, sides view, front, and rear. In our current dataset, the Polygon tool has been used to show the Parts Details of the car, which are visible in the image, along with the information if it has been damaged or not. The tool was then used to create an outline of the various damage classes that were listed in Table 1. One of the sample annotations is shown in Figure 3, which shows a major dent on the side of the car's hood.
Several of the car's parts have been annotated by insurance companies, which are then used in the tool to show the details of the car. Due to the class imbalance in the dataset, we excluded certain parts that have lesser annotations. These excluded parts were then merged to form a single part. The cost estimation of the parts was done according to Figure .8. a flowchart of the process. We can even localize and find the area of the damage using the proposed method, the crash or broken classes of the damage will be the cost of the part. While the dent class of any part is estimated based on the area of the polygon. This area will be in pixels and is calculated directly by the Mask RCNN, in our practical work we divided these pixels by a number to convert it to the real area in experimental work divided by 100. The localization area performance for the type of damage such as front crash is shown in Figure 9.

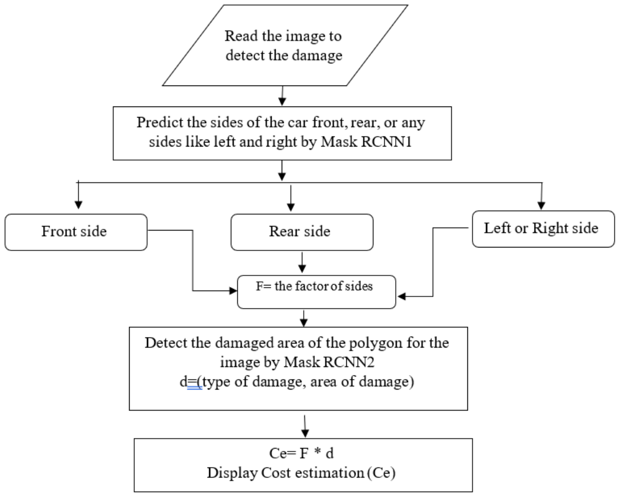

Figure 8. Flowchart of the cost estimation process

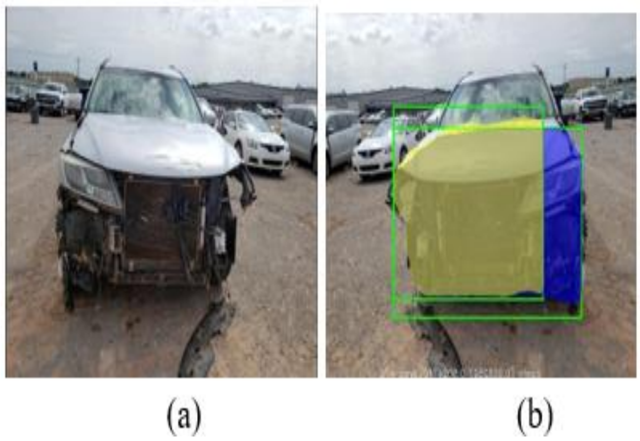

Figure 9. Damage localization. (a)Original front crash image, (b) The result of Mask RCNN (green box). Note that our proposed approach is capable to find the size and localize the area of the damage correctly.

6. FUTURE WORK.

For our future work, we want to improve the model to perform better results and could offer better performance accuracy by adding some hardware accessories like detecting some parts not original exchanged with the originals ones, and using more datasets for car damage to check the proposed method with more cases and try to check other models of deep learning like Yolo with Mask RCNN to make some comparisons between the two approaches in classifications and accuracy of detecting the damaged area and the type of the damages.

7. CONCLUSION.

In this work, we developed an approach depending on a deep learning model for car damage categorization and cost estimation in this research work.

We built a new dataset from the Copart website by collecting images from the web and manually labeling them because there was no publicly available dataset.

We tried some deep learning strategies, like training mask RCNN from random images, based on two purposes the first one is to detect the sides of the car and the second is to classify the damages more accurately. It's also worth noting that this led to estimating the damage cost evaluation more accurately. As a result, the advantage of feature extraction and representation learned from a large training set is highlighted.

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