Exterior Vehicular Damage Detection using Deep Learning

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Abstract

Automated photos can be very useful in auto accident detection, as it can greatly reduce the cost of processing insurance claims. An ideal scenario is where the auto user can upload a few photos of the damaged car taken from a mobile phone and perform the damage assessment and insurance claim automated actions. However, due to such a solution there is a challenging task with various factors. In addition, since the vehicles are highly reflective metal bodies it can be expected that there should be a considerable amount of material reflection between the photographs taken in such a controlled environment. Therefore, it is a very challenging task for standard computer vision techniques in this context. Detect the node of the damaged image that was previously plotted in a three-dimensional gate model which can be considered as damage to the vehicle. Since the body is very reflective, there is a huge amount of reflection between the images can be wrongly classified as damage objects. In order to detect the edges of the image due to the reflection of the intermediate object, in this paper, proposed convolutional neural network (CNN) is used to recognize that a given image is a damaged car or not. This approach represents great opportunities and also a promising attempt in classifying car damages into a few different classes is presented. Along the way, the main focus was on the influence of certain hyper-parameters and on seeking theoretically found ways to adapt them, all with the objective of progressing to satisfactory results as better as possible. Their search public and image recognition programs will open doors of collaboration in the future especially in the car insurance industry.

Keywords:- Vehicle, Car damage, Deep learning, CNN

I. INTRODUCTION

Today, in the car insurance industry, a lot of money is wasted due to claims leakage. Claims leakage or underwriting leakage is defined as the difference between the actual claim payment made and the amount that should have been paid if by applying all industry leading practices. To reduce those effects visual inspection and validation have been used but they introduce delays in the claim processing. There has been an effort put forward by too few start-ups to mitigate claim processing time. Nowadays an automated system for car insurance claim processing is very much needed. In this paper, Regional Convolutional Neural Network (RCNN) based method is employed for classification of car damage types. Specifically, common damage types such as bumper dent, door dent, glass shatter, head lamp broken, tail lamp broken, and scratch and smash are considered. We created our own dataset by collecting images from web and manually annotating them [1].

The classification task is challenging due to factors such as large inter-class similarity, barely visible damages. The system proposed in [2] is experimented with many techniques such as directly training a CNN, pre-training a CNN using auto-encoder followed by fine-tuning, using transfer learning from large CNNs trained on Image net and building an ensemble classifier on top of the set of pre-trained classifiers. It is observed that transfer learning combined with ensemble learning works the best. A method is identified to localize a particular damage type.

II. Motivation

Object detection is one of the main research contents of computer vision. It is to determine the category and location information of the object of interest in the image on the instance level. Currently the most popular target detection algorithms include RCNN, Faster RCNN and SSD. However, these frameworks require a large amount of training data, which cannot achieve end-to-end detection. A residual network (ResNet) is proposed in [2] which help the model to converge by using the residual module, accelerates the training of the neural network, and combines with the target detection model Mask RCNN to realize object detection and segmentation, greatly improving the accuracy of the model detection. Boundary segmentation is proposed the first end-to-end instance segmentation framework, full convolutional instance segmentation (FCIS).

The Mask RCNN framework is an algorithm with relatively fine instance segmentation results among existing segmentation algorithms. The proposed a building target detection algorithm based on Mask RCNN. The application field of Mask RCNN algorithm is very wide, but no one has used it in the field of automobile damage detection [3]. Mask RCNN combines both target and Segmentation based on Candidate Regions Algorithms are achieved. Bounding box and instance segmentation is predicted by FCIS. Small target detection is achieved by the Mask RCNN.

III. System Design

The entire system must follow the workflow as mentioned in Fig. 1. The processes involved in the entire system are: 1) Load image, 2) Preprocessing, 3) Segmentation car image, 4) Car separation layer, 5) Edge evaluation, 6) Evaluate the image metrics.

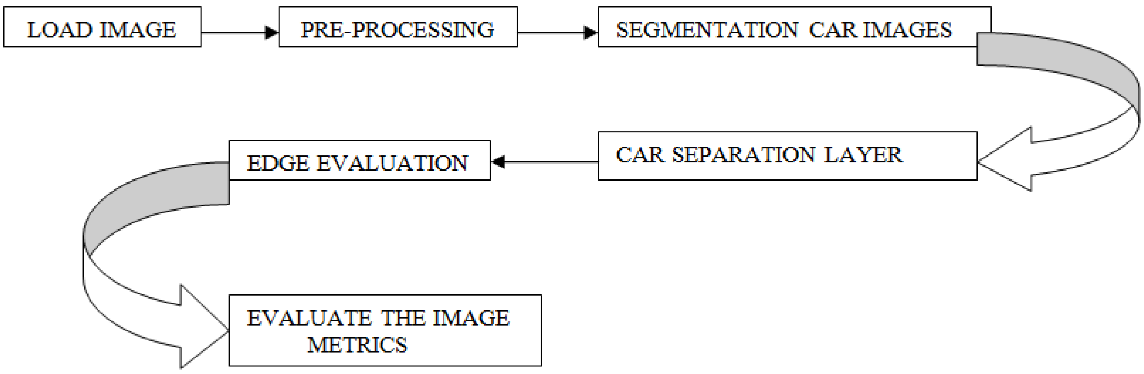

Fig. 1. Flow Diagram for Entire System Process

3.1. Load Images

Grouping an image into a predefined category is known as image classification. To achieve this, multiple images are needed with the class of interest and train the computer system to convert image pixels to symbols.

3.2. Pre-processing

In order to achieve better results, the method of preparing images with computer vision models is termed as pre-processing. It is heavily depends on the feature extraction method and the input image type.

3.3. Segmentation of car images

In order to detect a car on the image, we need to identify feature which uniquely represent a car. We could try using simple template matching or relaying on colour features but these methods are not robust enough when it comes to changing perspectives and shapes of the object.

3.4. Car separation layer

Each part of the image is analysed and passed to the classifier who draws bounding boxes around the cars. Every layer is detected by the CNN and separated through the separation hidden layer followed by the segmentation addition.

3.5. Edge Evaluation

Edge Evaluation will processed by the hidden layers of application layer. In a presentation layer responsibility of edge evaluation goes an unlimited. In an every real time application it checks every time for its versatility.

3.6. Deep Learning architecture

Deep learning algorithm has a set of permissions that permits an every input that must passes test case of hidden layers. If it fails to meet a test case then input will not enter into an activation layer that is hidden layer. It passes the set of limitations and unsophisticated algorithms.

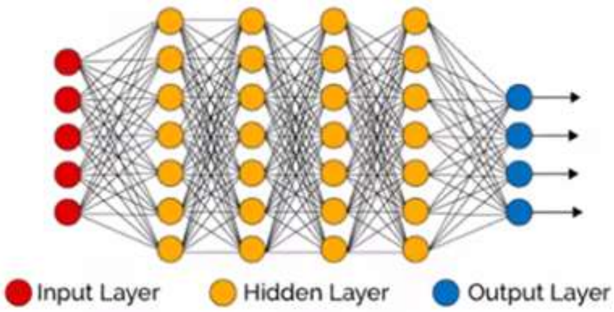

Fig. 2. Deep Learning Neural Network

IV. System Observation

The CNN approach is based on the idea that the model function properly based on a local understanding of the image. While a fully connected network generates weights from each pixel on the image, a convolutional neural network generates just enough weights to scan a small area of the image at any given time. Promising results have been seen using deep learning architectures. In terms of the deep feature extraction, we utilized InceptionV3 model trained on ImageNet image classification dataset due to its computational efficiency and success in vehicle re-identification problem.

The image of analysis during 200 iterations is given in Fig. 3, and the scratch detecton for the given input damaged car is given in Fig. 4. The error metrics values for input images are shown in Table. 1.

4.1. PSNR

PSNR stands for Peak Signal to Noise Ratio. PSNR computes the peak signal noise ratio of an image.it is used to calculate the noise ratio between original and compressed images.

MAXI is the maximum possible pixel value of the image then the PSNR is computed as given [7]:

$$PSNR = 20log_{10}\frac{MAX_I}{\sqrt{MSE}}$$

4.2. MSE

MSE stands for Mean Square Error. If a vector of n predictions is generated from sample of n data points on all variables and Y is the vector of observed values of the variable being predicted with Y^1 being the predicted values, then MSE is computed as given [8]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_i^1)^2$$

4.3. RMSE

RMSE stands for Root Mean Square Error. It's used to compare the actual value and the expected value of an application. RMSE is computed as given:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_i^1)^2}$$

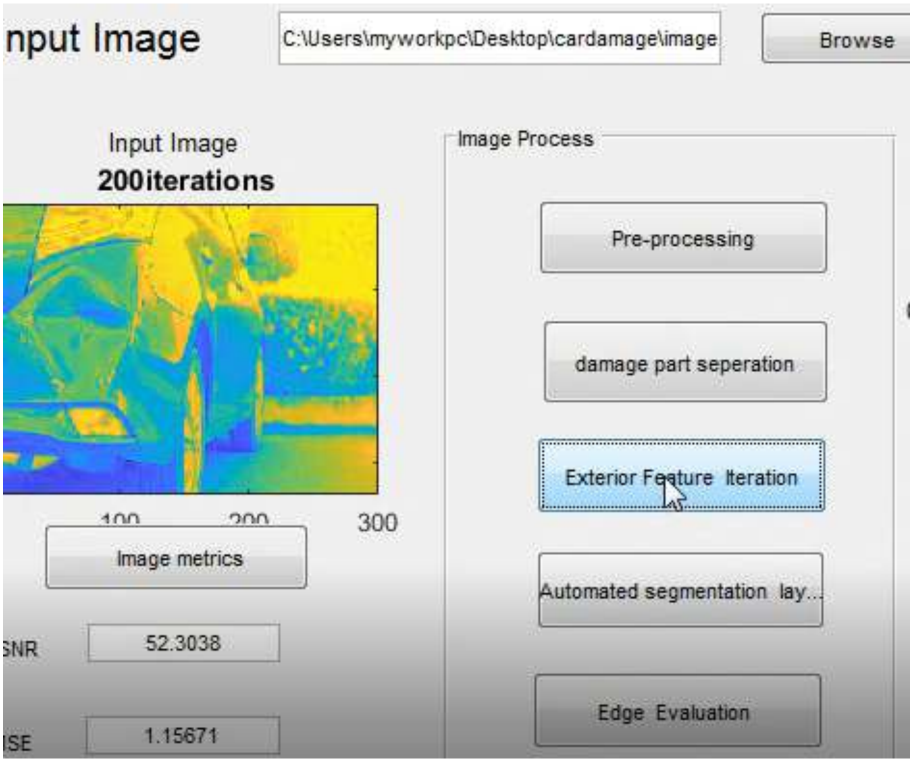

Fig. 3. Extracted Car Image after 200 iterations

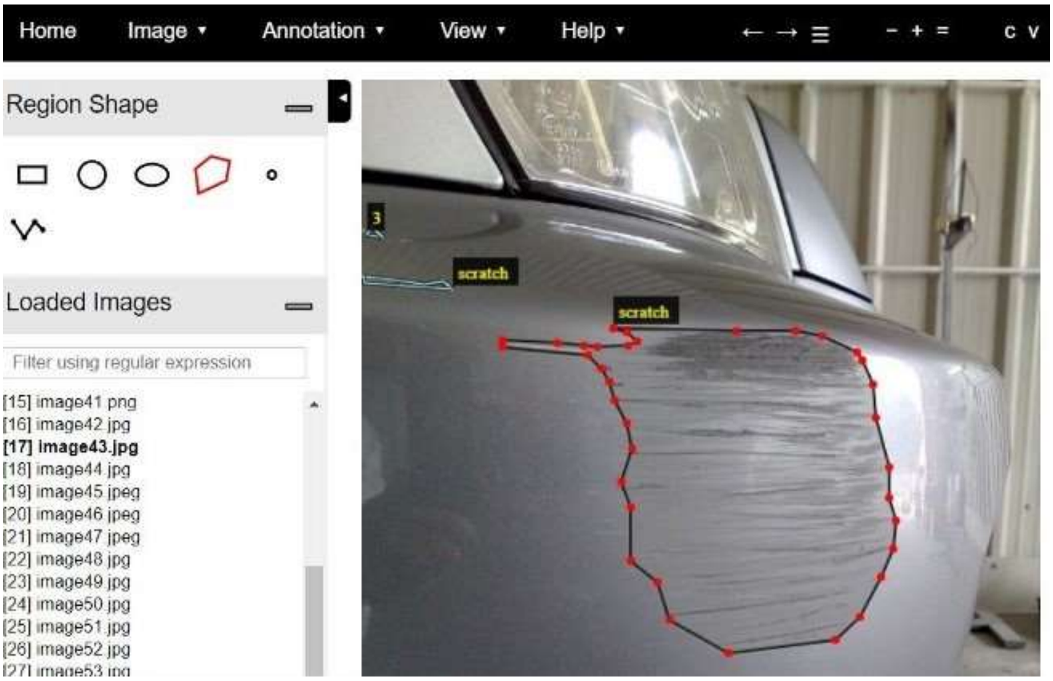

Fig. 4. Scratch detection

Table. 1. Error metrics for car damage images

S.No.	Car image name	PSNR (in dB)	MSE	RMSE
1	001.jpg	52.3038	1.15671	1.07551
2	002.jpg	35.4048	1.06451	1.00432
3	003.jpg	63.7551	1.13401	1.13824
4	004.jpg	44.3036	1.14281	1.14324
5	005.jpg	71.4324	1.17452	1.03456
6	006.jpg	28.4567	1.00543	1.00043
7	007.jpg	39.4048	1.15652	1.00431
8	008.jpg	56.4854	1.13456	1.17648
9	009.jpg	65.4551	1.12341	1.14352
10	010.jpg	34.5664	1.02541	1.00546
11	011.jpg	80.4552	1.18761	1.14567
12	012.jpg	59.7686	1.14537	1.17831
13	013.jpg	78.4556	1.23461	1.16541
14	014.jpg	54.7889	1.14561	1.14572
15	015.jpg	34.6575	1.14561	1.16754
16	016.jpg	69.7585	1.14567	1.15678
17	017.jpg	45.6474	1.18914	1.05578
18	018.jpg	56.4048	1.13561	1.13456
19	019.jpg	88.5056	1.16781	1.18951
20	020.jpg	23.7078	1.02341	1.07861

IV. CONCLUSION

In the work described in this paper, a detection algorithm based on deep learning for vehicle-damage detection is used to deal with the compensation problem in traffic accidents. After testing and improvement, the proposed CNN–based vehicle damage-detection method is more universal, and can better adapt to various aspects of car-damage images. The algorithm achieved good detection results in different scenarios. Regardless of the strength of the light, the damaged area of multiple cars or a scene with an overly high exposure, the fitting effect is better. CNN algorithm is adopted in this paper and some aspects have yet to be studied. For example, the detection accuracy is very high, but the mask instance segmentation cannot be completely correct, and some areas in which the damage is not obvious cannot be segmented.

References

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