TEST Engineering & Management

May – June 2020
ISSN: 0193-4120 Page No. 9793 – 9799

Categorizing Exterior Damage in Car Using Deep Learning Techniques

Ms.C. Pabitha[1], Dr.B.Vanathi[2]

[1] *Assistant Professor, Department of Computer Science and Engineering, SRM Valliammai Engineering College, Tamil Nadu, India*
[2] *Professor, Department of Computer Science and Engineering, SRM Valliammai Engineering College, Tamil Nadu, India*

Article Info
Volume 83
Page Number: 9793 – 9799
Publication Issue:
May - June 2020

Article History
Article Received*: 19 November 2019*
Revised*: 27 January 2020*
Accepted*: 24 February 2020*
Publication*: 18 May 2020*

Abstract:
Recently, the assembly of picture-based automobile insurance is a crucial part with considerable purview for automation reach. In this research work, we deal with the difficulty of classifying car damage, where a number of divisions in categorizing the level could also be fine-granular. To the present reason, we are exploring techniques based on deep learning. Initially we attempt to train a CNN directly with a set of coaching data. However, it isn't working well thanks to a little collection of labeled data. Hence, we investigate the domain-specific pre-training effect amid fine-tuning with an outsized number of annotated training-data. As Faster R-CNN and SVM haven't identified damaged cars with high accuracy, and therefore the Cascade R-CNN takes an immense amount of your time to coach and check the info that we are performing on to suit. Hence, we are training data into an R-CNN Mask that produces adequate results compared to traditional Neural Networks. Though there's tons of unknown like partial images, hence the classifier was built to detect amorphous damages. The model is layered over 3 classifications of detecting the car and examining whether the damage dealt is high or low. Finally, the classifier is projected with the flask environment to form the working experience easier, since it runs on a local host the compile time doesn't exceed 5 seconds regardless of the standard of the image. Experimental results indicate that Mask R-CNN works better than convolutional R-CNN as transfer learning is way more better when compared with area specific fine-tuning like Cascade and Faster R-CNN. We achieve 89.5 per cent accuracy with Mask R-CNN through transfer combination.
Keywords: *Damage detection, Classification, CNN, Mask-RCNN, Deep Learning, Transfer.*

1. INTRODUCTION

Nowadays, tons of cash is being wasted within the automobile insurance business thanks to leakage claims. Claims leakage also known as Underwriting leakage is characterized because the discrepancy in midst of the particular payment of claims made and therefore the sum that ought to be paid if all of the industry's popular practices are applied. Examining visually and testing won't obtain accurate results. However, they impose delays within the processing of claims. Efforts are made by a couple of start-ups to scale back the time interval of statements. While implementing this paper, we use Convolutional Neural Network (CNN) methods for classifying damage level inflicted in car and categorize them as major and minor.

We, experimented with a spread of techniques, like direct CNN training, after the completion of which, pre-training the CNN by means of auto-encoder and then followed it by fine-tuning, and also further usage of transfer learning from broad CNNs that are trained on ImageNet, this in turn creates an ensemble classifier that is mounted on top of the gathered classifiers which are already pre-trained. We discover that the usage of transfer learning, which includes group learning, performs well. It is also found out that, a way to locate a specific sort of impairement. Experimental results confirm the efficiency of the proposed solution.

While researching a Covolutional Neural Network, it is very difficult to perceive whether an image of the vehicle is of defects or not. The use of transfer learning in order to obtain the attainable solutions that are trained on a more general visual perception task, is very tedious but satisfactory performances are achieved, this indicates the better opportunities of the approach used. Further categorizing the level of damage according to the severity and grouping them as major and minor is done at the end. While trying to achieve these solutions, the major focus was also on some of used hyper-parameters and the way to implement them, obtained from the theoretically suggested ways. The project and its implementation helps to reduce the manual work and paves way to bridging the gap between automobile insurance company and image recognition promoting customer satisfaction to greater extent.

In today's world of automation and deep learning the area of computer vision has enormously advanced during the past few years, this is majorly due to the advances in computing power and day to day increase in image datasets. While trying to implement the research, we have analyzed some of the popular techniques and their method of usage and find the best suitable technique. We aim to accurately classify whether the vehicle on a given image is damaged or not. If damaged, what is the level of damage.

"Automated detection and recognition of auto damage increases transparency and credibility during a system of frequently changing drivers, like hire car or car sharing business"

2. BASIC FOUNDATIONS

In spite of many investigators addressing the problem of object detection, it is very challenging to diagnose the evaluation and quality of objects/products. [1] Proposes a new methodology to detect fruit using convolutional neural networks and deep learning. Multi modal Faster Region centered CNN (Faster R-CNN) method is used for object detection. The method is used for identifying the fruits and not the quality of fruit. [2] Paper analyzed various methods used by machine vision to identify fruits, detect the defects and remove the noise. The authors have explained several machine vision techniques for object recognition and hyper spectral imaging to detect defects/damage in fruits.

Detecting scratches in cars using CNN was proposed in [3], in which AlexNet architecture is applied and transfer learning technique is utilized. Processing time is larger as the analysis is also done to areas the vehicle doesn't corresponds to. [4] Combines the usage of sensing using remote imagery along with different resolution by using Convolutional Neural Network in order to classify images of building damages from satellite. The method did not detect simple sings of damages which may be useful for decision making to classify the vehicle according to damage level.

Corrosion is a defect that is caused in metal pipes, it should be detected early to avoid water contamination. [5] Analyzes the machine learning techniques to identify the pipe corrosion. SVM (Support Vector Machine) method is used to integrate and identify boundary between corrosion and non-corrosion. A hybrid model of MO-SVM-PCD is used to validate the training set. Accuracy can still be increased with more advanced higher-order statistical features. [6] Analyzes concrete surface cracks while comparing deep convolutional neural networks methods for concrete crack detection. The paper addresses the problem of over fitting during training and various techniques were applied to overcome the issue that arises. [7] Uses a Deep learning based computer vision technique for inspecting defects and damages in any products, also said to be inspection. It uses traditional image processing methodologies to fetch the region of interest ROI and also uses Hough transform to eradicate the not relevant background. Advanced machine learning techniques can be implemented to improve the results further. [8] Implements deep learning techniques for detecting automatically and localization of any defects/damages in building via images. The paper was not able to address different form of defects, multiple types. It also doesn't addresses the case of too much brightness and low lighting of images.

3. PROPOSED METHOD

Convolution neural networks also termed as ConvNets, is the sort of machine learning techniques that we'll use, for classification. The classifier may be a program that performs the so-called score function. This suggests that, provided the info case, it calculates the values for all available classes of C. The category which falls under the best value is then considered to be truth class for the info case.

Within the certain cases where C= 2 (e.g. defect or not defect) is mentioned as the classification factor for differentiation. The learner algorithm returns a classifier supported group of labeled training data. Inorder to get some preferential method in selecting a learner from the numerous amounts of available chances, it describes learning as a combination of three different components: Depiction, estimation and escalation. We experimented several techniques like training a CNN directly with image source, utilizing auto encoder by already trained Convolutional Neural networks which are followed by transfer learning techniques for fine tuning , from huge CNNs that are trained on Imagenet and then constructing an classifier based on ensemble methods on top of the collection of previously trained classifiers. We detected that when transfer learning is combined with ensemble based learning methods, it provides best result. We build a method to localize the specific damage type as major/minor category. Results of the experimental data suggest the solution is very effective.

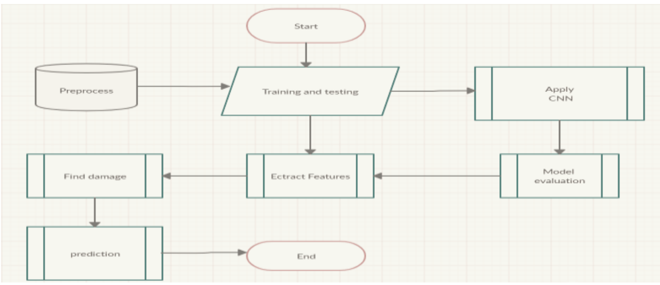

Fig -1: A pictorial representation of the proposed methodology

The representation of the learner, commonly mentioned because the model, is its most characteristic aspect. This defines the training space principle, i.e. the set of classifiers which will be learned. The representation of the ConvNet is decided by the specification. In other words, the CNN is depicted by a group of nodes2 arranged in one or several layers which are connected mainly via a feed-forward manner (so with none cycles).

A triple-layer neural network of 3 inputs, along with two hidden layers of 4 nodes each, and two outputs are used for our experiment. We have to keep in mind that each one connection are driven which can be called as arcs in a feed-forward fashion (i.e. from left to right) and there is no connections in between nodes within the same layer.

3.1 ML Algorithms:

Similar to the current applications or real-world computer vision issues, here, we try to use transfer learning from sufficient previously trained CNN to save an enormous amount of time in training repeatedly the whole weight matrix. one among the foremost powerful algorithms designed to predict vehicle exterior damage detection is Cascade R-CNN. On the whole, identical to every object detection mission, here, too, we've utilized three subtasks:

Removing Regions of Interest (ROI): Image is processed in a Convolutional Neural Network that returns a neighborhood of suggested methods like RCNN and RPN (Region Proposal N / W for Faster RCNN) then utilizes a RoI pooling layer, so that the extracted ROI of each one regions are of an equivalent size.

Classification technique: The identified regions are transferred to the whole connected network which categorizes the image classes based on the differences. In this experiment, it's getting the crack or scratch ('damage ') or background details.

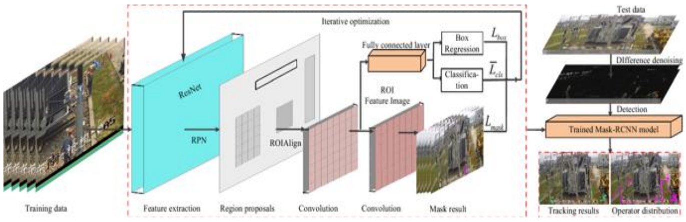

Fig -2: pictorial representation of Mask R-CNN model

Regression task: Eventually, regression for bounding box technique is employed to identify specific region to tighten bounding boxes (get accurate BB definition of relative coordinates)

In the proposed work, the bounding box shaped in rectangle/square is not enough, because the car defects/damages especially scratches are amorphous in nature (without a proper shape or structure). we'd like to spot the precise pixels within the bounding box which acknowledges to the class(damage). The precise region of the scratch pixel will aid to spot the situation and rank the damage accurately. So, we'd like to utilize another important procedure- **semantic segmentation** is the process of highlighting the region of Interest by means of shading the pixel to the whole region that is to be used in CNN i.e. Mask R-CNN, termed to be Masked region architecture.

3.2Mask R-CNN:

Mask R-CNN is a new novel approach that deals with segmenting the instances model in order to portrait a pixel-based representation for the region of our Interest. For this, Mask R-CNN is used which has two defined tasks:

1) Bounding Box based object detection (also termed as localization task) and

2) Semantic segmentation, that allows the segmentation of every objects within a picture/instance, no matter the format in which it is present.

Combining these two tasks, The R-CNN Mask is ready to use the segmentation done for an instance for any given picture.

While detecting object, this Mask RCNN is an identical architecture to Faster R-CNN, but the major difference is Region of Interest step, rather than implementing the ROI pooling, MaskR-CNN implements ROI align to permit the use of pixel to take care of Region of Interests and avoid any leakage of data. In case of segmentation based on semantic activities, Mask-RCNN uses fully convolutional network also termed as FCN. It, generates binary masks around Bounding Box instances by generating a pixel based classification of every area i.e. definite object that is of interest. Thus, on the whole, Mask R-CNN reduces the cumulative leakage/loss of the subsequent failure at each point of the Proceeding Segmentation.

Symbol	**Explanation**
µ	True class label, u 0, 1, 2…., *K*; using convention, while the background class is u-0.
p	Probability distribution based on discrete values for every Region of Interest, rather than conditional probability for all K+1 classes: $p = (p_{0,}……,p_k)$, this is calculated by a Soft Max function for all the K+1 outputs in a layer that is connected fully.
v	BB- bounding box for true value, $v = (v_x, v_y, v_w, v_h)$.
t^u	Predicted bounding box correction, $t^u = (t_x^u, t_y^u, t_w^u, t_h^u)$

Chart -1: Symbol Explanation

RPN loss class : loss in RPN is measured for every Region of Interest and aggregated for all Region of Interest in a single available picture, and the entropy loss is calculated by means of rpn network loss class, that is an aggregation of all loss class in rpn for all the available pictures in other words training dataset.

$$L_{rpn\_cls} = -\sum \log(p_u)$$

RPN Bounding Box-loss: The network regression loss in a RPN based Bounding Box is cumulative of RPN loss class. The values of BB loss is the range calculated between the arguments of truth value, i.e. the coordinates termed as x and y, of the region of the box, the dimensions, and the analyzed predicted values. This differences for minor values is

May – June 2020
ISSN: 0193-4120 Page No. 9793 – 9799

represented exponentially and for major differences as linearly.

$$L_{rpn\_bb\_reg}(t^u,v) = \sum L_i^{smooth}(t_i^u - v_i)$$

There occurs several losses and the phase in which it appears are categorized as: the first loss during the object detection phase and the last three loss is mainly during the semantic based segmentation process. Due to these failure the training and testing data phases makes the network to reduce the loss of every component in validation. This is represented as follows:

$$L_{overall} = L_{rpn\_cls} + L_{rpn\_bb\_reg} + L_{mrcnn\_cnn} + L_{mrcnn\_bb\_reg} + L_{mrcnn\_mask}$$

4. DATASET DISTRIBUTION

In order to enhance the accuracy of the classifier, a mixture of 1000 damaged and 1000 perfectly-looking car pictures were gathered and annotated in an amorphous way. To order to check the info set and therefore the classifier, a further 500 harm car images and 500 perfectly-looking car images are fed. These images are annotated using third-party tools called labellmg.

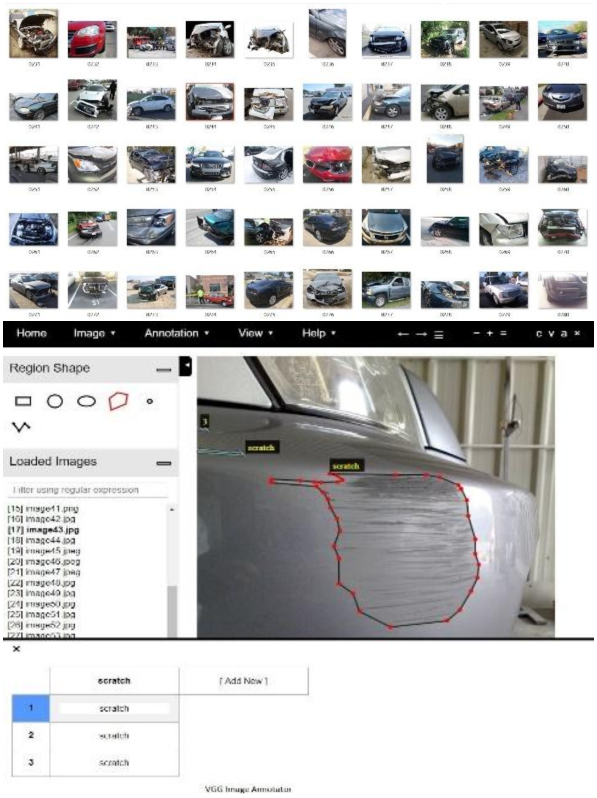

Fig -3: Dataset and Annotations

5. MODEL VALIDATION AND TRAINING

In this project, we use the tensorflow backend to coach the model. The dataset after it's been cleaned are going to be translated to a.csv file (separate comma values); and loaded into the training model. The csv file is then fed into the passive training model. Data manipulation is completed using python language which, in effect, runs all the libraries to compile this R-CNN Mask. With each iteration, the model learns the way to predict the damage caused by the vehicle.

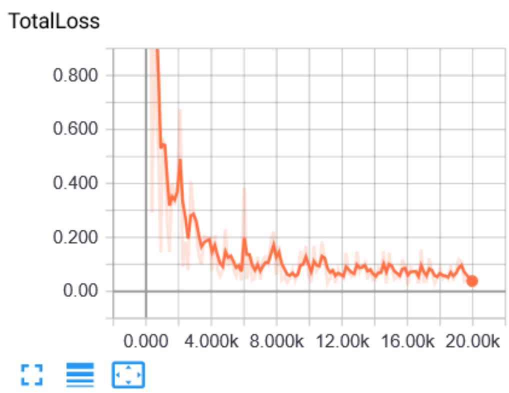

Fig -4: Total Loss

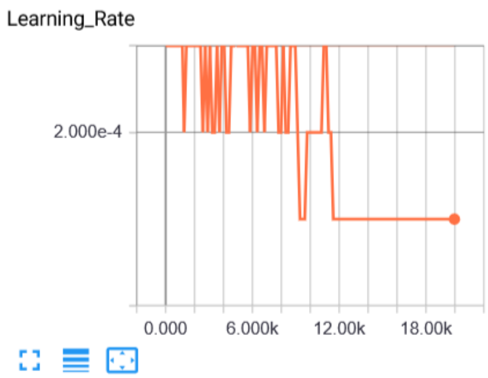

Fig -5: Learning Rate

6. MODEL ANALYSIS AND OUTPUT

Model Prediction: After performing sufficient auditing of loss, monotonically based testing/ training and validation loss, we will perform the test of the trial objects by choosing the validation images randomly so that it confirms the accuracy of the masked region in a damaged car.

May – June 2020
ISSN: 0193-4120 Page No. 9793 – 9799

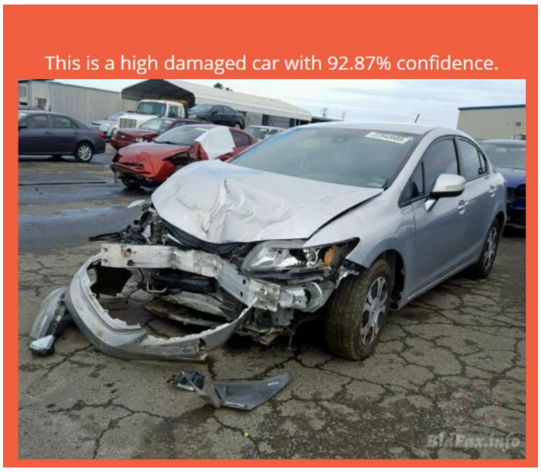

Fig -6: High Damage

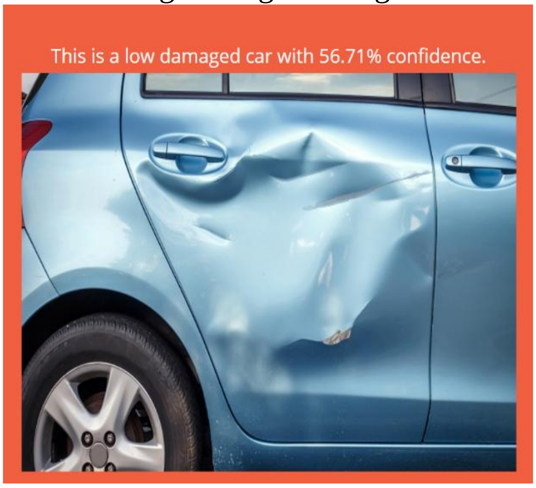

Fig -7: Low Damage

The model is attached to the front of the python flask, which is the interface for uploading the specified image, in order that the image is then assessed using the car external damage detector classifier and therefore the result's displayed on the idea of what proportion damage the car has dealt..

Fig -8: No Damage

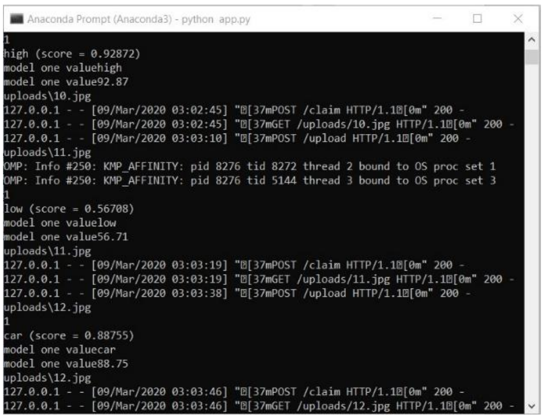

Fig -9: CMD output

7. CONCLUSION

Several deep learning techniques are used for dealing with damage detection; here we proposed a different deep-learning technique for the classification of car damage. We experimented with deep learning techniques like R-CNN Mask Machine Learning Techniques, Convolution Automatic Previously Trained Encoder then by supervised technique of fine tuning and highly preferred transfer learning approach. We've found that the usage of transfer learning has worked the simplest and offered to produce great experimental result . We also note that only common features of the car can't be sufficient for the detection of damage. The suggested approach offers an efficient and high degree of accuracy.

In the future, the vehicle shall be supported the external damage detected; and therefore the refore the estimated cost of repair of the vehicle shall be determined on the idea of the external damage identified and the internal damage assumed on the idea of access to the inventory, which shall include repair and labor costs for every component within the first and second sets of parts.

8. REFERENCES

[1] Inkyu Sa, et. al "DeepFruits: A Fruit Detection System Using Deep Neural Networks"at sensors MDPI, August 2016

[2] Shadman Sakib1 et. al "Implementation of Fruits Recognition Classifier using Convolutional Neural Network Algorithm for Observation of Accuracies for Various Hidden Layers"

[3] César Giovany Pachón-Suescún ,et.al . Scratch Detection in Cars Using a Convolutional Neural Network by Means of Transfer Learning, International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 16 (2018) pp. 12976-12982

May – June 2020
ISSN: 0193-4120 Page No. 9793 – 9799

[4] D.Duarte a , et.al, "Satellite Image Classification Of Building Damages Using Airborne And Satellite Image Samples In A Deep Learning Approach" , ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume IV-2, 2018.

[5] Nhat-Duc Hoang, et. al "Image Processing – Based Detection of pipe Corrosion using Texture Analysis and Metaheuristic –optimized Machine Learning Approach", Advances in Recent Nature-Inspired Algorithms for Neural Engineering. July 2019.

[6] Marek Slonski, "A Comparison of Deep Convoultional neural networks for iamge-based detection of concretre surface cracks. Computer assisted methods in Engineering and Science, 2019.

[7] Jinjiang Wang,et.al , "Machine Vision Intelligence for product defect inspection based on deeep learning and Hough transform. Journal of Manufacturing system, April 2019.

[8] Husein Perez,et.al , "Deep Learning for detecting Building defects using Convolutional Neural Networks" Snsors August 2019.

[9] W.A. Rukshala Harshani ;et.al , "Image processing based severity and cost prediction of damages in the vehicle body: A computational intelligence approach", 2017 National Information Technology Conference (NITC)

[10] Mingjiang Zhang ; et.al , "Research on the Application of Deep Learning Target Detection of Engineering Vehicles in the Patrol and Inspection for Military Optical Cable Lines by UAV", 2018 11th International on Computational Intelligence and Design (ISCID)

[11] B. Sivasankari ; et.al , "Auto Detection Of Joints And Axle Failure In Heavy Load Vehicles Using Artificial Intelligence", 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS)

[12] Qinghui Zhang ; et.al "Vehicle-Damage-Detection Segmentation Algorithm Based on Improved Mask RCNN" IEEE Access

[13] Jinling Yao ; et.al "Small-Scale Rail Flaw Detection Car Design and Damage Position Estimation" , 2017 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC)