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VEHICLE DAMAGED DETECTION USING DEEP LEARNING

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ABSTRACT

Object Detection based Vehicle Damage Detection system can potentially save insurance companies Million. In this paper we propose a Vehicle Damage Detection System based on YOLO v4. We created a dataset of damaged vehicles and annotated regions consisting of Dents, Shattered Glass, damaged tail lights and scratches. We then pre-processed the images inline with the requirements of YOLO v4 and trained the model to achieve an mAP@50 of 81.20. The system proposed in this paper surpasses all previously proposed methods and gives promising results.

Keywords: Convolutional Neural Network, Vehicle Damage Detection, Deep Learning, Yolo V4.

I. INTRODUCTION

One of the key research topics in computer vision is object detection. On the instance level, it determines the category and location information of the object of interest in the image. Car insurance companies spend millions of dollars each year owing to claims leakage in today's society, when the rate of car accidents is on the rise. In the insurance industry, AI technology based on machine learning and deep learning can help with issues such as data analysis and processing, fraud detection, risk reduction, and claim automation [1,2]. However, developing current applications to address such issues remains difficult, particularly when using deep learning to assess automotive damage. Deep learning is an effective method for tackling complicated problems, but it necessitates more resources for model building, i.e., deep learning demands a large dataset and takes longer to compute.

This study focuses on two difficulties for developing an efficient deep learning system for automotive damage assessment: car damaged datasets for training and computation time reduction. Deep Learning is a sub-branch of machine learning that has been successfully shown on a variety of platforms for dealing with lots of data. Through stacked blocks of layers that make up the Deep Learning skeleton, Deep Learning models may capture and understand information that is hidden in data to anticipate distinct patterns. [3,4]. Deep Learning-based models have been effectively applied in various applications in a wide range of research areas, including computer vision, speech and audio identification, and damage detection, mainly due to breakthroughs in parallel computation and the development of Deep Learning. In this study, we propose an automated approach for classifying damaged vehicles and predicting how they were damaged. The Convolution Neural Network (CNN) can be utilised to comprehend, detect, and analyse many types of damage in minor and major automotive components. Bumper dent, door dent, broken glass, tail light, head light broken, and scratch are all examples of damages. CNN is utilised for object identification tasks, and in the proposed system, it is used in the context of recognising vehicle damage. The Damaged Vehicle dataset is used for the classification task. There is no publicly available dataset for car damage classification that we are aware of. As a result, we developed our own dataset by manually annotating photographs found on the internet. Due to characteristics such as high inter-class similarity and scarcely evident defects, the classification task is difficult.

II. RELATED WORK

Vehicle Damage Detection

In their research, Zhang et al [5] performed a technique of vehicle damage identification based on Transfer learning and an upgraded version of RCNN, in which first data sets are gathered for processing, and then data

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sets are produced and then divided into training sets and test sets. The findings show that the AP (Average Precision) value, combined with detection and masking accuracy, is fairly excellent and effectively solves the difficulties encountered.

Moreover, Dhieb et al [6] attempted to use Transfer Learning, Deep Learning, and instance segmentation to locate the damages existing in automobiles and split the types of damages based on the severity of the damage. The findings obtained a superior result when compared to another pre-trained model such as VGG16 by employing the Inception-ResnetV2 pre-trained model with a totally connected Neural Network. Jayaseeli et al [7] also worked on automobile damage identification using mask RCNN, in which the pictures were processed for 21 epochs and the final result was shown using the colour splash approach, with the damaged region indicated. Their model showed an overall deficit of just 0.3888. MobileNet and VGG19 which are pre-trained CNN Models were used by [8] and they had trained their model to reach an accuracy of 70% and 50% for MobileNet and VGG19 respectively. Their model had the added benefit of being able to find and differentiate with different sorts of damages, and this result made it stand out from the other models available.

YOLO

YOLO is short for You Only Look Once. It approached object detection like a regression problem instead of classification by introducing a unified model for object detection.

YOLO v1: [9] The entire model was trained jointly and its loss function directly corresponded to the detection performance. They used Darknet framework which was trained on ImageNet-1000 dataset. The authors started by dividing the input image into an S × S grid. If the center of an object fell into a grid cell, that grid cell was responsible for detecting that object. Each grid cell predicted B bounding boxes and confidence scores for those boxes. These confidence scores reflected how confident the model was that the box contained an object. It trained the classifier network at 224 × 224 and increases the resolution to 448 for detection.

YOLO v2: [10] improved on YOLO v1 by introducing, 1) batch normalization to decrease the shift in unit value in the hidden layers to improve the stability of the neural network, 2)scaling up the input size from 224 x 224 to 448 x 448, 3) anchor boxes, responsible for predicting the bounding boxes designed for a given dataset by using k-means clustering, 4) detections on a 13 × 13 feature map for detecting smaller objects, 5) Multi-Scale Training, every 10 batches the network randomly switched to a different input image dimension allowing the network to learn and predict the objects from various input dimensions, 6) Darknet 19 architecture with 19 convolutional layers and 5 max pooling layers and a softmax layer for classification.

YOLO v3: [11] improved YOLO v2 by introducing, 1) Predictions across three different scales, done by applying 1 x 1 detection kernels on feature maps of three different sizes at three different places in the network, 2) predicts an objectness score for each bounding box using logistic regression, 3) Each box performed multilabel classification, they dropped softmax and just used independent logistic classifiers, 4) new feature extractor, Darknet-53, which had 53 convolutional layer, 53 more layers were stacked onto this resulting it in being slower than YOLO v2

YOLO v4: [12] has broken down object detectors into 4 distinct blocks as shown in the Figure 1, The backbone, the neck, the dense prediction, and the sparse prediction.

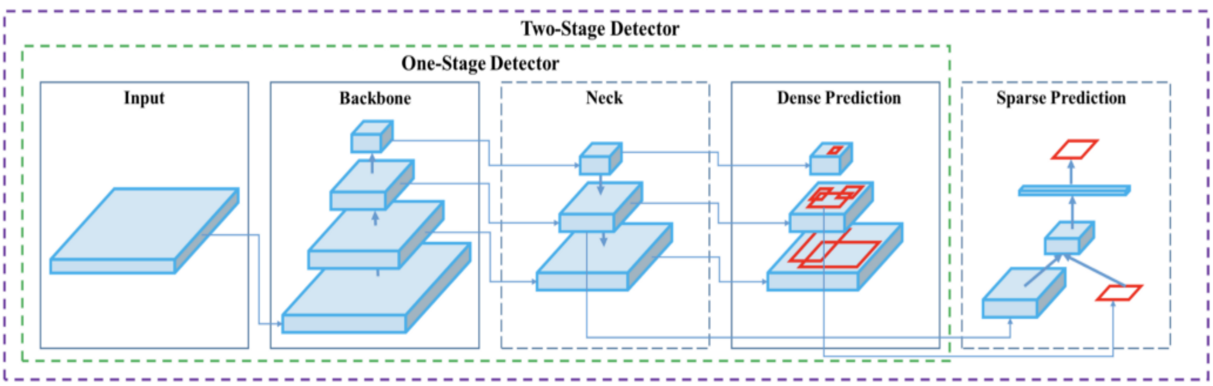

Figure 1: Breakdown of YOLOv4 architecture

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They also classified various methods employed for improving object detectors into 1) Bag of Freebies (BoF), methods that only change the training strategy or only increase the training cost and 2) Bag of Specials (BoS), Plugin modules and post-processing methods that only increase the inference cost by a small amount but can significantly improve the accuracy.

For the backbone which acts as the feature extractor the authors chose CSPDarknet53 with CutMix and Mosaic data augmentation, DropBlock regularization and Class label smoothing for BoF and Mish activation, Cross-stage partial connections (CSP), Multiinput weighted residual connections (MiWRC) for BoS.

For the neck(detector) which is responsible for feature aggregation, the authors chose CIoU-loss, CmBN, DropBlock regularization, Mosaic data augmentation, Self-Adversarial Training, eliminate grid sensitivity, using multiple anchors for a single ground truth, Cosine annealing scheduler, Optimal hyperparameters, Random training shapes for BoF and Mish activation, SPP-block, SAM-block, PAN path-aggregation block, DIoU-NMS for BoS

For the head the authors chose YOLOv4.

III. METHODOLOGY

Dataset

There is no publicly available dataset for car damage detections, hence we created our own dataset consisting of images belonging to different types of car damages. We annotated them using LabelImg with the YOLO format for four commonly observed types of damages such as Dent, Broken Glass/Glass Shatter, tail light broken and scratch. The images were scrapped from web and were manually annotated.

Authors of [4] have classified data augmentation under BoF, we have applied the following methods listed in the paper for data augmentation,

1) Photometric distortion, creates new images by adjusting brightness, hue, contrast, saturation and noise,

2) Geometric distortion, rotating, flipping, random scaling and cropping,

3) Mixup, weighted linear interpolation of two existing images,

4)CutMix, patches are cut and pasted among training images where the ground truth labels are also mixed proportionally to the area of the patches.

Training

We resized our images to 416x416, the model was trained with a batch size of 64, the learning rate was initiated at 1e-3 which was later on reduced after 6400 iterations and 7200 iterations. The models were trained on a Tesla K80 GPU.

IV. RESULTS AND DISCUSSION

The model trained on 416x416 images achieved mAP@50=81.20 %.

Table 1: Results of YOLO v4 on 416x416 mAP@50=81.20%

Confidence Threshold	Precision	Recall	F1-score	Avg. IOU(%)
0.0	0.25	0.82	0.38	19.12
0.25	0.81	0.76	0.79	64.13
0.40	0.81	0.76	0.79	64.13
0.50	0.87	0.76	0.81	64.13

Figure 2: Sample Images of the DATASET

V. CONCLUSION

The main application for Vehicle Damage Detection is for insurance companies as insurance losses are the main issues faced by these companies which leads to these companies losing millions and millions of dollars each year. These losses are caused by inefficient claims processing, embezzlement, and bad business deliberation. With significant advancements in deep learning methods, these techniques have begun to be utilized in the insurance industry to address such challenges and mitigate their negative implications [13].

By using the method, we have used in this paper, Automobile Insurance companies can imply this method to monitor the leakage of claims where scammers sometimes overstate or fabricate incidents in order to support fraudulent claims [14,15].

But by using our proposed method they can severely reduce the intensity of such scams as this process happens instantaneously without involving anyone. Definitely more work has to be done in order to get this technology used by the mainstream insurance companies.

Better Models based on Vision Transformers and larger datasets may provide better results and can be of interest in Future works.

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