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Car Damage Detection using CNN

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Abstract - In today's modern society, automobiles play a crucial role, and the automatic classification of car damages holds particular significance for the auto insurance industry. Our proposed solution involves the implementation of two Convolutional Neural Network (CNN) models. Specifically, the VGG16 model is employed to identify and assess the location and severity of car damage, while the Mask R-CNN is utilized to accurately mask the damaged regions. Both models collectively provide valuable insights into the extent of damage to a car, enabling insurance companies to expedite claims processing without the need for time-consuming and resource-intensive manual verification.

The CNN models effectively filter out images without damages, allowing only those with identified damage to be passed on to the object detection model. This strategic approach enhances the overall performance of the model. The core objective of this research project is to achieve maximum accuracy through the utilization of CNN models. TensorFlow, a pre-trained framework, was employed in the development of the object detection model, emphasizing efficiency and reliability in the insurance claims process.

Key Words: E-commerce, Car Damage, Detection, Classification, VGG, Mask RCNN, Severity, Location, Masking

1. INTRODUCTION

Applications such as insurance claims systems, accident reporting systems, car garages, and car trading services can greatly benefit from the integration of a car damage detection interface [3]. This interface streamlines processes ranging from damage detection and level estimation to final cost estimation. The incorporation of Artificial Intelligence (AI) and Machine Learning (ML) models addresses the labor-intensive nature of processing insurance claims by automating damage detection, resulting in substantial cost savings and improved time efficiency [3].

In addition to insurance, AI and ML models can be applied in car garages for damage level detection and cost estimation. Repair companies may leverage these models for customer scouting in various locations, such as mall parking and valet parking. Furthermore, employing these models in second-hand car sales ensures the verification of vehicle authenticity, thereby protecting the interests of potential buyers.

The insurance industry, historically resistant to change, is experiencing a transformative shift. Manual validation of large-scale claims is proving insufficiently prompt in handling the growing volume of insurance claims. Automated car insurance claim processing systems, equipped to detect and estimate damages, offer a viable solution [3]. These systems expedite the determination of claim amounts based on damage type and affected vehicle parts. The efficiency of automatic damage assessment through image analysis has been demonstrated, with ongoing improvements expected as more data is gathered.

One of the significant challenges faced is the reduction of model training time. Traditional CNN models tasked with image classification encounter the challenge of identifying optimal weights through numerous forward and backward iterations, a time-consuming process that may take days or weeks when using GPUs. However, leveraging pre-trained CNN models on extensive benchmark datasets like ImageNet mitigates this challenge [3]. Transfer learning enables the extraction of weights from pre-trained models, accelerating the training process and adapting models to specific tasks.

The implementation of our project involves two main parts. The first part utilizes VGG models [10], with three models trained using transfer learning. The initial pre-trained model, based on the ImageNet dataset, determines whether the object in the image is a car [10]. The first model identifies whether the car is damaged, and if so, the second model is engaged to detect the location of the damaged portion. The third model then assesses the severity of the damage. Training involves self-defined labels assigned through manual classification of the dataset [10].

2. Literature Survey

The existing body of literature on car damage detection reveals a prevailing trend in utilizing pre-trained models for feature extraction and classification. Reference [1] introduces a car damage classification/detection pipeline employing the YOLO object detector and a CNN model tailored for the damaged area. Notably, their research demonstrates the superiority of transfer learning over fine-tuning, achieving an impressive 89.5% accuracy through a combination of transfer and ensemble learning.

In a similar vein, [2] focuses on car damage classification, exploring deep learning techniques such as training CNN from random initialization and pre-training based on Convolution Auto-encoder. The incorporation of pre-trained models, rooted in extensive and diverse datasets, aims to mitigate overfitting and enhance feature recognition. This approach highlights the importance of leveraging pre-existing knowledge for effective damage classification.

Addressing dataset preparation, [3] collects photographs and creates a dataset for broken cars, categorizing damage into distinct classes. Augmenting the dataset through rotations, cuts, variable zooms, and flips, they employ pre-trained models (AlexNet, V3 origin, VGG19, ResNet50, mobile networks) and integrate YOLOV3 for damage localization. This multi-model strategy enhances the accuracy of damage detection, showcasing the significance of dataset diversity and pre-trained models.

Similarly, [4] classifies images into eight damage categories, employing synthetic enlargement through random rotations and flips due to dataset limitations. Despite an initial accuracy below 75%, they enhance results through retraining using pre-trained models like Inception, AlexNet, VGG19, VGG16, and ResNet, coupled with SoftMax classifiers. Their experimentation underscores the efficacy of SoftMax over linear SVM, both in terms of performance and training efficiency.

In a real-world dataset context, [5] employs deep learning algorithms, specifically VGG16 and VGG19, for car damage detection and evaluation. The study investigates the impact of domain-specific pre-trained CNN models, fine-tuning them for improved accuracy. Through a blend of transfer learning and L2 regularization, the researchers achieve high accuracy in damage detection, localization, and severity assessment. Notably, their findings indicate the superiority of VGG19, achieving an accuracy of 95.22% over VGG16.

In summary, these studies collectively underscore the significance of pre-trained models and diverse datasets in enhancing the accuracy and efficiency of car damage detection systems. The utilization of transfer learning, ensemble methods, and innovative dataset augmentation techniques emerges as common strategies for improving model performance in this domain.

3. Proposed System

A. Dataset Acquisition and Curation

Our research drew upon a rich source of car damage data procured from the Car Damage Detective Projects hosted on GitHub. This dataset, tailored for Convolutional Neural Networks (CNNs), was complemented by incorporating images retrieved through strategic keyword searches on Google, encompassing terms such as "bumper dent," "door dent," and "glass shatter." The dataset played a dual role: (1) serving as the foundation for training and evaluating damage detection, and (2) forming the basis for damage classification. Rigorous categorization efforts were undertaken, resulting in the systematic division of the dataset into training and testing subsets. Images were meticulously sorted into seven distinct forms of damage, including bumper dent, glass break, scratch, door dent, damaged front, damaged headlight, and damaged tail light. Additionally, images representing the "Normal" class (no damage) and the "smashed/crashed" class for fully damaged cars were curated to ensure dataset comprehensiveness..

B. Data Augmentation for Enhanced Robustness

Recognizing the potential pitfalls of overfitting due to limited datasets, our approach included rigorous data augmentation techniques. By applying a spectrum of image transformation methods, including rotation within a range of 10 degrees, shear-range of 0.15, zoom range of 0.1, horizontal flip, and height and width range changes of 0.1 each, along with a channel-shift range of 10 degrees, we effectively augmented the dataset. This augmentation strategy aimed not only to expand the dataset size but also to imbue the model with enhanced robustness. The diversified perspectives of the images obtained through these techniques contributed to the development of a model that could generalize well across varied scenarios.

C. Damage Detection Using YOLO v4 Framework

For precise damage detection and classification, we harnessed the capabilities of the YOLO v4 framework. YOLO v4, renowned for its proficiency in object detection, relies on convolutional neural networks for streamlined model training. A prerequisite for constructing and training effective object recognition or classification models is a meticulously labeled or annotated image dataset. Thus, our approach involved the utilization of a carefully annotated image dataset to craft a bespoke object detection model. This model excels in accurately classifying diverse car damages, demonstrating its efficacy in the nuanced task of damage detection within the automotive context.

4. Proposed methodology

VGG16 Architecture Implementation

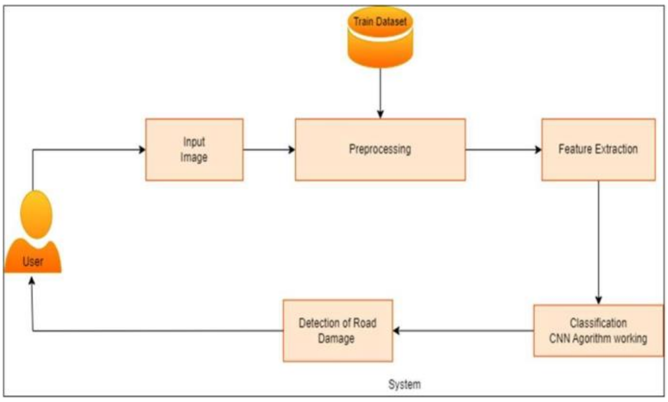

Fig 1:- System Architecture

The methodology employed for our research incorporates the VGG16 network architecture [2], renowned for its prowess in image classification tasks. The input to the VGG16 network comprises a two-dimensional image with dimensions (224, 224, 3). As illustrated in Fig2, the initial two layers feature the same padding and consist of 64 channels employing a 3x3 filter size. Subsequently, a max-pooling layer with a stride of (2, 2) follows, leading into two layers of convolution with 256 filters each and a filter size of (3, 3). This is succeeded by another max-pooling layer with a stride of (2, 2).

Continuing the architecture, two additional convolution layers are implemented, each utilizing a filter size of 3x3 and 256 filters. The subsequent section integrates two sets of three convolution layers, accompanied by a max-pooling layer. Each set features 512 filters with a size of (3, 3) and includes padding. The output from this stage undergoes processing through a two-layer convolution stack.

It's noteworthy that the choice of filter size in the convolution and max-pooling layers is 3x3, distinguishing VGG16 from architectures like AlexNet and ZF-Net, which opt for larger filter sizes such as 11x11 and 7x7, respectively. This strategic utilization of filter sizes enhances the network's ability to capture intricate patterns in the images.

In the upcoming stages of our research, we plan to tailor and fine-tune the VGG16 architecture to optimize its performance specifically for car damage detection. This adaptation will involve incorporating transfer learning and leveraging our curated dataset to further enhance the model's accuracy and efficiency in identifying and classifying various forms of car damage.

CONCLUSIONS

This research endeavor aimed to construct a two-layered AI model with a primary focus on enhancing performance by discerning undamaged images and directing the filtered subset to an object detection model. The overarching objective was to localize and classify car damages into four distinct categories: scratches, dents, smashes, and glass shatters. To benchmark the accuracy and speed of identifying and categorizing damaged car images, various transfer learning models were employed and evaluated in comparison.

To enrich our dataset, images were meticulously curated from both Google searches and a GitHub repository. Leveraging transfer learning models, the dataset underwent comprehensive training to predict damage categories. Notably, our findings highlight that MobileNet outperformed other models, yielding superior results in terms of accuracy. The implemented Convolutional Neural Network (CNN) model achieved an impressive accuracy rate of 98%, as validated through extensive testing on diverse images and videos, showcasing robust performance.

The models developed in this research exhibited proficiency in detecting damage, accurately determining severity levels, and precisely pinpointing damage locations. Fine-tuning VGG models played a pivotal role in elevating their accuracy, enabling accurate predictions even in challenging edge cases. Moreover, the Mask RCNN model effectively masked out damaged regions, demonstrating resilience in handling varying backgrounds, light intensities, and multiple viewing angles.

As a forward-looking perspective, future work can delve into data expansion strategies to further refine model training and enhance overall performance. Additionally, incorporating resources and data for calculating the approximate cost of repairs could augment the practical utility of the developed models. This research represents a significant stride towards automating and optimizing the car damage assessment process, laying the foundation for advancements in the intersection of artificial intelligence and automotive industry applications.

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