Assessing Car Damage with Convolutional Neural Networks

Abstract—Manual estimation of damages in fields like construction, vehicular accidents has been the mainstay of the insurance business. However, such methods are replete with biases and inaccurate estimations. This paper deals with estimating car damage, primarily with auto insurers as our key potential customers. For this purpose, three distinct Transfer Learning approaches are used which detect the presence of damage, location, and severity of the damage. The basis for algorithms used lies in Convolutional Neural Networks, customized to optimize accuracy. Each approach is analyzed and varying degrees of accuracy were achieved across different models deployed ranging from 68% to 87%. Accuracy as high as 87.9% was obtained during the course of experiments. This research fine-tunes a number of existing approaches and opens doors for collaboration in image recognition, particularly for the car insurance domain.

Index Terms—Computer vision, Transfer learning, Convolutional Neural Networks (CNN), Image recognition, ImageNet

I. Introduction

Digital Signal Processing is a unique branch of engineering, as it paves the way for unprecedented collaboration between Computer Science and Electronics engineering. Any signal can be labelled as a n-dimensional signal. An image is typically a 2 or 3 dimensional signal. Image processing is one of the most important application of 2-dimensional signal processing. With the development of a number of signal processing algorithms, machine learning techniques and the computational prowess to implement them, a variety of images can now be processed to the finest levels of granularity.

In this paper, Convolutional Neural Network (CNN) based methods for classification of car damage severity are implemented. Many techniques such as directly training a CNN and pre-training a CNN using transfer learning from large CNNs trained on ImageNet on top of the set of pre-trained classifiers were tested. It was observed that transfer learning combined with additional layers provides the best results, that is building an ensemble classifier on the top of the set of pretrained classifiers. A method was devised to classify the extent of damage. Experimental results validate the effectiveness of our proposed solution, across a number of evaluation parameters. The main focus was on the influence of certain hyper-parameters and on seeking theoretically founded ways to adapt them, all with the objective of progressing to satisfactory results as fast as possible.

II. Literature Survey

Deep learning is an efficient method used for classification. Kalpesh Patil, et. al. in [1] have used the concept of deep learning in order to classify car damage. The model used is trained on CNN directly. The preprocessing includes the steps of domain-specific pre-training followed by fine-tuning. The paper has conducted a combined and separate study of Transfer Learning and Ensemble Learning. The research has a setback of unavailability of a proper dataset which has resulted in creation of dataset by annotating images. The use of Convolution Autoencoder based pre-training followed by supervised fine-tuning and transfer learning is a novelty factor of this research.

Deep learning methodology can also be used for detecting presence or absence of damage and conducting further analysis. The researchers in [2] have applied this in the field of automotives. In this paper, CNN is used for object recognition. The task of classification has been performed on Damaged Vehicle dataset. Mask RCNN is used for segmenting, decomposing and sub-dividing the various instances of Machine Learning. The scope of research is limited to a particular dataset. Extensive research on new data can be performed for testing the quality of the model. Yet the fact that it is an automated system that can classify the damaged vehicle and predict how the damage has occurred remains a unique factor of this research.

The concept of faster R-CNN can be helpful for real-time object detection with Region Proposal Networks. This concept is implemented in [3]. RPN (Region Proposal Network) is trained end-to-end to generate high-quality region proposals, which are used by Fast R-CNN for detection. RPN and Fast R-CNN are merged into a single network by sharing their convolutional features using neural networks with attention mechanisms. The RPN component is essentially used for the unified network to focus on a particular object. The research does not include exploitation and preprocessing on the data. This process could have been used to improve results. The research has built a unified, deep learning based object detection system to run at near real-time frame rates.

Computer Vision Technology can be used for assessment of damage to an object. Xianglei Zhu, et. al. in [4] have developed an unified intelligent framework based on this concept. This paper uses RetinaNet algorithm to identify damaged parts. The accuracy with this algorithm is improved. Mask R-CNN is adopted for the identification of vehicle parts, the damaged parts are determined by the method of sampling, and the time complexity is greatly reduced. The accuracy achieved in this research can be improved in order to get better results. A combination of characteristics of vehicle damage data and suitable data can further strengthen this system. The research has successfully reduced time complexity in damage detection and the use of RetinaNet gives good accuracy in damage detection.

The use of Improved Mask RCNN can be used for vehicle damage detection. In [5], this approach is followed using Segmentation algorithm. A deep learning approach is used to detect vehicle-damage for compensation problem in traffic accidents. The algorithm has 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 and the robustness is strong. The limitation of this research lies in the mask instance segmentation. In many cases the obvious damage is not considered and segmented leading to inaccurate results. This research contributes to detection of damage of vehicles in a more efficient method through improved Mask algorithm.

Convolutional Neural Network (CNN) is a widely used algorithm for the purpose of classification problems. This method is used by Jeffrey de Deijn in [6]. The research was able to detect car damage with fairly accurate results. The type, location and size of damage is detected with moderate accuracy. The addition of Ensemble learning could have further improved the results from this research. The use of ConvNets to detect car damage detection and transfer learning are the novelty factors of this research.

III. Methodology

Overview of the proposed approach is shown in Fig. 1. Firstly, detection of the presence of car damaged takes place (logistic or logit classification). Secondly, the extraction of the features of the car damages has been explained further. Finally, image classification has been applied on the feature vectors to determine the severity of the damage to the car.

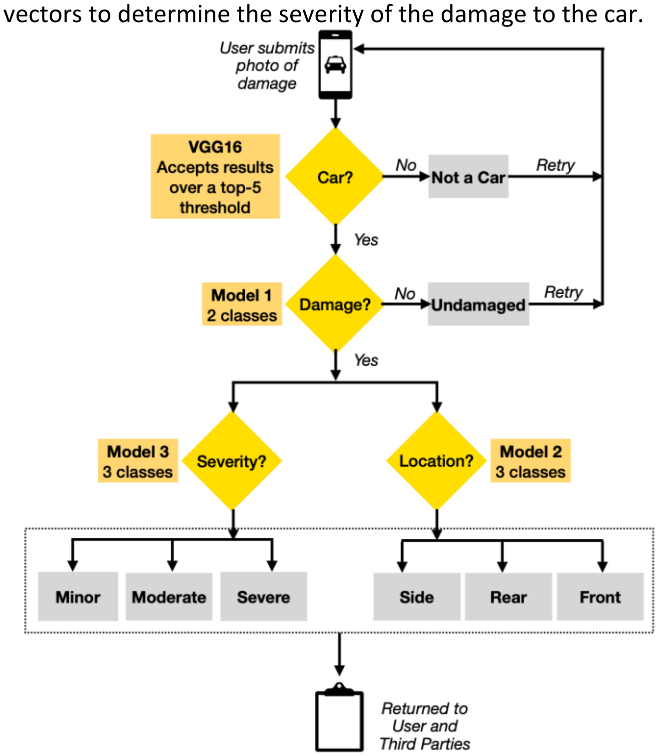


Fig. 1. Overview of the Proposed Methodology

A. Car Detection

The approach narrows down to two separate models pipelined. The first task is to differentiate between a whole and a damaged car followed by detecting the extent of damage and classify accordingly. Each class has at least 300 images to train upon.

B. Feature Extraction

An extensively comparison of the performances of many deep feature approaches was done in terms of feature extraction and decided to use the VGG16 model with ImageNet weights due to its simplistic model architecture and computational efficiency.

C. Transfer Learning

The VGG16 architecture was selected because it has a relatively simple architecture and Keras ships with a model that has been pre-trained on ImageNet. It is just a number of

Conv2D and MaxPooling2D layers with a dense network on top with a final softmax activation function. Additional dense trainable layers with sigmoid function above this model have been added.

D. Classification

After successfully extracting the features for the two classes, two binary classification model for the pair of two classes were built.

IV. Preprocessing

The RGB (Red-Green-Blue) images are Gray-scaled. The images are are resized throughout the dataset using a predefined image size in order to change them into a desirable format. The image data and corresponding class index are appended to training data. The training data is randomly shuffled to ensure that each data point creates an independent change on the model, without being biased by the same points before them. Pickle file is generated to save the serialized format of training data to a file and load it later to directly train the different models without repeating the hassle of data preprocessing.

V. Experiments

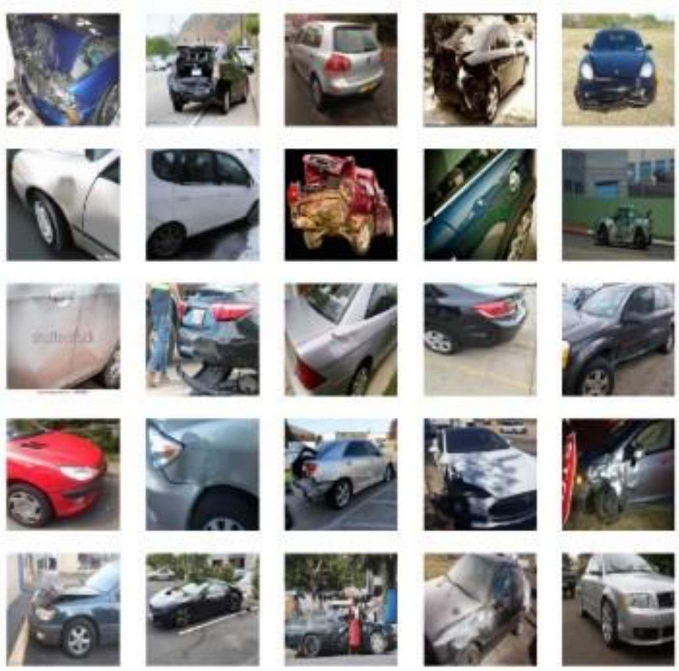


Fig. 2. Sample images for different car damages

A. Dataset

The image dataset which we have used throughout our experiment is made available under Open Data Commons Attribution License. Data has been scraped from Google Images using Selenium, hand-labeled for classification and supplemented with the Stanford Car Image Dataset. Ian London's General Image Classifier Project was used for scraping Google Images. Various different target classes of the dataset and their train and test size is depicted in Table II.

TABLE II
Description of Dataset

Class	Train Size	Test Size
Whole	920	230
Damage	920	230
Front Damage	419	73
Rear Damage	288	50
Side Damage	272	48
Minor Damage	278	48
Moderate Damage	315	55
Severe Damage	386	68

B. Model Training

In the first set of experiments, we trained a CNN starting with the random initialization. The CNN architecture consists of 5 layers: Conv2D-MaxPooling2D-Flatten-Dense128Dense1. Convolutional layer has 32 filters of size 3 × 3 and RELU non-linearity is used for the convolutional layer. The total number of parameters is 51M. Later assessing the results, we switched to VGG16 architecture because it has a relatively simple architecture and Keras ships with a model that has been pre-trained on ImageNet dataset. It is just a number of Conv2D and MaxPooling2D layers with a dense network on top with a Softmax activation function. Finally, binary/ sparse categorical cross-entropy loss function was added to the output layer of existing model for categorizing between target classes.

C. Experimental Results

All models are assessed using validation accuracy and loss metrics. The experimentation starts with a customised CNN model which yields an accuracy of around 63%. Next, the VGG-16 model is retrained for the dataset, which yields an accuracy of 87.9%. For the use case of this project, the VGG-16 model is employed for further training two different models, each outputting the location and severity of the model using the target classes respectively. Graphs in Fig. 3, Fig. 4, and Fig. 5 represent the performance of models for car damage detection, car damage location identification, and damage severity analysis respectively. The damage location and severity models in Fig. 4 and Fig. 6 show lower validation accuracy and loss metrics owing to the small dataset for the

TABLE I Experimental
Results

Model	Parameters	Train Accuracy	Train Loss	Validation Accuracy	Validation Loss	Test Accuracy	Test Loss	Epochs
Damage	17,926,209	0.9120	0.2106	0.8710	0.3120	0.8696	0.3496	7
Severity	40,537,411	0.7843	0.5263	0.7143	0.7204	0.7980	0.6432	5
Location	21,138,243	0.9058	0.2938	0.6837	0.7055	0.7045	0.6568	5

respective classes. The performance evaluation parameters for these three model have been tabulated in Table I.

For the car damage detection model, the best performance of validation accuracy and loss is at epoch number 7. For the damage location model, the epoch number for the best performance of validation accuracy and loss is at epoch number 2. For the damage severity model, the epoch number for the best performance of validation accuracy and loss is at epoch number 3.

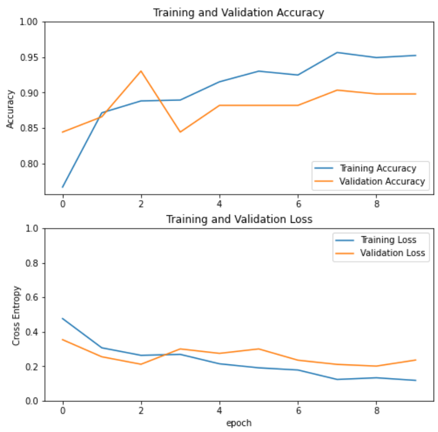
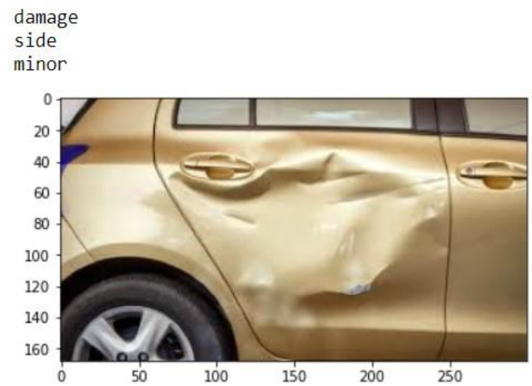


Fig. 3. Car damage model



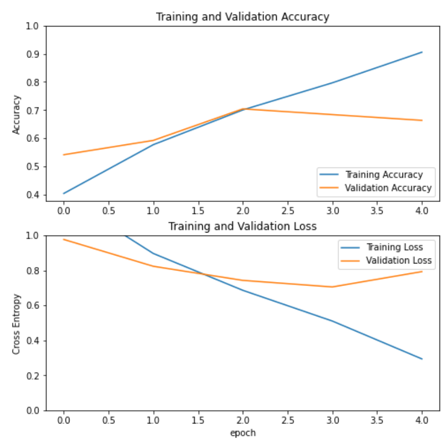
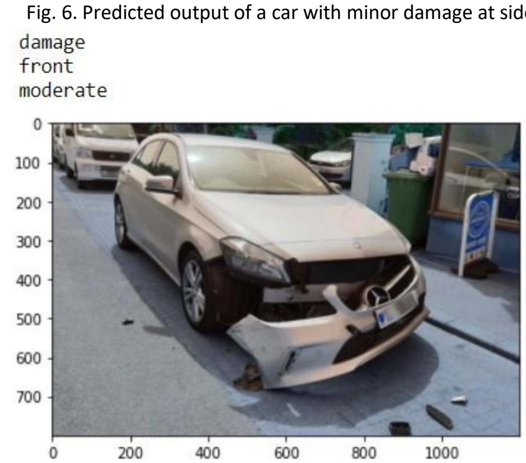


Fig. 4. Damage location model

Fig. 6. Predicted output of a car with minor damage at side



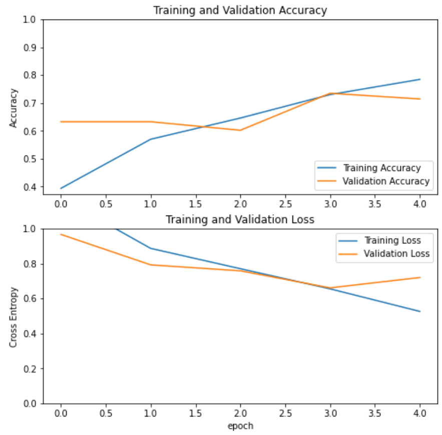


Fig. 7. Predicted output of a moderately damaged car at front

VI. Conclusion and Future Scope

Convolutional Neural Networks are accurate at evaluating car damage extent, even when trained on only 300 images per class. With a higher quality dataset which includes pivotal parameters like location information and repair costs, the research could go a step further in predicting the cost of damage repair based on the image.

This research opens doors for future collaborations on image recognition projects in general and for the car insurance field in particular. The research successfully recognized the presence of damage, damage location, and extent yielding validation accuracy, avoiding human bias. These can be further improved Fig. 5. Damage severity model by incorporating the on the fly data augmentation techniques.

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