Car Damage Assessment Based on VGG Models

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***Abstract*—Nowadays, the proliferation of automobile industries is directly related to the number of claims in insurance companies. Those companies are facing many simultaneous claims and solving claims leakage. In Advanced Artificial Intelligence (AI), machine learning and deep learning algorithms can help to solve these kinds of problems for insurance industries. In this paper, we apply deep learning-based algorithms, VGG16 and VGG19, for car damage detection and assessment in real world datasets. The algorithms detect the damaged part of a car, assess its location and severity. Initially, we discover the effect of domain-specific pre-trained CNN models, which are trained on ImageNet dataset, and followed by fine-tuning, because some of the categories can be fine-granular to get our specific tasks. Then we apply transfer learning in pre-trained VGG models and use some techniques to improve the accuracy of our system. After analyzing and implementing our models, we can find out that the results of using transfer learning and regularization can work better than those of fine-tuning. We get the accuracy of 94.56% of VGG16 and 94.35% of VGG19 in the damaged detection, the accuracy of 74.39% of VGG16 and 76.48% of VGG19 in damage localization, the accuracy of 54.8% of VGG16 and 58.48% of VGG19 in damage severity.**

***Index Terms*—damage assessment, insurance, deep learning, transfer learning, pre-trained VGG models**

I. Introduction

Do you know that the insurance industry is one of the first industry which invested in innovation, the latest technology and AI [1]? In today's world, when the rate of car accidents are increasing depending on expanding car industries, car insurance companies waste millions of dollars annually, due to claims leakage [2]. The sense of AI technology based on machine and deep learning can solve problems such as analyzing and processing data, detecting frauds, lessening risks and automating claim process in insurance industries [3]. So, insurance organizations are looking for faster damage assessment and agreement of claims.

Typically, training a CNN requires an extremely large amount of training data, and can be very time-consuming to perform image classification tasks, taking days or even weeks to complete it. What is more, the purpose of training CNN is to identify the correct weights for the network by multiple forward and backward iterations. Pre-trained CNN models, which have been previously trained on large benchmark datasets like ImageNet dataset, can save some time consuming, directly get their weights and apply their architectures for implementing the learning on the specific tasks via transfer learning. There is a good performance for car damaged classification using transfer learning with pre-trained CNN model [4]. Moreover, pre-trained CNN models can be used as a feature extractor and a fine-tuned. But, their frameworks are very complicated to understand because the variance is intensity. So there is a way how to focus on the impact of certain hyper-parameters and exploring theory to adapt them [5].

In this paper, we choose to use the pre-trained VGG models of VGG16 [6] and VGG19 [6] trained on the ImageNet dataset [7] because of their simple and effective architectures for the capability of object detection and classification in photographs, their model weights are freely available to load, and use for our specific tasks. In addition to this, we don't need to prepare our new datasets into annotation ones by using them. Then, we utilise our models with transfer learning and L2 regularization to reduce the over-fitting problem. After that, we apply fine-tuning to adjust some hyper-parameters. Following that, we use data augmentation to improve our small dataset creating into a large one. To sum up, we try to improve our system to get our specific tasks.

II. Related Works

There are many research papers based on image detection and classification. Among others, some damage detection and classification processes have been put forward to apply at car body damage assessment. In generally, Convolutional Neural Networks (CNNs) carry out well for many computer vision tasks such as object detection, recognition and classification. According to [8], they proposed an end to end system with a transfer learning based on CNN models on ImageNet dataset to perform different tasks of localization and detection but not calculate the level of damage part. The similarity in paper [4], they also trained CNN model with both of transfer learning and ensemble learning by comparing with the result of fine-tuning in the pre-trained CNN model on ImageNet dataset focusing on the accuracy of damage detection. The researchers used the basic concept of transfer learning and ensembling in pre-trained CNN model on ImageNet dataset to get the result of damage classification from car images [3][9]. In a new style approach as [10], they applied the YOLO object detection model [11] to train and detect damage region as their important pipeline to improve their performances of damage detection.

III. Proposed Methods

In this section, we explain our facing problems and how we solve those problems with effective ways in our systems.

A. Transfer Learning

Every deep learning model trains and places each task from the ground up, while transfer learning concentrates on feature extraction and appropriate data from source tasks and then applies the required data to a target task [3]. When the source and the target data are similar, transfer learning may improve the performance of the target tasks as a result.

We choose to apply it with the pre-trained VGG models to defeat the over-fitting problems on our small dataset and solve for classification, regression and clustering problems. What is more, it has demonstrated significant progress on how to solve classification problems when the small dataset is not enough to train a CNN model [12]. Also, it can significantly reduce the training time when we use the weights of pre-trained VGG models. The classes of the pre-trained VGG models are the source tasks, and the detected damaged parts of their locations, and their damaged levels are the target tasks in our system.

B. Influence of Hyper-Parameters

Adapting the hyper-parameters based on diagnostics in a theoretically way can help to obtain good results with a limited number of tasks. Keeping track of the loss and metric functions during our training datasets can determine good specifications of the learning rate, batch size and the amount of data augmentation in our system. The smaller the learning rate, the larger the batch size and the more stable the learning process, but it is more expensive to use a larger batch size in our system. Fine-tuning transferred parameters can give great results according to other related papers. Thus we fine-tune the last layers of pre-trained VGG models to adjust hyper-parameters in our models.

C. Regularization

Regularization is the controlling of the model complexity. Generally, it is to prevent the over-fitting problem. The most usual way is to add it to the loss function. There are many techniques of regularization such as L1 regularization, L2 regularization, dropouts, early stopping, batch normalization, and data augmentation. Among them, L2 regularization was expected to give the best performance, no need to concern with explicit feature selection [13]. Therefore, we use L2 regularization to fit the over-fitting problem in our system.

D. Dataset Description

Using cross-validation to estimate our models would need too much computational time because it is very expensive to train CNNs for a long time. Therefore, we decided to split the dataset randomly into separate sets for training (80%) and validation (20%). We randomly put train and validation sets, because creating and training with an ensemble of models would have taken very much time. After training multiple times with different splits, this split proved useful. Finally, the train and test were split such that they have similar images. We create our three datasets based on 1150 car damaged images, which consist of different types of car damage when there is no openly obtainable dataset for car damage classification. To reach our classification procedure, we need to have our three datasets which are manually collected from google images using selenium, which must include respective images without cars, with undamaged cars, and with damaged cars, and ImagNet dataset [7]. While we are dealing with small datasets, we require to use data augmentation to artificially expand and adapt our datasets to improve their performance and decrease their tolerance to the over-fitting issue during training. Therefore, we utilise randomly rotation, zooming, dimension shift and flipping renovation plans to differ the generated data. We explain more about our three datasets in the dataset subsection.

IV. Experimental Setup

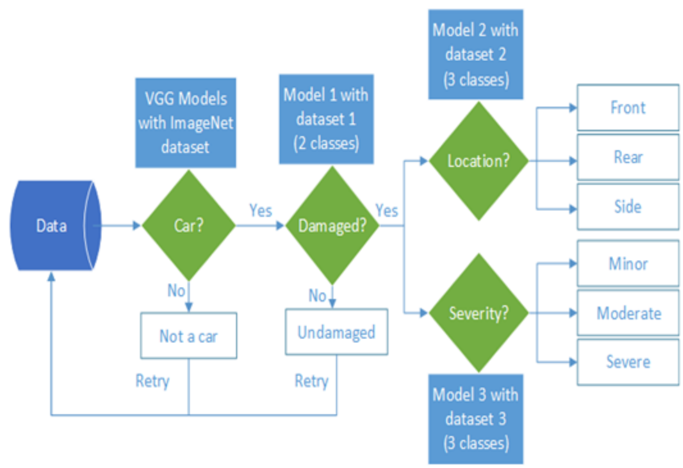

Fig. 1. A flow chart of developing car damage assessment pipelines.

Figure 1 shows the overall system of car damage assessment pipelines. There are four phases with three models, which are based on our three datasets such as dataset 1, which consists of two classes to complete task 2, dataset 2, which includes three classes to do task 3 and dataset3, which composes of three classes to perform task 4 in our system. Moreover, we explain detailly about of our four tasks with four datasets in under subsections. In the first phase, we get input data as taking a picture and uploading it or using our datasets, and then we choose one of pre-trained VGG models trained on ImageNet dataset to recognize a car or not a car. After choosing the model and testing it, we move on to the second phase. In this phase, we create to get into model 1 with our dataset 1 to determine damaged or undamaged. When we reach the third phase, we also train to create model 2 with dataset 2 to detect the location of the damaged part of a car. Finally, we arrive in the final phase, model 3 with dataset 3 is used to assess the severity of the damaged part of a car. After all of those, we accept some satisfying results.

A. Tasks

In this section, we explain about our target tasks which are divided into four sections. Their different tasks and their possible outcomes are listed below.

- Task 1. Recognizing cars: it is a car or no car.
- Task 2. Recognizing damaged part on car images: this car is damaged or undamaged.
- Task 3. Classifying the location of the damaged car: this damaged part is in a front, rear or side view of the car.
- Task 4. Assessing the severity of the damaged part of the car: this damaged part is how minor, moderate or serve level it is.

B. Dataset

We describe about our three collected datasets with their goals in the following.

- ImageNet dataset. It consists of 12 sub-trees: mammal, bird, fish, reptile, amphibian, vehicle, furniture, musical instrument, geological formation, tool, flower, fruit: to do for task 1.
- Dataset 1. Train and validation sets with undamaged cars and without cars: to do for task 2.
- Dataset 2. Train and validation sets with damaged and undamaged cars: to do for task 3.
- Dataset 3. Train and validation sets with damaged cars: to do for task 4.

C. Defining Damage Level

There are three situations to consider for a car damaged level. According to Libertymutual.com, the classification of damages are as follows [14].

- Minor Damage - scratches headlight or small dent in hood of a car.
- Moderate Damage - large dents in hood, fender or door of a car.
- Severe Damage - broken axes, bent or twisted frames and destroy air bags of a car.

D. VGG16 Model

Karen Simonyan and Andrew Zisserman introduced VGG16 [6] and submitted to Large Scale Visual Recognition Challenge 2014 (ILSVRC-2014). Their model achieves 92.7% of top-5 test accuracy on ImageNet dataset The input of VGG16 is a fixed 224 × 224 RGB image, which passes through a stack of convolutional layers, where they use filters with a very small 3 × 3 receptive field, and also utilises the max-pooling, which is performed over a 2 × 2 window with stride 2. The stride and padding of all convolutional layers are fixed to one pixel. The details of VGG16 structure is as follows.

- The first and second convolution layers are constituted of 64 feature kernel filters.
- The convolutional layers of third and fourth are 124 feature kernel filters and the output will be decreased the input size of 224 × 224 × 3 into 56 × 56 × 128.
- The fifth, sixth and seventh of convolutional layers use 256 feature maps.
- The convolutional layers from eighth to thirteen are two sets of convolutional layers have 512 filters.
- The fourteen and fifteen layers are full connected hidden layers have 4,096 nodes with ReLU and the node of the last one is 1,000 with softmax.

E. VGG19 Model

Karen Simonyan and Andrew Zisserman upgraded VGG19 [6] model based on VGG16 as the 19-layer or 19-weight convolutional network. The detail about of VGG19 structure is as follows.

- 64 feature kernel filters are used by the first and second convolutional layers.
- The third and fourth of convolutional layers are 124 feature kernel filters and the output will be decreased the input size of 224 × 224× 3 into 56 × 56× 128.
- The convolutional layers from fifth to eighth use 256 feature maps.
- 512 filters are used by the two sets of convolutional layers from ninth to sixteen.
- The full connected hidden layers of seventeen and eighteen layers have 4,096 nodes with ReLU and the last one has 1,000 nodes with softmax.

V. Results and Discussion

We use three different metrics: precision, recall, and F1-score to estimate the performance of our different transfer learning models such as VGG16 and VGG19. The higher those metrics are, the best our model outperforms.

Table I shows the values of those different metrics in damage detection, damage location and damage severity in both VGG16 and VGG19 models. From their results, the performance of VGG19 is as near as VGG16 even we do not have enough time to train that model like VGG16. We achieve the precision of 94%, 71% and 61% in damage detection, damage location and damage severity in VGG16 respectively. In Table II, we explain about the overall accuracy of our models. We accept the accuracy of 94.56% and 94.35% in the damaged detection, the accuracy of 74.39% and 76.48% in damage localization, the accuracy of 54.8% and 58.48% in damage severity respectively by using both of transfer learning and regularization in VGG16 and VGG19 models. Figure 2 shows the confusion matrix of the test performance of the last three tasks of VGG16. We use L2 regularization with its value 0.02 with 60 epochs in our models. All of the above, our pre-trained models not only detect damaged part but also assess its location and severity.

VI. Conclusion and Future Work

We described applicable deep learning-based algorithms for car damage assessment in the real world datasets. We created new datasets when there is no openly obtainable dataset for car damage classification. What is more, we experimented with the deep learning-based pre-trained VGG models from random initialization. Those models followed by supervised fine-tunning and transfer learning with L2 regularization technique

TABLE I
PERFORMANCE ANALYSIS OF CAR DAMAGE ASSESSMENT

	Performances of damage detection			Performances of damage location			Performance of damage severity		
Pre-trained VGG models	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
VGG16	**0.94**	**0.94**	**0.94**	**0.71**	0.69	0.69	**0.61**	0.55	0.53
VGG19	0.91	0.91	0.91	0.69	0.66	0.66	0.59	0.54	0.51

TABLE II
ACCURACY OF CAR DAMAGE ASSESSMENT

	Performances of damage detection			Performances of damage location			Performance of damage severity		
Pre-trained VGG models	Without L2	With L2	Fine-tuning	Without L2	With L2	Fine-tuning	Without L2	With L2	Fine-tuning
VGG16	**0.9456**	**0.9456**	0.9283	0.7030	**0.7439**	0.7342	0.5338	**0.5480**	0.5248
VGG19	0.9356	**0.9435**	0.9103	0.7263	**0.7648**	0.6815	0.5673	**0.5848**	0.5316

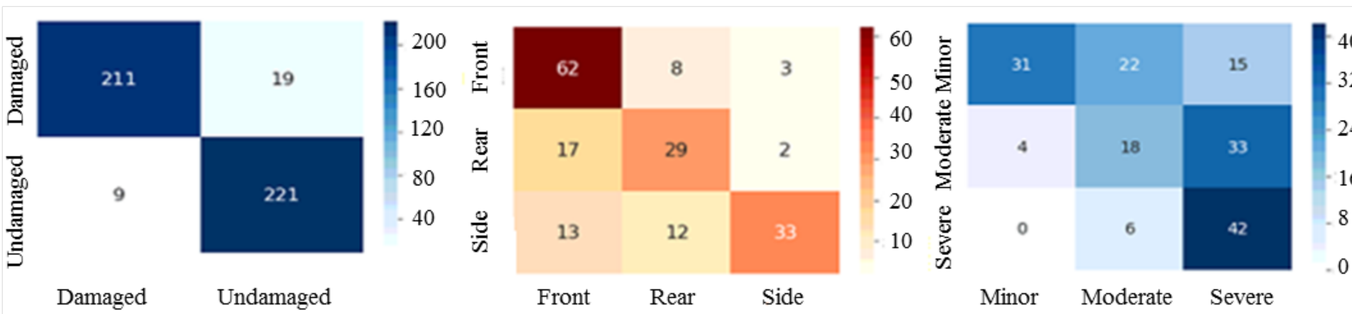

Fig. 2. Confusion matrices for car damage assessment of VGG16

to fit our specific task. We observed that training with a small dataset is not sufficient to get the best accuracy based on deep learning approach. In addition to this, it was not enough to use just one of the regularization technique in our system. After analysing our models, we find out that the results of using transfer learning and regularization can work better than those of fine-tuning. All of the above, our pre-trained models not only detect damaged part but also assess its location and severity. That why this solution can help the asset for insurance companies to solve claims leakage problems.

Regarding to our proposed models, we still face the over-fitting problem in our models. Thus, in future work, we need to utilize other types of regularization techniques with a large dataset. If we have higher quality datasets, including the features of a car (make, model and the year of manufacture), location information, type of damaged part and repair cost, we can predict the cost of a car damaged part to be more reliable and accurate.

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