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# Car Damage Identification and Categorization Using Various Transfer Learning Models

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***Abstract*—Cars play a critical role in today's modern world, and the ability to automatically classify car damages is of specific importance to the auto insurance industry. On a daily basis, car insurance companies cope with car inspection and testing. These inspections are labour-intensive, time-consuming, and sometimes inaccurate processes. Clients and insurance firms alike face costs and discomforts as a result of certain processes. Term strategy to assist, boost, or improve such strict monitoring processes may be feasible with current technology, even if entire modification is still a long way off. This research work analyzes the problem of automatic car damage detection and classification – this is an issue of importance to insurance companies in handling auto insurance claims quickly. In the classification of images, object recognition and image segmentation, developments in computer vision algorithms that employ deep learning have generated promising results. Convolutional Neural Networks (CNN) can be used for detection, analysis and estimation of various types of damage in different parts of the car. This research work has used the transfer learning-based models, InceptionV3, Xception, VGG16, VGG19, ResNet50, and MobileNet in the Kera's library to train our model to predict the damage and to compare the efficacy of these models. The proposed dataset is trained with these pre-trained models in order to obtain the maximum accuracy and speed with negligible loss so that the model could be employed in real-life to predict the claim. Our analysis indicates that MobileNet is more accurate and the training speed is also less when compared to other models. An accuracy of 97.28% in predicting damage and classifying it into different types was achieved – this is substantially better than results achieved in the past in a similar test set.**

***Index Terms*—Car Damage Identification and Categorization, Convolutional Neural Networks (CNNs), Transfer Learning**

## I. Introduction

Insurance is a very old industry and it has been quite resistant to change until recently. Manual validation of large-scale claims is not sufficiently quick in meeting dealing with large numbers of insurance claims. Claim amounts are determined by the type of damage and the affected part of the vehicle and an automated car insurance claim processing system - that efficiently detects and estimates damages - could be of great help. Automatic damage assessment employing analysis of images has proved to be fast and efficient, and will improve further as more and more data is collected. Deep learning enables us to automatically detect scratches, teeth, rust, and breakages, to determine the affected part of the vehicle and to quantify the severity of the damage. After processing, reports can be generated with a list of damages and an estimate of the cost of repair.

Ability to detect damages in dataset taken cars is a subset of image classification because, at its most fundamental level, identifying claims in images entails categorising an image into a particular type as well as collection of classes. There has been a great deal of research on image classification, but there haven't been many works on car visual damage detection. Nonetheless, and be capable of detecting car damage automatically is a research topic with numerous practical uses. Automobile insurance companies deal with car accidents on a daily basis. Cars are frequently required to be serviced for damage, which is problematic for clients as well as extremely expensive for companies. As a result, it's critical to be able to automate car damage detection, making it easy for customers and affordable.

Sophisticated computer vision algorithms that use deep learning have yielded interesting results in image classification, object detection, and image segmentation. Reference [1] applies CNNs for classification/detection of vehicle damages. They focus on 7 frequently reported broad types of car damage - broken, scratched, bumper tooth, door tooth, broken head lamp, cracked glass, and damaged tail lamps. It began with the fundamental CNN model, pre-training CNN using an auto-encoder accompanied by upgrading image-classification models that have been given pre-training upon this dataset of Image Net. They have used ResNet50 pre-trained on the dataset of ImageNet. In order to enhance accuracy, they use an 'architectural' pipeline - it extracts the damaged vehicle part from the image; this damage information is further passed to a trained classifier network.

The proposed research work has studied deep learning-based algorithms, InceptionV3, VGG16, VGG19, ResNet50, MobileNet and Xception for dam detection and their evaluation from real-world datasets. Algorithms identify the damaged part of the car and estimate its extent. Initially, this research work has examined the impact of domain-specific pre-trained CNN models – these have been given training on an ImageNet dataset – and then fine tuning (this is necessitated by the fine-granularity of some categories) in order to perform our particular tasks. Then, transfer learning has been performed in all the pre- trained six models and utilizes some methods with a view to improve the accuracy. After implementation and analysis, it has been observed that, the performance of MobileNet is better than the other models in both speed of processing as well as efficiency in classifying damages accurately.

## II. Literature Review

There are many studies conducted for the car damage detection. Majority among them are using one of these pre- trained models for feature extraction and classification. Reference [1] develops and implements a car damage classification/detection pipeline. They conceived and built a classification / detection pipeline for automotive damage. The state-of- the-art YOLO object detector used to identify the region being damaged to distinguish the area with a CNN model qualified for the area being damaged. They research the results of pre- training to prove that transfer learning performs better than fine tuning. For a transfer and ensemble learning combination, they reach 89.5% accuracy. [2] focuses on the problem of classifying car damage. They worked with various techniques based on deep learning like training CNN from random initialization, pre-training based on Convolution Auto-encoder, followed by supervised fine tuning and transfer learning. They used models that had been pre-trained on a huge and varied dataset to prevent overfitting and discover so much basic elements due to the limitations of our dataset. They used a state-of-the-art YOLO object detection model to recognise the defect area, gaining a highest possible map ranking of 77.78 on the carried testing dataset. They also develop a pipeline which always integrates the classification and recognition tasks to provide a more correct assessment of vehicle injury. [3] deals with segmentation models such as the R-CNN mask, PANet, and a VGG16 network based on transfer learning to perform various tasks of localizing and detecting different groups of parts and damage found in the vehicle. They suggest an end- to-end framework to optimise both the firm and the client's processes. This system includes images of the wrecked car as input to provide relevant information such as the damaged parts and an evaluate of the scale of destruction to each part. This can then be used to determine the cost of maintenance, which will be used to determine the insurance payout portion. They already claimed that the proposed solution offers better map rankings for section and damage translation. [4] applies Convolutional Neural Networks (CNNs) to damaged car images to assess the extent of damage - they use transfer learning to evaluate the merits of object recognition models that are available. [5] applies to real world datasets deep learning-based algorithms, VGG16 and VGG19, to car damage detection and evaluation. They investigate the impact of domain-specific pre-trained CNN models trained on the ImageNet dataset and fine-tuned in this paper. The researchers then use transfer learning to improve the accuracy of pre- trained VGG models, as well as other techniques. They use a blend of transfer learning and L2 regularisation to attain accurateness in damaged detection, damage localization, and damage severity. Their study indicates that VGG19 is better than VGG16 with an accuracy of 95.22%. Reference [6] uses convolutional neural networks for identification whether a car image actually shows damage. They demonstrated that their transfer learning VGG16 approach has the potential to deliver excellent results when the dataset is larger and of higher quality. They correctly classified the type, location, and size of the damage with 75.1 percent,68.7%, and 54.2 percent accuracy, respectively.

## III. Proposed System

### A. Dataset

This research work has used a car damage dataset acquired from one of the GitHub Car Damage Detective Projects-Assessing Car Damage with Convolution Neural Networks and also utilizes the keywords "bumper dent", "door dent", "glass shatter" etc. from Google search engine. The entire dataset is used for two purposes: (1) damage detection training and evaluation, (2) classification of damage. We divided our dataset into two train and test categories. Then we manually sorted and classified images into 7 forms of damage commonly seen, such as bumper dent, glass break, scratch, door dent, damaged front, damaged headlight and damaged tail light. We also collected images belonging to Normal class, that is, no damage class and smashed/crashed class for fully damaged cars.


Fig. 1. Sample images for car damage types. Rows from top to bottom indicates damage types Crashed, Bumper dent, Glass shatter, Scratch, Door dent, Front damage, Headlight damage, Tail-lamp damage

### B. Data Augmentation

Training our model with small datasets causes over-fitting, so data augmentation was applied in order to increase the dataset size to address this problem and strengthen our model. By applying image transformation methods such as rotation-range of 10 degrees, shear-range of0.15, zoom-range of0.1, horizontal-flip and height and width range change of 0.1 each and also channel-shift-range of 10 degrees, we enlarged the dataset. These techniques have been used to obtain various perspectives of the images and thus enable us to develop a model that can be better generalized.

### C. Data Augmentation

In the sense of car damage recognition, being ignorant of any past implementations of ConvNets, it was difficult to predict a priori how far we could get within this analysis. Therefore, we decided to divide the process of damage classification into several steps so that as we advance, we can start with a reasonably easy task and increase complexity. That is, we will first establish a method to classify whether or not a given image contains a car. After that, we proceed to our key task of classifying whether or not a car is damaged. Since the damage can look very different depending on the type, location and intensity of the damage, we expect this task to become more challenging than the first. We will already be very satisfied if we can do comparatively well on this mission. In the end, in order to get an idea of how complexity increases here in respect to our main objective we will also do a few experiments to identify, localize and evaluate damage.

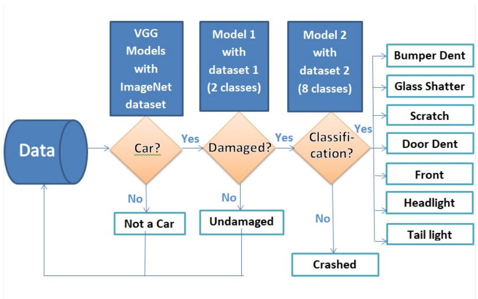


Fig. 2. A flow diagram of the evaluation of car damage

### D. Damage Detection

The damages detected can be divided into classes using the dataset used only for training . For object detection, we used the YOLO v4 framework, which uses convolutional neural networks to train the model right out of the box. We need an image dataset that is labelled or annotated in order to construct and train any object recognition or classification model, whether using a standalone convolutional neural network or the YOLO v4 system. As a consequence, we'll need a marked image dataset to construct a custom object detection model to classify the car's losses.

- YOLOv4 Object Detection
  It's a cutting-edge framework for real-time object detection. To detect objects in images or videos, it employs a Convolutional Neural Network. YOLO V4 is a faster, more precise version that can process any video at 65 frames per second. The YOLO system excels at identifying several objects in an image or video, making it capable of not only forecasting various classes in an image but it also their exact position.
- Image Labeling/Annotation
  Drawing bounding boxes around various items in a given image is known as image tagging or annotation. One of the various Annotation methods is the Bounding Box labelling method. In this study, we used a method called label picture, which is very easy to use and is either free or open source, and it helps us to build bounding boxes. We save our own images in Yolo format with this method. We don't have to modify any images in the dataset while we use this method, and we can transcribe images of any scale. During preparation, Yolo takes care of image size.

### E. Transfer Learning

Transfer learning enables utilization of an already extant model, trained on a vast dataset. This makesthe training of new deep learning models more economical and we are guaranteed consistency because the datasets have been vetted. Convolutional Neural Networks have shown greater accuracy in classifying images and have surmounted most computer vision challenges.

We used the following pre transfer learning models to train our dataset to evaluate the most precise model with less time to predict the damage.

- Inception V3
  The third version in a sequence of Deep Learning Convolutional Architectures is Google's Inception V3. It is a large-scale method for image recognition which can be used for problems with transfer learning. It is a network of 48 layers with an input size of 299x299. TensorFlow and Keras can be used to implement it quickly.
- VGG16 and VGG19
  This is a 16-and 19-layer Keras network model with an input size of 224x224.It was launched by the Visual Geometry Group of the University of Oxford. The two models are compatible with Keras and Caffe toolbox. The VGG16 and VGG19 combination product is known as VGGNet.
- Xception
  This translates into "Extreme Inception." This is an extension of the initial model proposed by the developer of Keras and has replaced the usual modules with depthwise separable convolution modules like MobileNet. It only works with the TensorFlow system.
- MobileNet
  This model, suggested by Google, is only compatible with the framework for TensorFlow. For smartphone focused and embedded applications, it is ideally suited. It uses separable convolutions that are depth wise. Its key benefit is that the number of parameters in the neural network is minimized.
- ResNet50
  Another pre-trained model particularly useful in Residual Neural Networks is the ResNet architecture. The variant of 50 layers is ResNet50. The network learns the residuals of the input layer in the residual learning. ResNet50 is a smaller variant of ResNet152 and is widely used as a transfer learning starting point.

For prediction, feature extraction and fine-tuning, we use deep learning models along with pre-trained weights in Kera's applications.

### F. Feature Extraction

Feature extraction is a dimensionality reduction process in which an initial collection of raw data is reduced for processing to more manageable classes. It is the name for methods that select and integrate variables into characteristics, essentially minimizing the amount of data that needs to be processed while still representing the original data set accurately and fully. For a given analysis, feature extraction may also decrease the amount of redundant data.

### G. Fine-tuning

Data from an existing neural network is used for initialization of the training process and fine-tuning of the deep learning algorithms increase the accuracy of a new network model. The fine-tuning slashes the time needed for a new deep learning algorithm to be programmed and processed because it has included crucial knowledge from a pre-existing deep learning algorithm.

## IV. Experiment and Result Analysis

In order to achieve a better result in identifying and classifying the damage caused by the damaged car images, our aim was to compare the transfer learning models available in the Keras application. In the Keras, we have several models available from which we decided to experiment with InceptionV3, ResNet50, VGG16, VGG19, Xception and MobileNet. With each of these pre-trained models, we have trained our dataset and using the model we have defined if the car is damaged and if it is damaged, which category includes it.

| Model | Training Loss | Train Accuracy | Validation Loss | Validation Accuracy |
|---|---|---|---|---|
| Xception | 0.0584 | 97.94 | 0.1628 | 94.57 |
| VGG16 | 0.0290 | 99.28 | 0.3019 | 91.30 |
| VGG19 | 0.0573 | 99.03 | 0.2196 | 92.93 |
| ResNet50 | 0.0217 | 99.31 | 0.1468 | 95.11 |
| InceptionV3 | 0.1032 | 95.51 | 0.1662 | 94.02 |
| MobileNet | 0.0126 | 99.74 | 0.1640 | 97.28 |

Fig. 3. Different pre-trained modelts – their Test Validation accuracy

The various damaged sections of the car were easily detected and tagged using the collected dataset and YOLOv4 object detection. The most challenging task was model training, which necessitated the use of a GPU, which directed us to Google Colab for our study. After labeling the images, we came up with eight categories of damage, ranging from minor to severe. Then, using the pre-trained model, we attempted to accurately work out the transfer learning model. The graphs represent the effects of different levels of precision and their differences.

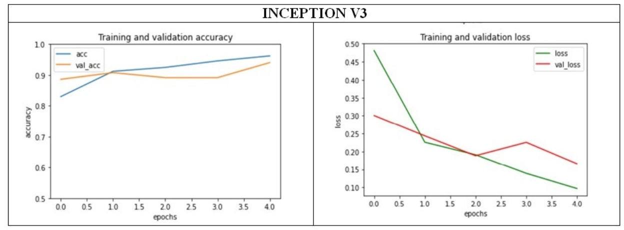


Fig. 4. Training and validation accuracy and loss plots of Inception V3

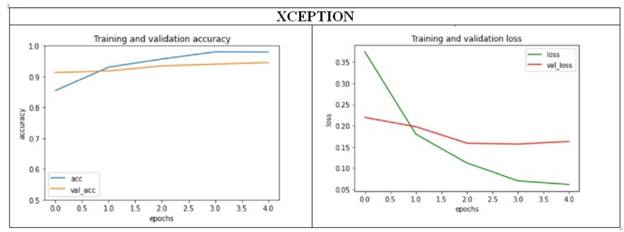


Fig. 5. Training and validation accuracy and loss plots of Xception

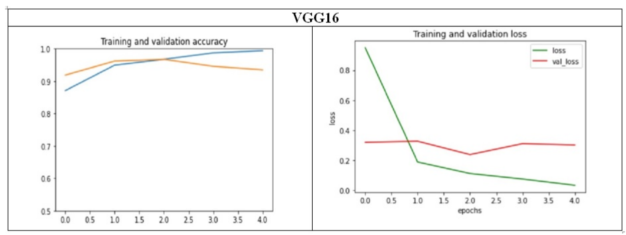


Fig. 6. Training and validation accuracy and loss plots of VGG16

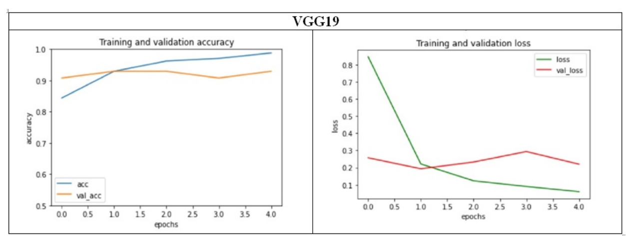


Fig. 7. Training and validation accuracy and loss plots of VGG19

Through this comparison of transfer learning models MobileNet V2 achieved the highest accuracy and took less amount of training time. It almost identified and categorized images with 97.28% accuracy. The training and validation loss were also less for MobileNet when compared to ResNet50 and VGG19.

## V. Conclusion

Images and their storing are critical components of our understanding of reality. As a result, we are still unable to

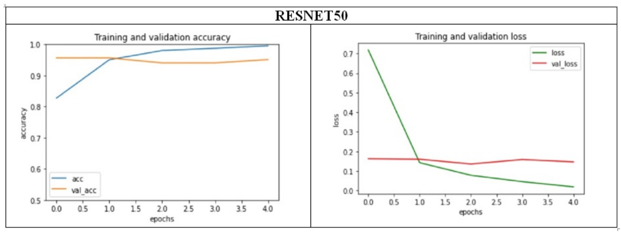


Fig. 8. Training and validation accuracy and loss plots of ResNet50

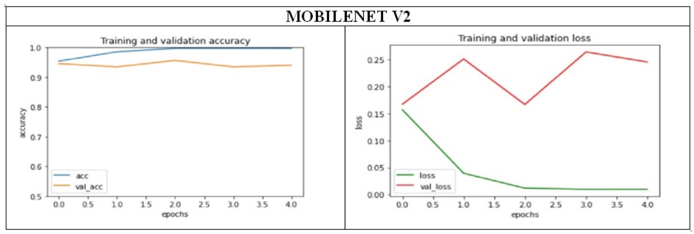


Fig. 9. Training and validation accuracy and loss plots of MobileNet V2

recognize and monitor the image's concept when viewing unfinished images. This is no use to us, and therefore today's machine learning technologies are capable of maintaining lost or damaged parts of such image data, allowing us to understand the context and accurately evaluate the photos captured. With the advent of Transfer Learning, the exponential advances in Computer Vision, and by extension, image recognition, have accelerated ever further. As the insurance market becomes more competitive, processing of damage claims using images has gained relevance, particularly small but more regular claims. The use of Convolutional Neural Networks (CNNs) to decide the degree of damage using images is investigated in this study. We looked at the benefits of a system using transfer learning.

In this paper, we compare the accuracy and speed of identifying and categorizing damaged car images using different transfer learning models. For this, we've collected images from both the Google search and the GitHub repository. Using transfer learning models, we train our dataset to predict damage. We find that MobileNet provides better results compared to other models. Compared to previous studies, we have obtained a better outcome, using this model we can predict the damage and process claims more quickly and accurately. We assume that training the model with more real-time images would allow the model to learn more, and for real-life scenarios, near 100% accuracy can be achieved.

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