DEEP LEARNING BASED CAR DAMAGE CLASSIFICATION

Kalpesh Patil   Mandar Kulkarni   Shirish Karande

TCS Innovation Labs, Pune, India

ABSTRACT

Image based vehicle insurance processing is an important area with large scope for automation. In this paper we consider the problem of car damage classification, where some of the categories can be fine-granular. We explore deep learning based techniques for this purpose. Initially, we try directly training a CNN. However, due to small set of labeled data, it does not work well. Then, we explore the effect of domain-specific pre-training followed by fine-tuning. Finally, we experiment with transfer learning and ensemble learning. Experimental results show that transfer learning works better than domain specific fine-tuning. We achieve accuracy of 89.5% with combination of transfer and ensemble learning.

***Index Terms*—** Car damage classification, CNN, transfer learning, convolutional auto-encoders

1. INTRODUCTION

Today, in the car insurance industry, a lot of money is wasted due to claims leakage [1][2]. Claims leakage / Underwriting leakage is defined as the difference between the actual claim payment made and the amount that should have been paid if all industry leading practices were applied. Visual inspection and validation have been used to reduce such effects. However, they introduce delays in the claim processing. There has been efforts by to few start-ups to mitigate claim processing time [3][4]. An automated system for the car insurance claim processing is a need of an hour.

In this paper, we employ Convolutional Neural Network (CNN) based methods for classification of car damage types. Specifically, we consider common damage types such as bumper dent, door dent, glass shatter, head lamp broken, tail lamp broken, scratch and smash. To best of our knowledge, there is no publicly available dataset for car damage classification. Therefore, we created our own dataset by collecting images from web and manually annotating them. The classification task is challenging due to factors such as large inter-class similarity, barely visible damages. We experimented with many techniques such as directly training a CNN, pre-training a CNN using auto-encoder followed by fine-tuning, using transfer learning from large CNNs trained on Imagenet and building an ensemble classifier on top of the set of pre-trained classifiers. We observe that transfer learning combined with ensemble learning works the best. We also device a method to localize a particular damage type. Experimental results validate the effectiveness of our proposed solution.

2. RELATED WORKS

Deep learning has shown promising results in machine learning applications. In particular, CNNs perform well for computer vision tasks such as visual object recognition and detection [5] [6]. Application of to structural damage assessment has been studied in [7]. Authors proposes deep learning based method for Structural Health Monitoring (SHM) to characterize the damage in the form of cracks on a composite material. Unsupervised representation is employed and results have been shown on a wide range of loading conditions with limited number of labeled training image data.

Most of the supervised methods need large amount of labeled data and compute resources. Unsupervised pre-training techniques such as Autoencoders [8] proved to improve the generalization performance of the classifier in case of small number of labeled samples. For images, Convolutional AutoEncoders (CAE) [9] have shown promising results.

A very well known technique which has worked effectively in case of small labeled data is transfer learning [10] [11]. A network which is trained on a source task is used as a feature extractor for target task. There are many CNN models trained on Imagenet which are available publicly such as VGG-16 [12], VGG-19 [12], Alexnet [6], Inception [13], Cars [14], Resnet [15]. Transferable feature representation learned by CNN minimizes the effect of over-fitting in case of small labeled set [10].

Traditional machine learning techniques have also been experimented for automated damage assessment. Jaywardena et al [16] proposed a method for vehicle scratch damage detection by registering 3D CAD model of undamaged vehicle (ground truth) on the image of the damaged vehicle. There has been attempts to analyze damage in geographical regions using satellite images [17][18][19]. To best of our knowledge, deep learning based techniques have not been employed for automated car damage classification, especially for the fine-granular classification.

Classes	Train size	Aug. train size	Test size
Bumper Dent	186	1116	49
Door dent	155	930	39
Glass shatter	215	1290	54
Head-lamp broken	197	1182	49
Tail-lamp broken	79	474	21
Scratch	186	1116	46
Smash	182	1092	45
No damage	1271	7626	318

Table 1. Description of our dataset.

3. DATASET DESCRIPTION

Since there is no publicly available dataset for car damage classification, we created our own dataset consisting of images belonging to different types of car damages. We consider seven commonly observed types of damages such as bumper dent, door dent, glass shatter, head lamp broken, tail lamp broken, scratch and smash. In addition, we also collect images which belong to a no damage class. The images were collected from web and were manually annotated. Table 1 shows the description of the dataset.

3.1. Data augmentation

It is known that an augmentation of the dataset with affine transformed images improves the generalization performance of the classifier. Hence, we synthetically enlarged the dataset approx. five times by appending it with random rotations (between -20 to 20 degrees) and horizontal flip transformations.

For the classification experiments, the dataset was randomly split into 80%-20% where 80% was used for training and 20% was used for testing. Table 1 describes the size of our train and test sets.

Fig. 1 shows sample images for each class. Note that the classification task is non-trivial due to large inter-class similarity. Especially, since the damage does not cover the entire image (but a small section of it), it renders classification task even more difficult.

4. TRAINING A CNN

In the first set of experiments, we trained a CNN starting with the random initialization. Our CNN architecture consist of 10 layers: Conv1-Pool1-Conv2-Pool2-Conv3-Pool3-Conv4-Pool4-FC-Softmax where Conv, Pool, FC and Softmax denotes convolution layer, pooling layer, fully connected layer and a softmax layer respectively. Each convolutional layer has 16 filters of size 5×5. A RELU non-linearity is used for every convolutional layer. The total number of weights in the network are approx. 423K. Dropout was added to each layer which is known to improve generalization performance. We trained a CNN on original as well as on the augmented dataset.

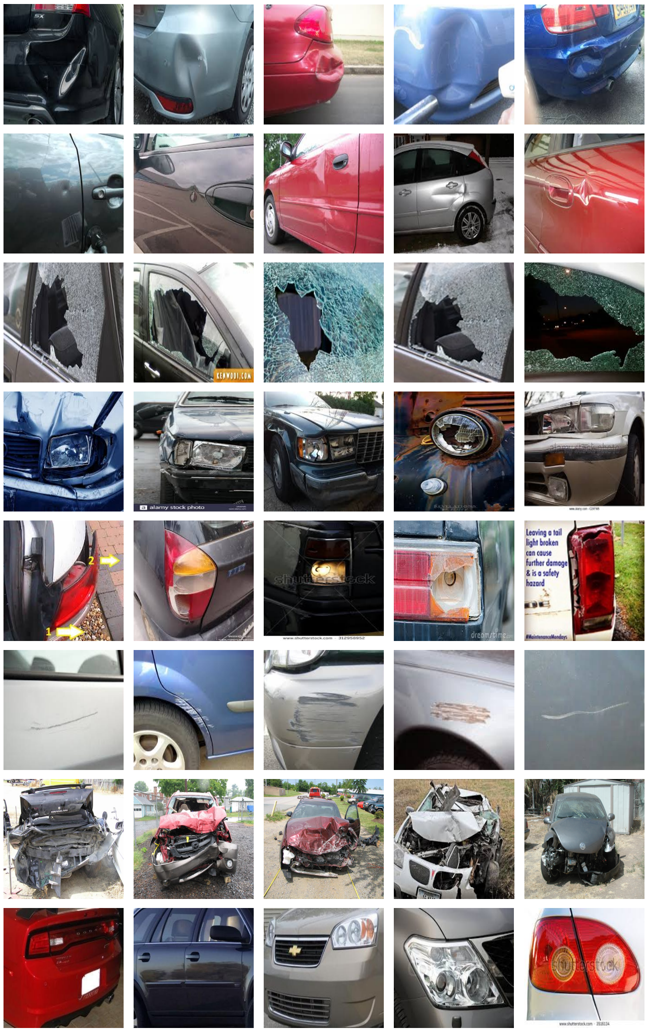

Leaving a tail light broken can cause further damage & is a safety hazard

Fig. 1. Sample images for car damage types. Rows from top to bottom indicates damage types Bumper dent, Door dent, Glass shatter, Head-lamp broken, Tail-lamp broken, Scratch, Smash, No damage

Table 2 shows the result of the CNN training from random initialization. It can be seen that the data augmentation indeed helps to improve the generalization and provides better performance that just original dataset.

We are aware that the data used for training the CNN (even after augmentation) is quite less compared to the number of parameters and it may result in overfitting. However, we performed this experiment to set a benchmark for rest of the experiments.

4.1. Convolutional Autoencoder

Unsupervised pre-training is a well known technique in the cases where training data is scarce [8]. The primary objective of an unsupervised learning methods is to extract useful features from the set of un-labeled data by learning the input data distribution. They detect and remove input redundancies,

Method	Without Augmentation			With Augmentation		
	Acc	Prec	Recall	Acc	Prec	Recall
CNN	71.33	63.27	52.5	72 46	64 03	61 01
AE-CNN	73.43	67.21	55.32	72 30	63 69	59 48

Table 2. Test accuracy with CNN training and (CAE + fine-tuning).

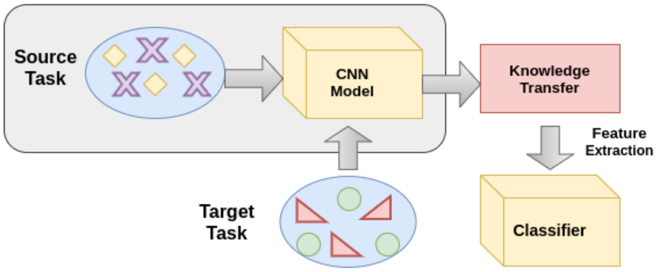


Fig. 2. Transfer learning setup used in our experiments. Source task is Imagenet classification while Target task is car damage classification.

and usually only preserve essential aspects of the data which tend to assist the classification task. A fully connected auto-encoders, especially in case of images, leads to large number of trainable parameters. Convolutional AutoEncoders (CAE) provides a better alternative because of less number of parameters due to sparse connections and weight sharing [9]. CAE is trained in the layer wise manner where unsupervised layers can be stacked on top of each other to build the hierarchy. Each layer is trained independently of others where output of a previous layer acts as an input for the subsequent layer. Finally, the complete set of layers are stacked and fine-tuned by back-propagation using cross-entropy objective function . Unsupervised initialization tend to avoid local minima and increase the networks performance stability.

For training a CAE, we used unlabeled images from Stanford car dataset[20]. The size of the dataset was synthetically increased by adding rotation and flip transformations. Since the target images belong to car damage type, we expect that learning the car specific features should help the classification task. The layers are then fine tuned using a smaller learning rate as compared to the training. The row, AE-CNN, in Table 2 shows the result with autoencoder pre-training. It can be seen that an autoencoder pre-training does help the classification task. The similar experiment was performed using augmented car damage images and there as well we see improvement in the test accuracy as compared to no pre-training.

5. TRANSFER LEARNING

Transfer learning has shown promising results in case of small labeled data [10] [11]. In the transfer learning setting, a knowledge from the source task is transferred to the target task. The intuition is that some knowledge is specific for individual domains, while some knowledge may be common between different domains which may help to improve performance for the target domain / task. However, in the cases where the source domain and target domain are not related to each other, brute-force transfer may be unsuccessful and can lead to the degraded performance. In our case, we use the CNN models which are trained on the Imagenet dataset. Since the Imagenet dataset contains car as a object, we expect the transfer to be useful which we extensively validate by experimenting with multiple pre-trained models. Fig. 2 shows the transfer learning experiment setup we use. Since we use the pre-trained models which are trained for Imagenet, the Source task is the Imagenet classification. A pre-trained model is used as a feature extractor for Target task i.e. car damage images. Table 3 indicates the details of pre-trained networks used, their parameters and feature dimension.

We input car damage images to each network and extract feature vectors. We then train a linear classifier on these features. We experimented with two linear classifiers, a linear SVM and a Softmax. In case of linear SVM, the penalty parameter C was set to 1 for all experiments. In case of the Softmax classifier, we use Adadelta optimization scheme and cross entropy loss. We train the classifier for 100 epochs and chose the model with best classification performance. Also, since data augmentation helps the classifier in generalization, we train linear classifiers on augmented feature set as well. Table 3 indicates the accuracy, precision and recall for these pre-trained models. It can be seen that the Resnet performs the best among all the pre-trained models. The data augmentation boost the performance in most of the cases. During the experimentation, it was observed that the Softmax classifier works better than linear SVM and it is faster to train.

Surprisingly, the pre-trained model of GoogleNet fine-tuned using car dataset, performed the worst. It indicates that only car object based features may not be effective for classifying damages. The poor performance of autoencoder based approach may as well be due to this effect. It underlines the effectiveness of feature representation learned from large and diverse input data distributions.

We observe that the major factor in the mis-classifications is the ambiguty between damage and 'no damage' class. This is not surprising because, the damage of a part usually occupies a very small portion of the image and renders identification difficult even for the human observer. Fig. 3 shows few examples of test images of damage which are mis-classified as no damage.

5.1. Ensemble method

To further improve the accuracy, we performed an experiment with ensemble of the pre-trained classifiers. For each training image, class probability predictions are obtained from multiple pre-trained networks. The weighted average of class pos-

Model	Params	Dim	Without Augmentation						With Augmentation					
			Linear SVM			Softmax			Linear SVM			Softmax		
			Acc	Prec	Recall	Acc	Prec	Recall	Acc	Prec	Recall	Acc	Prec	Recall
Cars [14]	6.8M	1024	57.33	47 24	56 46	60 38	47 23	32 39	58 45	48.58	56 97	64 25	52 73	39 16
Inception [13]	5M.	2048	68.12	57 46	55 53	71 82	61 75	56 71	68 60	58.50	54 44	71 50	69 47	52 81
Alexnet	60 M.	4096	70.85	61 68	64 60	70 85	61 42	58 09	73 26	62.83	61 72	73 91	66 83	63 36
VGG-19 [12]	144M.	4096	82.77	78 62	73 16	84 22	80 76	73 60	82 29	76.30	70 60	83 90	80 74	73 41
VGG-16 [12]	138M.	4096	83.74	77 79	75 41	84 86	81 91	73 56	82 93	78.62	71 96	82 72	78 99	70 30
Resnet [15]	25.6M.	2048	86.31	80 87	78 30	**88.24**	84 38	81 10	87 92	84.40	78 94	87 92	83 68	79 47

Table 3. Classification performance for transfer learning. Comparison of test accuracies with different pre-trained CNN models. Note that Resnet performs the best.

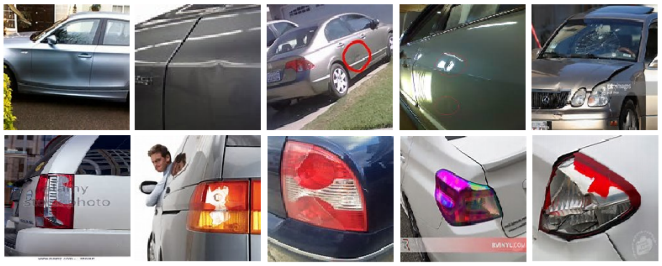


Fig. 3. Examples of test images mis-classified as ’no damage’ class with Resnet. Note that the damaged portion is barely visible.

teriors is then used to obtain the final decision class. The weights to be used for the linear combination are learned by solving following least squares optimization

$$C = \frac{1}{N}\sum_{i=1}^{N} ||P_i w - g_i||_2^2 \qquad (1)$$

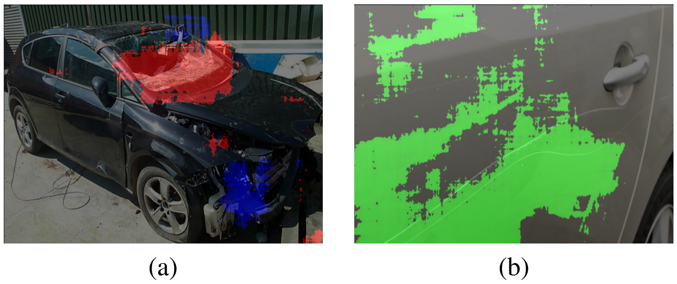
Here, $P_i \in R^{m \times n}$ indicates the matrix of posteriors for the i^{th} training point, n indicates the number of pre-trained models used and m indicates the number of classes. w indicates the weight for each posterior and g_i indicates the (one-hot encoded) ground truth label for the i^{th} training data point. N is the total number of training points. The optimization is solved using the gradient descent where learning rate is adjusted which yields the best test performance. Since Softmax performed the best, we use it for obtaining class posteriors. Table 5.1 shows the result of the experiment. It can be seen that the ensemble (Top-3 and All) works better than the individual classifiers, as expected.

Ensemble	Without Augmentation			With Augmentation		
	Acc	Prec	Recall	Acc	Prec	Recall
Top-3	89.37	88.05	80.91	88 40	85 88	78 91
All	**89.53**	88.16	80.92	88 24	86 45	78 41

Table 4. Classification performance for Ensemble technique using Top-3 and All models

5.2. Damage localization

With the same approach, we can even localize the damaged portion. For each pixel in the test image, we crop a region of size 100 × 100 around it, resize it to 224 × 224 and predict the class posteriors. A damage is considered to be detected if the probability value is above certain threshold. Fig. 4 shows the localization performance for damage types such as glass shatter, smash and scratch with Resnet classifier and probability threshold of 0.9.



(a)

(b)

Fig. 4. Damage localization. (a) Glass shatter (red) and Smash (blue), (b) Scratch (green). Note that our approach is able to localize damage correctly.

6. CONCLUSION

In this paper, we proposed a deep learning based solution for car damage classification. Since there was no publicly available dataset, we created a new dataset by collecting images from web and manually annotating them. We experimented with multiple deep learning based techniques such as training CNNs from random initialization, Convolution Autoencoder based pre-training followed by supervised fine tuning and transfer learning. We observed that the transfer learning performed the best. We also note that only car specific features may not be effective for damage classification. It thus underlines the superiority of feature representation learned from the large training set.

7. REFERENCES

[1] "http://www.ey.com/publication/vwluassets/ey-does-your-firm-need-a-claims-leakage-study/ey-does-your-firm-need-a-claims-leakage-study.pdf," .

[2] "https://www.irmi.com/articles/expert-commentary/controlling-claims-leakage-through-technology," .

[3] "http://www.sightcall.com/insurance-visual-claims-fight-fraud-and-reduce-costs/," .

[4] "http://www.tractable.io/," .

[5] Bengio Y. Lecun Y., Bottou L. and Haffner P., "Gradient-based learning applied to document recognition," *Proceedings of IEEE*, vol. 86, no. 11, 1998.

[6] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in Neural Information Processing Systems 25*, F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, Eds., pp. 1097–1105. Curran Associates, Inc., 2012.

[7] Michael Giering Mark R. Gurvich Soumalya Sarkar, Kishore K. Reddy, "Deep learning for structural health monitoring: A damage characterization application," in *Annual Conference of the Prognostics and Health Management Society*, 2016.

[8] Dumitru Erhan, Yoshua Bengio, Aaron Courville, Pierre-Antoine Manzagol, Pascal Vincent, and Samy Bengio, "Why does unsupervised pre-training help deep learning?," *Journal of Machine Learning Research*, vol. 11, no. Feb, pp. 625–660, 2010.

[9] Jonathan Masci, Ueli Meier, Dan Cireşan, and Jürgen Schmidhuber, "Stacked convolutional auto-encoders for hierarchical feature extraction," in *International Conference on Artificial Neural Networks*. Springer, 2011, pp. 52–59.

[10] Jason Yosinski, Jeff Clune, Yoshua Bengio, and Hod Lipson, "How transferable are features in deep neural networks?," in *Advances in neural information processing systems*, 2014, pp. 3320–3328.

[11] Maxime Oquab, Leon Bottou, Ivan Laptev, and Josef Sivic, "Learning and transferring mid-level image representations using convolutional neural networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2014, pp. 1717–1724.

[12] Karen Simonyan and Andrew Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.

[13] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jonathon Shlens, and Zbigniew Wojna, "Rethinking the inception architecture for computer vision," *arXiv preprint arXiv:1512.00567*, 2015.

[14] Linjie Yang, Ping Luo, Chen Change Loy, and Xiaoou Tang, "A large-scale car dataset for fine-grained categorization and verification," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2015, pp. 3973–3981.

[15] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, "Deep residual learning for image recognition," *arXiv preprint arXiv:1512.03385*, 2015.

[16] Srimal Jayawardena et al., *Image based automatic vehicle damage detection*, Ph.D. thesis, Australian National University, 2013.

[17] F Samadzadegan and H Rastiveisi, "Automatic detection and classification of damaged buildings, using high resolution satellite imagery and vector data," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 37, pp. 415–420, 2008.

[18] K Kouchi and F Yamazaki, "Damage detection based on object-based segmentation and classification from high-resolution satellite images for the 2003 boumerdes, algeria earthquake," in *Proceedings of the 26th Asian conference on Remote Sensing, Hanoi, Vietnam*, 2005.

[19] Ellen Rathje and Melba Crawford, "Using high resolution satellite imagery to detect damage from the 2003 northern algeria earthquake," in *13th World Conference on Earthquake Engineering, August*, 2004, pp. 1–6.

[20] Jonathan Krause, Michael Stark, Jia Deng, and Li Fei-Fei, "3d object representations for fine-grained categorization," in *Proceedings of the IEEE International Conference on Computer Vision Workshops*, 2013, pp. 554–561.