

DAMAGE ASSESSMENT FOR CAR INSURANCE

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Abstract - Over the last few years, for the auto insurance claims process, improvements in the First Notice of Loss and rapidity in the investigation and evaluation of claims could drive significant values by reducing loss adjustment expense. Image based vehicle insurance processing is an important area with large scope for automation. In this report we are going to 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. Success in this will allow some cases to proceed without human surveyor, while others to proceed more efficiently, thus ultimately shortening the time between the first Notice of Loss and the final payout. In the proposed car damage classification model 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. Followed by the estimate damage cost calculation according the prediction of damaged car parts

Key Words: Car damage classification, CNN, transfer learning, convolutional auto-encoders

1. INTRODUCTION

Currently, AI is advancing at a great pace and deep learning is one of the contributors to that. It is good to understand the basics of deep learning as they are changing the world we live. Deep learning is a sub-field of machine learning dealing with algorithms inspired by the structure and function of the brain called artificial neural networks. In other words, It mirrors the functioning of our brains Deep learning algorithms are similar to how nervous system structured where each neuron connected each other and passing information. One of the differences between machine learning and deep learning model is on the feature extraction area. Feature extraction is done by human in machine learning whereas deep learning model figures

out by itself Today, in the car insurance industry, a lot of money is wasted due to claims leakage. Money lost through claims management inefficiencies that ultimately result from failures in existing processes (manual and automated). In other words, it's the difference between what you did spend and what you should have spent on a claim. The cause can be procedural, such as from inefficient claim processing or improper/errant payments, or from human error, such as poor decision-making, customer service, or even fraud. Claim Leakage is often discovered through an audit of closed claim files. CNN is used as the default model for anything to deal with images. Hence in this project, 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, headlamp broken, tail lamp broken, scratch and smash. Nowadays there are papers that have mentioned the use of Recurrent Neural Network (RNN) for the image recognition. Traditionally RNNs are being used for text and speech recognition. According to study after experimenting with many techniques such as directly training a CNN, pre-training a CNN using autoencoder followed by fine-tuning, using transfer learning from large CNN's 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.

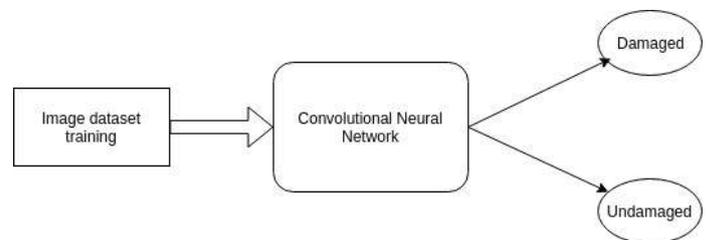


Figure 1: Basic architecture of CNN

2. LITERATURE SURVEY

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

[2] 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.

[3] 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.

[4] 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.

[5] 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.

[6] 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.

3. Proposed Work

The overall Damage Assessment for Car Insurance (DACI) can be divided in four parts:

- Collecting Datasets
- Training and Testing Of Datasets
- Backend

- **Collecting Datasets**

We have collected ten commonly observed types of damages such as Bumper, door, door glass, grille, headlamp, hood, mirror, roof, taillamp, and windshield in addition we also collected some images which does not belong to damage class, some images were collected from web and somewhere manually annotated.

- **Training and Testing of Datasets**

3000 plus images were taken for training and 200-300 for testing. 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.

- **Backend**

We created separate python programs for each of those commonly observed car parts for recognizing in image whether that car part is damaged or not, and will tell if it is not present in image.

- ❖ **Generating a CNN model**

The created python programs for each of car parts were used to train the CNN model for recognizing in image whether that car part is damaged or not, and will tell if it is not present in image. The model consist of ten 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

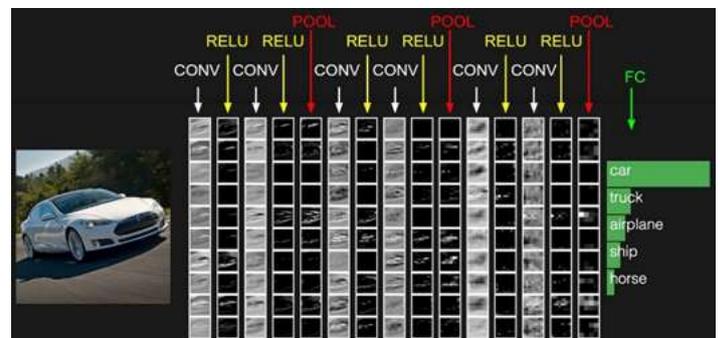


Figure 2: CNN Layers

Car image will be passed through all these 10 models one by one, and each model will give its respective output in following three classes

- Damaged part
- Undamaged part
- Missing part

4. RESULTS

User will upload a car image or images and number plate of car, and we extract car registration number in text form using Googles Tesseract OCR.

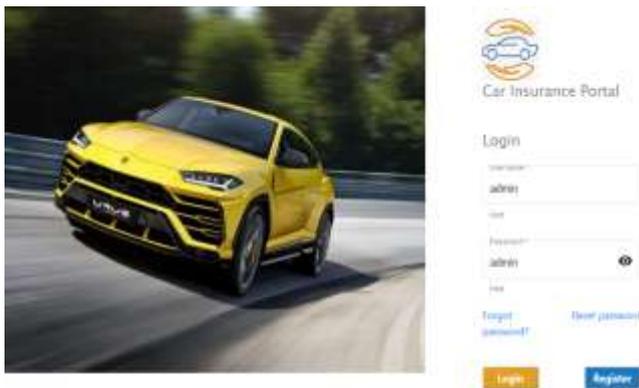


Figure 3: Registration/login page

After Login output of prediction in three classes - Damaged part, Undamaged part, Missing part

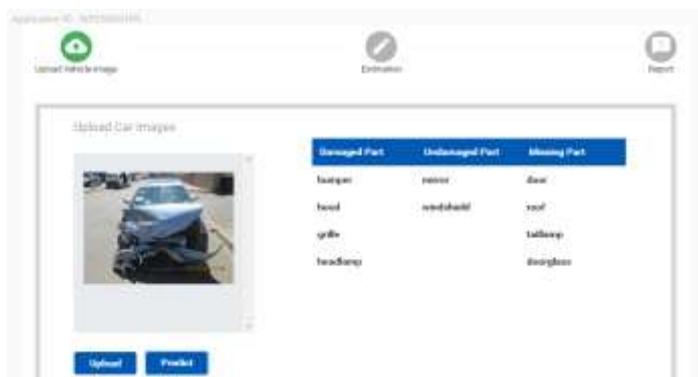


Figure 4: Classification of car parts

User will select the correct number among 3 outputs which our system generated.

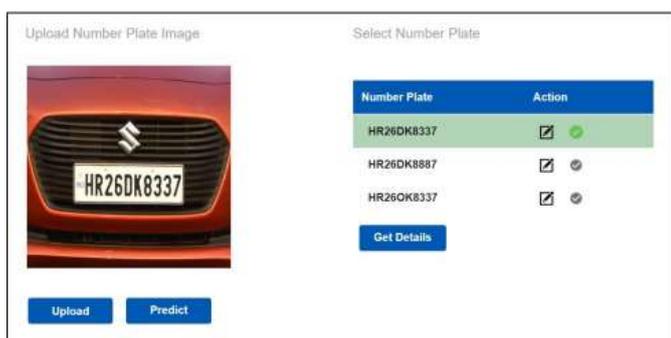


Figure 5: Number plate selection

And then This registration number will be passed to RTO, and following fields will be fetched from RTO —

| Field | Value |
|---------------------|-----------------------------|
| Maker | SUZUKI MOTORCYCLE I PVT LTD |
| Model | ACCESS 125 BSIII |
| Owner Name | MISS PRIYANKA |
| Registration Date | 06-03-2017 |
| Registration Number | MP09UE6126 |
| RTO Name | INDORE |

Figure 6: Output from RTO

We are calculating cost for the parts which are damaged. As each make and model of the car have different costs, we can use RTOs fetched information to specify make and model of the car, and fetch respective models' costs from database.

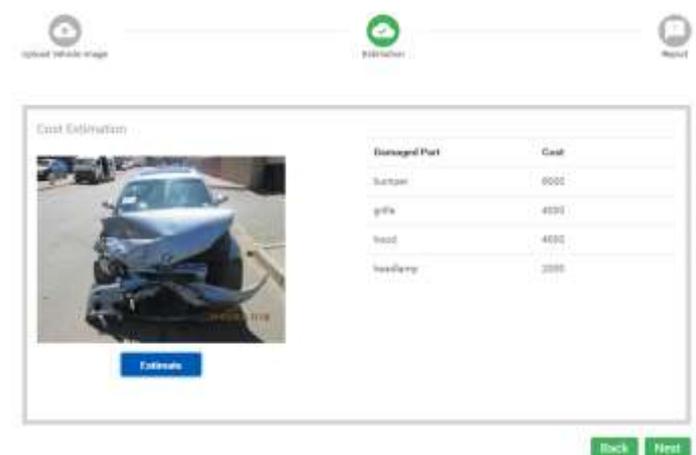


Figure 7: Cost of Damaged parts

And then report of estimation in pdf format will be generated

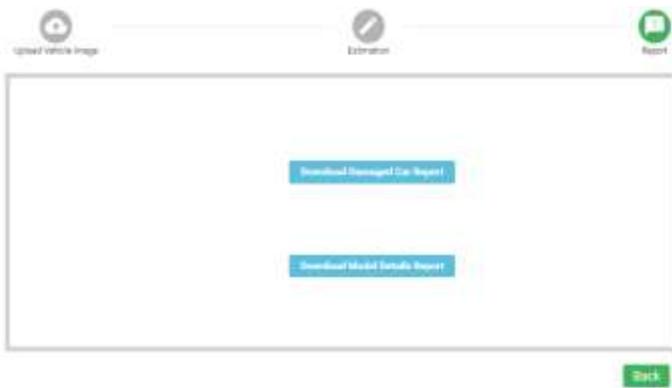


Figure 8: Downloading option for reports



Figure 9: Report of damaged car

5. CONCLUSION

This paper has generally discussed the design and implementation of damage assessment for car insurance (DACI) by developing deep learning car damage classification model on website development platform where user will upload image or images of damaged car with help of phone’s camera. then according to damage calculation, the total cost of car will be displayed in a report format. This system is tested over a wide range of images yielding high accuracy rate

6. REFERENCES

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

[2] 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.

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[5] 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.

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