

Assessing Vehicle Damage – the ML way

Whitepaper | April 2019



Deep Learning: Transforming Insurance

An AI-driven approach to Insurance Industry

What was once science fiction is fast becoming a fact of today's business world. Artificial intelligence holds vast potential for insurers interested in reinventing their business models and transforming customer experience.

Abstract

In this research, we propose to replace the traditional methods of vehicle damage inspection (for car insurance) with a Machine Learning based automated solution.

Deep Learning based models are used to recognize whether a car in a given image is damaged and its type/severity.

A promising attempt in classifying car damages into multiple classes is presented. The emphasis is on fine-tuning this model iteratively with the objective of achieving satisfactory accuracy scores.

This research open doors for future collaborations on image recognition projects in general and for the car insurance field in particular by enabling insurers to assess customer vehicle damage and expedite claims settlement.

Table of Contents

Abstract	1
Problem Statement.....	3
The Idea	3
Introduction.....	3
Solution Overview	4
Solution Details.....	5
Building the Dataset.....	5
Deep Learning Model.....	6
Implementation	7
Sample Output	7
Cost Estimator	7
An Alternate Approach	8
Business Benefits	8
Conclusion.....	8
References	8
About the Authors	Error! Bookmark not defined.

Problem Statement

Today, in the car insurance industry, a lot of money is wasted due to claims leakage. 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 and lead to manual intervention.

The Idea

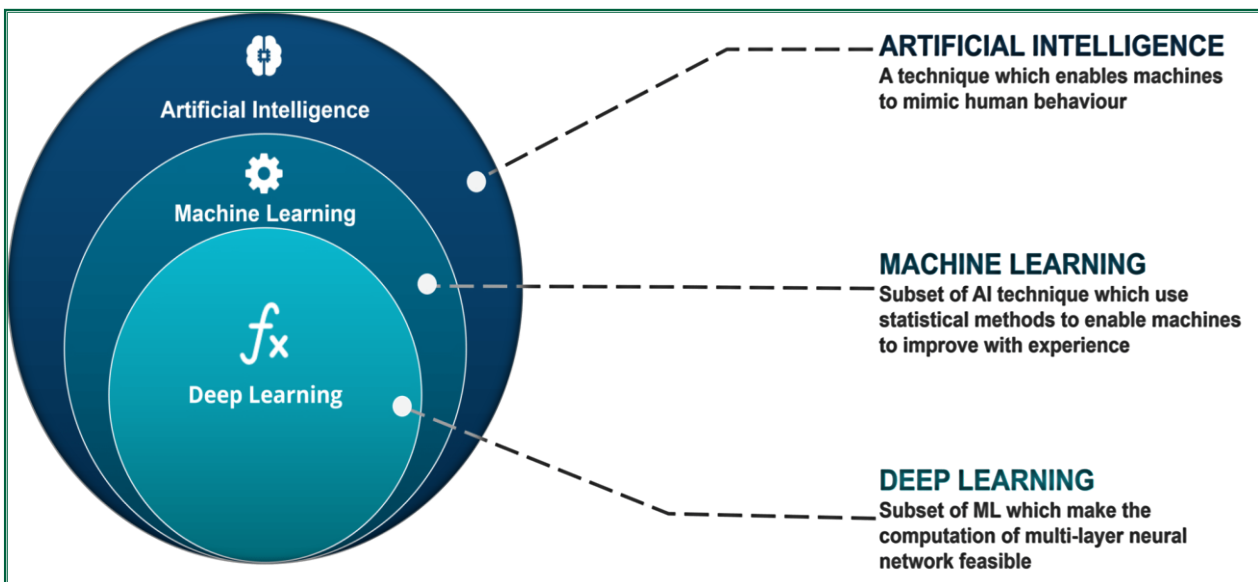
An automated system for the car insurance damage assessment is the need of the hour. In this solution, we propose a deep learning based approach to automate vehicle damage assessment thereby facilitating faster claims processing and doing away with manual inspection.

Introduction

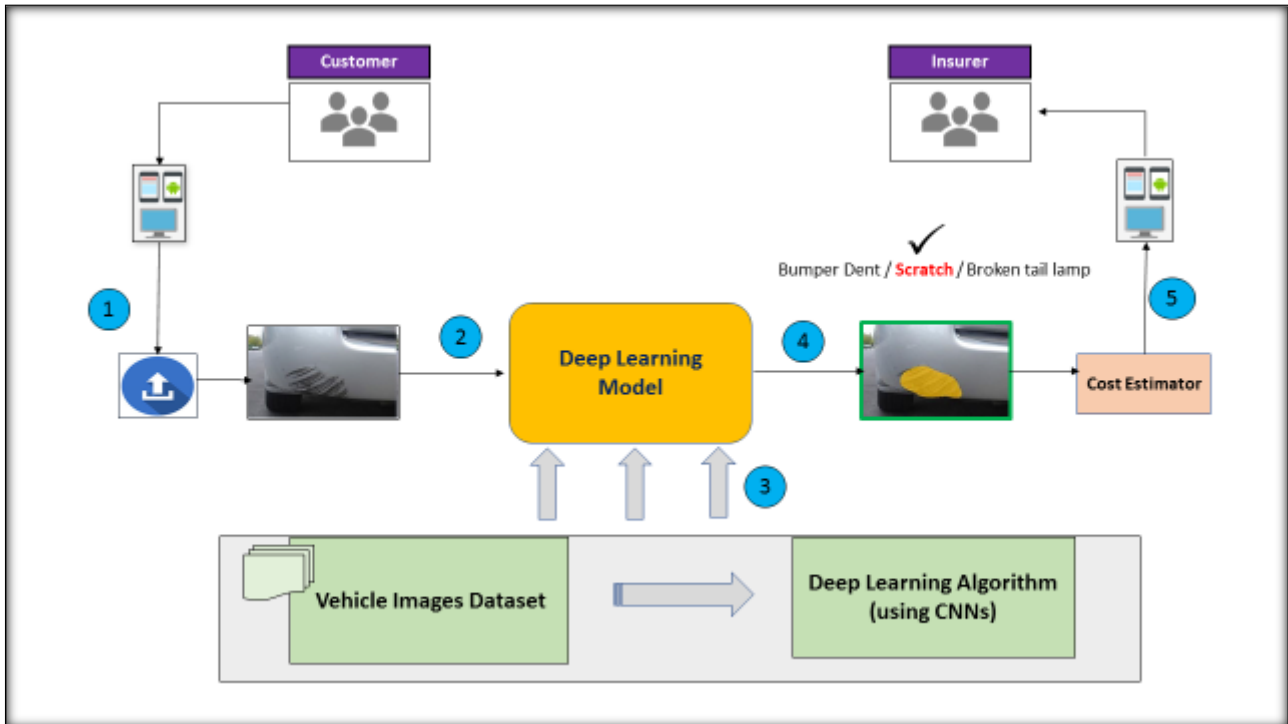
Artificial Intelligence is a technique which allows the machines to act like humans by replicating their behavior and nature. Artificial Intelligence makes it possible for the machines to learn from their experience.

Machine Learning is a major field in artificial intelligence (AI) that provides systems the ability to learn to perform tasks from experience (i.e. training data) without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it to learn for themselves.

Deep learning is a type of machine learning that deals with algorithms inspired by the structure and function of the human brain. Deep learning systems are similar to how our nervous system is structured, where neurons are connected to each other and pass impulse or information. The Figure below captures the relationship between AI, ML and DL.



Solution Overview



1. Customer uploads an image of their damaged vehicle on the web portal/mobile app.
2. An AI/deep learning-based model analyses the uploaded images and classifies them as one or more of the following types of damages:
 - Bumper dent
 - Door dent
 - Glass shatter
 - Broken head lamp
 - Broken tail lamp
 - Miscellaneous scratch
 - Smash
3. The deep learning model is built on
 - A deep learning algorithm (based on Convolutional Neural Networks)
 - A training dataset (comprising of various labelled images of damaged and undamaged vehicles).
4. The trained model in step 3 (based on past historical classification) analyzes the input images from step 2 and appropriately labels the damage.
5. Based on the damage type and severity identified above, the system generates a cost estimate of the damage (to be paid by the insurance company)

Solution Details

The solution comprises of two main components:

- Deep learning model
- Cost Estimator

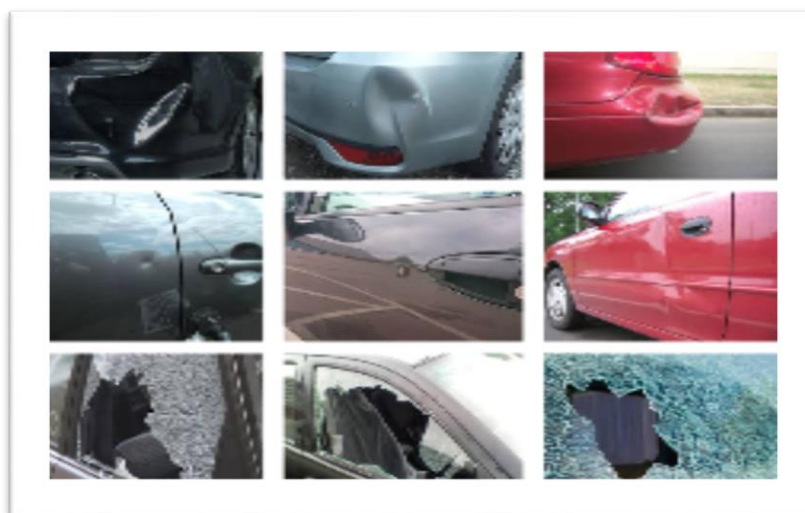
One of the important phases prior to building above two components is the data collection and preparation. The below section provides an overview of this phase.

Building the Dataset

The critical step in building any Deep learning model is the input data. It consists of thousands of labelled images that comprise of primarily three datasets:

- **Images without cars:** This consists of building a dataset of different image categories, other than cars, by collecting sample images from the web.
- **Images with undamaged cars:** This consists of building a large dataset of different car models.
- **Images with damaged cars (and types of damages):** This dataset can be built using various sample images that can be scraped and downloaded from the web. For dataset diversity, we ensure that we obtain images of cars damaged with different types and severities. Labels have to be manually assigned to each damaged car. We assign only one label of every category to each of the images. When, for example, the car on an image is both dented and scratched, we assign the one that stands out the most. The final output of this step is a labelled collection of images of damaged cars as:
 - **Type:** Dent, Glass, Hail, Scratch
 - **Location:** Front, Rear, Side, Top
 - **Severity:** High, Medium, Low

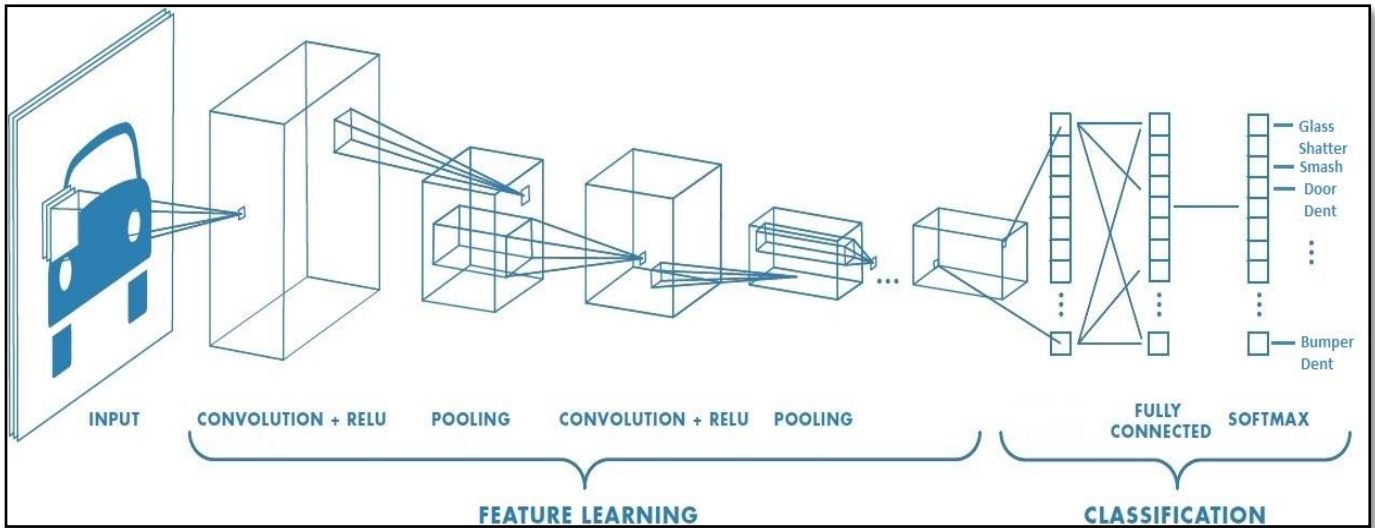
The size of the dataset can be synthetically increased by adding rotation and flip transformations. Since the target images belong to car damage type, we expect that learning the car-specific features should help the classification task.



Sample Images from Dataset

Deep Learning Model

Now that we have input data in place, we can proceed with building our deep learning model which classifies/maps the input image to a target damage type/severity. Our model is going to be based on *convolutional neural networks*. A Convolutional Neural Network, also known as CNN or ConvNet, is a class of neural networks that specializes in processing data that has a grid-like topology, such as an image.



The CNN architecture described above can be leveraged for building our deep learning model that will perform damage assessment. A typical CNN consists of multiple layers of nodes that are connected to each other as shown in the image above. These layers perform operations that alter the data with the intent of learning features specific to the problem.

For our problem statement, we recommend a CNN architecture consisting 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. The various layers are explained as below:

- **Convolution** puts the input image (damaged vehicle) through a set of convolutional filters, each of which activates certain features from the damaged vehicle image. It creates minimum learnable parameters (with respect to computing different filters for every region) of the input image.
- **Rectified linear unit (RELU)** The purpose of applying the rectifier function is to increase the non-linearity in our images. The reason we want to do that is that images are naturally non-linear (e.g. the transition between pixels, the borders, the colors, etc. are non-linear features).
- **Pooling** Similar to the convolutional layer, the pooling layer connects nodes to local regions of the input. It simplifies the output by performing nonlinear down sampling, reducing the number of parameters that the network needs to learn.
- **Fully connected layer** “fully connected” means that every node in the first layer is connected to every node in the second layer. Fully Connected layers perform classification based on the features extracted by the previous layers.
- **Softmax Function** is used to map the non-normalized output of the network to a probability distribution over predicted output classes.

Softmax function and fully connected layer are responsible for providing the classification output.

Implementation

For developing our model, we can leverage Keras, which is a high-level deep learning library written in Python that runs on top of TensorFlow. TensorFlow is a deep learning framework which provides capability to build and deploy AI models. The model is iteratively built to optimize the parameters (the weights and biases associated with connection between different layers) and thereby achieve a better accuracy.

Once the model reaches satisfactory performance, it can be deployed as an API using

- Cloud services (Azure VM/AWS EC2 with Apache server)
- Flask

Sample Output

Once our Deep Learning model is trained, built, tested and deployed, it is ready to be "applied" on the input image(s) uploaded by the user.

With the deep learning model in action, we can classify or map the damage to specific body parts of the car, and even localize it.

A sample output of this step would be

- Damaged Part(s) identified,
- Scale of damage (whether requires Repair or Replacement) for each damaged part

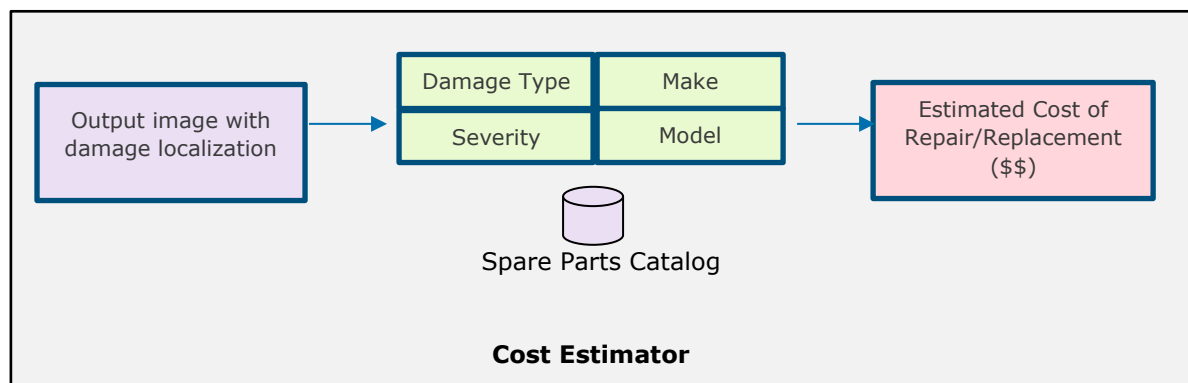
This output will then serve as an input to the Cost Estimator.



Cost Estimator

The output of Deep Learning model can then be passed to a cost estimator (API).

The cost estimator API is a service that connects to the Vehicle parts inventory database, and queries the Spare Parts and Services Catalogues (db/nosql tables) of different make and model to return a total cost estimate for the parts to be serviced/repaired or replaced.



An Alternate Approach

In practice, it is very uncommon to have sufficient data and resources to successfully train a full ConvNet from scratch. Generally, *transfer learning* refers to storing the knowledge gained while solving one problem and then use this to address another problem that is similar to the former one. In the context of ConvNets, this comes down to obtaining complete (pre-trained) architectures and retraining (or fine-tuning) a part of the model to serve our own purpose.

As an alternate approach, We can leverage the VGGNet with sixteen 'weight-layers' (excluding, e.g., pooling layers introducing no additional weights), because of its relatively simple, but effective architecture.

Business Benefits

The list below explains the various benefits to implementing the proposed solution

- Fair assessment of a vehicle damage by replacing manual intervention with an automated machine learning model
- Fast-track claims processing
 - Estimated effort saving from ~ (2 – 3 weeks) to ~ (1-2 hours)
- Elimination of manual intervention (in majority scenarios) to inspect the vehicles and validate the damages
- Better customer experience as the process is simplified.

Conclusion

An automated system based on Deep Learning is developed/proposed for quantification or calculation of damage to a vehicle.

This enables the insurers to provide instant disbursement of insurance money related to vehicle damage/repairs, thereby challenging the traditional workflows followed in the insurance industry. Such an automated solution can also act as a key differentiator for a potential buyer for selecting an insurance provider.

References

S.No.	Reference
1.	Very Deep Convolutional Networks for large-scale Image Recognition
2.	Automatic Car Damage Recognition using Convolutional Neural Networks
3.	AI for Accident & disaster recovery
4.	ImageNet Classification with Deep Convolutional Neural Networks



About Sogeti

Sogeti is a leading provider of technology and engineering services. Sogeti delivers solutions that enable digital transformation and offers cutting-edge expertise in Cloud, Cybersecurity, Digital Manufacturing, Digital Assurance & Testing, and emerging technologies. Sogeti combines agility and speed of implementation with strong technology supplier partnerships, world class methodologies and its global delivery model, Rightshore®. Sogeti brings together more than 25,000 professionals in 15 countries, based in over 100 locations in Europe, USA and India. Sogeti is a wholly-owned subsidiary of Capgemini SE, listed on the Paris Stock Exchange.

Learn more about us at www.sogeti.com

This document contains information that may be privileged or confidential and is the property of the Sogeti Group.
Copyright © 2018 Sogeti.