General

ID[1]			
Use case name	AI solution for Car Damage Classification		
Context	Other (Insurance)		
Application domain	Cloud services		
Status	PoC		
Contributor	Name	Affiliation	Contact
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Scope[2]	Car damage classification for common damage types such as bumper dent, door dent, glass shatter, head lamp broken, tail lamp broken, scratch and smash.		
Objective(s)	1. To create an automated system for car damage classification using CNNs. 2. Experiment using transfer and ensemble learning to find which is better for training a CNN for car damage classification.		
Narrative	Short description (not more than 150 words)	Image based vehicle insurance processing is an important area with large scope for automation. We have considered the problem of Car damage classification. 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. We hosted the trained model on cloud that can be plugged into applications using API and can be used for automated first level assessment of the damage, in car insurance sector.	
	Complete description	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 have been efforts by a few start-ups to mitigate claim processing time [3] [4]. An automated system for the car insurance claim processing is a need of the hour. 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 the 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 and 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 devise a method to localize a particular damage type. We achieve accuracy of 89.5% with combination of transfer and ensemble learning. The same technique can be used for localization of damages. Further, only car specific features may not be effective for damage classification. It thus underlines the superiority of feature representation learned from the large training sets. We hosted the trained model on cloud that can be plugged into applications using API and can be used for automated first level assessment of damages, in car insurance sector.		
Key performance indicators (KPIs)	ID	Name	Description	Reference to mentioned use case objectives
	1	Accuracy	We performed 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.	Objective 2
	2			
AI features	Taks(s)	Recognition		
	Method(s)[3]	Deep learning		
	Hardware[4]			
	Terms and concepts used[5]	Deep learning, ensemble learning, transfer learning, CNN, Localization, manual annotation		
Challenges and issues	1. Small size of the damages 2. Less Quantity of data 3. Ambiguity in damaged and non-damaged images			
Societal concerns				

Data (optional)

Data characteristics	
Description	We created a dataset consisting of images belonging to different types of car damage. We consider seven commonly observed types of damage such as bumper dent, door dent, glass shatter, head lamp broken, tail lamp broken, scratch and smash. In addition, we also collected images which belong to a no damage class.
Source[6]	The images were collected from web and were manually annotated
Type[7]	
Volume (size)	
Velocity (e.g. real time)[8]	
Variety (multiple datasets)[9]	multiple web sources
Variability (rate of change)[10]	
Quality[11]	Medium

Process scenario (optional)

Scenario conditions					
No.	Scenario name	Scenario description	Triggering event	Pre-condition[12]	Post-condition[13]
1					
2					
3					
4					

Training (optional)

Scenario name	Training				
Step No.	Event[14]	Name of process/Activity[15]	Primary actor	Description of process/activity	Requirement

Specification of training data[16]	

Evaluation (optional)

Scenario name	Evaluation				
Step No.	Event[17]	Name of process/Activity[18]	Primary actor	Description of process/activity	Requirement

Input of evaluation[19]	
Output of evaluation[20]	

Execution (optional)

Scenario name	Execution				
Step No.	Event[21]	Name of process/Activity[22]	Primary actor	Description of process/activity	Requirement

Input of Execution[23]	
Output of Execution[24]	

Retraining (optional)

Scenario name	Retraining				
Step No.	Event[25]	Name of process/Activity[26]	Primary actor	Description of process/activity	Requirement

Specification of retraining data[27]	Retraining data has to include recent data

References

References						
No.	Type	Reference	Status	Impact on use case	Originator/organization	Link
1	Conference Paper	International Conference on Machine Learning and applications	Published		Tata Consultancy Services Limited	https://ieeexplore.ieee.org/abstract/document/8260613/

Footnote

[1] Leave this cell blank.

[2] The scope defines the limits of the use case.

[3] AI method(s)/framework(s) used.

[4] Hardware system used.

[5] Terms and concepts listed here can be used to extend the work of WG 1 (AWI 22989 and AWI 23053) as necessary.

[6] Origin of data, which could be from instruments, IoT, web, surveys, commercial activity, or from simulations.

[7] Structured/unstructured Images, voices, text, gene sequences, and numerical. Composite: time-series, graph-structured

[8] The rate of flow at which the data is created, stored, analysed, or visualized.

[9] Data from a number of domains and a number of data types. The wider range of data formats, logical models, timescales, and semantics complicates the integration of the variety of data.

[10] Changes in data rate, format/structure, semantics, and/or quality.

[11] Completeness and accuracy of the data with respect to semantic content as well as syntactical of the data (such as presence of missing fields or incorrect values)

[12] Describe which condition(s) should have been met before this scenario happens.

[13] Describe which condition(s) should prevail after this scenario happens. The post-condition may also define "success" or "failure" conditions.

[14] The event that triggers the step. This might be completion of the previous event.

[15] Action verbs should be used when naming activity.

[16] Training data can be further specified.

[17] The event that triggers the step. This might be completion of the previous event.

[18] Action verbs should be used when naming activity.

[19] Specify input of evaluation.

[20] Specify output of evaluation.

[21] The event that triggers the step. This might be completion of the previous event.

[22] Action verbs should be used when naming activity.

[23] Specify input of evaluation.

[24] Specify output of evaluation.

[25] The event that triggers the step. This might be completion of the previous event.

[26] Action verbs should be used when naming activity.

[27] Retraining data can be further specified.

