LITERATURE SURVEY ON INTELLIGENT VEHICLE DAMAGE ASSESSMENT AND COST ESTIMATOR FOR INSURANCE COMPANIES

Auto Insurance Claim Using CNN Model

Li Ying & Dorai Chita, presented the CNN Model 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. This paper proposed a novel application where advanced technologies in image analysis and pattern recognition are applied to automatically identify and characterize automobile damage. Success in this will allow some cases to proceed without human adjusters, while others to proceed more efficiently, thus ultimately shortening the time between the first Notice of Loss and the final pay-out.

To investigate its feasibility. they built a prototype system which automatically identifies the damaged area(s) based on the comparison of ages. Performance of the before- and after-accident automobile in of the prototype system has been evaluated on images taken from forty scaled model cars under reasonably controlled environments, and encouraging results were obtained. It is a belief that, with the advancement of image analysis and pattern recognition technologies, their proposed idea could evolve into a very promising application area where the auto insurance industry could significantly benefit. The main drawback in this model was that the automobile damaged can be analyzed only having white background otherwise it will be not able to give the desired results and the study also indicates that there may be an error in the result, it may not give that accurate result like 85-90% affective.

Image Based Vehicle insurance

U. Waqas, N. Akram, S. Kim, D. Lee and J. Jeon, they presented the Image-based vehicle insurance processing and loan management has large scope for automation in automotive industry. In this paper consideration of the problem of car damage classification, where categories include medium damage, huge damage and no damage. Based on deep learning techniques, Mobile Net model is proposed with transfer learning for classification. Moreover, moving towards automation also comes with diverse hurdles; users can upload fake images like screenshots or taking pictures from computer screens, etc. To tackle this problem a hybrid approach is proposed to provide only authentic images to algorithm for damage classification as input. In this regard, moiré effect detection and metadata analysis are performed to detect fraudulent images. For damage classification 95% and for moiré effect detection 99% accuracy is achieved. The main drawback was that Images in bad lighting, awkward angles, variety in vehicle models, images taken in rain or snow, minor scratches on vehicles, etc. Even though it used several angles and vehicle models in a small dataset to achieve automation but still the range is broad.

Damage Analysis of AI based Machine Learning

Phyu Mar Kyu and Kuntpong Woraratpanya they presented the sense of Artificial Intelligence (AI) based on machine learning and deep learning algorithms which can help to solve the problem for insurance industries for damage analysis. In this paper, they applied deep learning-based algorithms, VGG16 and VGG19, for car damage detection and assessment in real world datasets. The algorithms detect the damaged part of a car and assess its location and then its severity. Initially, it discovers the effect of domain-specific pre-trained CNN models, which are trained on an ImageNet dataset, and followed by fine-tuning, because some of the categories can be fine granular to get a specific task. Then it applies transfer learning in pre-trained VGG models and use some techniques to improve the accuracy of the system. To achieve the accuracy of 95.22% of VGG19 and 94.56% of VGG16 in the damaged detection, the accuracy of 76.48% of VGG19 and 74.39% of VGG16 in damage localization, the accuracy of 58.48% of VGG19 and 54.8% of VGG16 in damage severity with the combination of transfer learning and L2 regularization. From their results, the performance of VGG19 is better than VGG16. After analysing and implementing the models, it finds out that the results of using transfer learning and L2 regularization can work better than those of fine-tuning. The drawback of this model was since car damaged assessment is a specific domain, it is lack of publicly available datasets for car damaged images with labelling. Training a model with a small dataset is the most challenging.

Damage Detection at Deep learning based Architecture

Najmeddine Dhieb, Hakim Ghazzai, Hichem Besbes, and Yehia Massoud they presented automated and efficient deep learning-based architectures for vehicle: damage detection and localization. The proposed solution combines deep learning, instance segmentation, and transfer learning techniques for features extraction and damage identification. Its objective is to automatically detect damages in vehicles, locate them, classify their severity levels, and visualize them by contouring their exact locations. Numerical results reveal that our transfer learning proposed solution, based on Inception-Resnet V2 pre-trained model followed by a fully connected neural network, achieves higher performances in features extraction and damage detection/localization than another pre trained model, i.c.. VGG16. The transfer learning could significantly reduce the training times when it uses the weights of pre trained VGG models. Furthermore, it had demonstrated significant progress on how to solve classification problems when the small dataset was not enough to train a CNN model. The classes of the pre-trained VGG models are the source tasks, and the detected damaged parts of their locations, and their damaged levels are the target tasks in our system. The main drawback of this model was A reduction of model training time is also the most challenge. Typically, a traditional CNN model can be very time- consuming to perform image classification tasks and identify the correct weights for the network by multiple forward and backward iterations. This process may take days or even weeks to complete it using GPUs.

Mask R-CNN

Mask RCNN is a deep neural network aimed to solve instance segmentation problem in machine learning or computer vision. In other words, it can separate different objects in an image or a video. You give it an image, it gives you the object bounding boxes, classes and masks.There are two stages of Mask RCNN. First, it generates proposals about the regions where there might be an object based on the input image. Second, it predicts the class of the object, refines the bounding box and generates a mask in pixel level of the object based on the first stage proposal. Both stages are connected to the backbone structure [1].

Car Damage Assessment using CNN

The project involved developing and training a CNN model with 10 convolutional layers and 3 pooling layers with Relu as the activation function at each layer and the final layer being a Fully Connected Layer. The dataset used in training the model was obtained through web scraping. The model performed well on high quality images hut gave inaccurate results on blurred images. The main disadvantage was the back of widely available labelled dataset [2].

Automatic Car Damage Assessment through videos

Wei Zhang, Yuan Cheng, Xin Guo, Qingpei Guo, Jian Wang, Qing Wang, Chen Jiang, Meng Wang, Furong Xu, Wei Chu proposed a method to detect and analyze car damage through user input videos. The approach involved 2 modules Damage recognition and localisation and component recognition and localisation to segment the damage and components at pixel level to get accurate results. The model required high quality videos as input to generate accurate results [3].

Recognition of Car Manufacturers using Faster R-CNN and Perspective Transformation

Israfil Ansari, Yeunghak Lee, Yunju Jeong, Jaechang Shim proposed a method to detect car logos from CCTV footages. The approach involved performing perspective transformation on CCTV footages to get a clear view of the logos and then detecting and localizing the car logos through faster RCNN [4].

Vehicle Logo Detection and Classification using Discriminative Pixel-patches Sparse Coding

Yi Ouyang developed a system to detect and classify vehicle logos with the help of sparse coding. The method localised the car logos by detecting the number plate with the help of 3-channel pixel regression technique then performing multi class structural linear SVM for logo classification [5].

Vehicle Type classification With Deep Learning

The paper researches various algorithms to classify the car body type from images as SUV, sedan, pick-up truck. Dataset used was the stanford dataset with 224 images and achieved an accuracy of 76 percent when arithmetic mean computation was on a hierarchical tree on ResNet 34 architecture [6].