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Preventing Car Damage using CNN and Computer Vision

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Abstract: ***This research contain convolutional neural network are used to recognize whether a car on a given image is damage or not, from where it is damage and severity of the damage. Using transfer learning to take advantage of available models that are trained on a more general object recognition task, very satisfactory performance has been achieved, which indicate great opportunities of this approach. Car accidents are stressful and the auto claims process is ripe for disruption. Using computer vision to accurately classify vehicle damage and facilitate claims triage.***

Keywords: car damage, convolutional neural network, neural network

I. INTRODUCTION

In today's world, insurance is a vast diligence. With vast number of cars evident on the paths of most modern firms, it is no astonishment that vehicle insurance is a booming industry. The countrywide average auto insurance outlay rose 5.3% to $935.80 in 2016 from $889.09 in 2015, rendering to the National Association of Insurance Commissioners. In 2016, the average outflow was highest in New Jersey ($1,309.29), and New York ($1,301.64).

With the number of road accidents rising everyday there is an enormous load on the insurance companies to course loan and due to manual intrusion, the accuracy of the process is hampered.

This programme design grants an insurance industry use case: car damage analyser. When a car becomes impaired in accident, the guarantor pays the required cost. However, the shop may overprice the expensive. Likewise, the approximation procedure is blue-collar and involves mortal experts and time to estimate damage.

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Image cataloguing is emergent prerequisite for each types of bodies, and insurance companies. Occupying machine learning, it simpler to train a model which will distinguish the damaged cars, make estimates about what type of repair is looked-for, and estimate how much it may cost.

II. RELATED WORKS

Deep learning has shown promising results in machine learning applications. In particular, CNNs perform well for computer vision task such as visual object recognition and detection [1] [2]. Application of CNNs to structural damage assessment has been studied in [3]. The author insinuates a deep learning-based method for Structural Health Monitoring (SHM) to typify the impairment in the form of flaws on a multiple material. Unsupervised representation is retained and consequences have been presented on an eclectic satiety of heaping condition with regulated number of labelled instruction image data.

There are many CNN models trained on ImageNet which are available publicly such as VGG-16[10], VGG-19[10], Alexnet [2], Inception [11], Resnet [12]. Transferable feature representation learned by CNN minimizes the effect of over-fitting in case of a small labelled set [10].

III. DATASET DESCRIPTION

Since there is no widely accessible dataset for car damage categorisation, we crafted our own dataset comprising of pictures belonging of diverse types of car damage. In addition, we also serene images which fit to no damage class. The image was collected from web and were manually annotated.

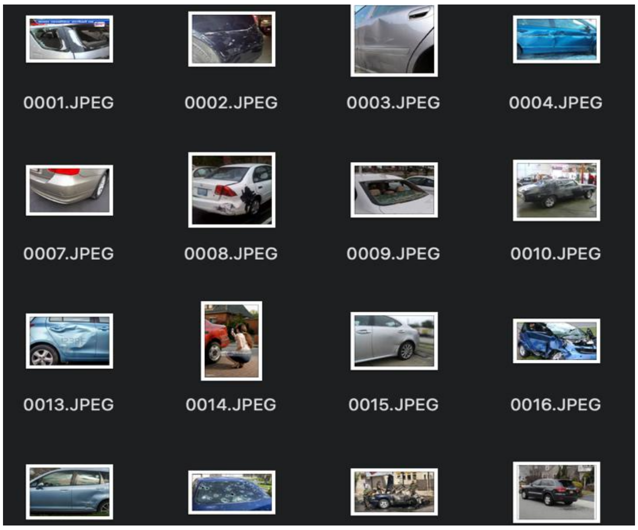


Fig 1. Sample of car damage

Table 1 Dataset for MODULE 2

Classes	training	validation
Damage	930	230
whole	930	230

Table 2 Dataset for MODULE 3

classes	training	validation
Front	475	150
Rear	300	150
Side	300	150

Table 3 Dataset for MODULE 4

classes	training	validation
Minor	278	100
moderate	325	100
severe	400	100

IV. IMPLEMENTATION DETAILS

A. Pyhton

Python can be demarcated as general-purpose, excessive balanced coding language. It was originally proposed by Guido van Rossum in 1991 and developed by Python Software Foundation. It was mainly developed for prominence on code readability, and its composition permits computer operator to definite conceptions in less program.
In this research, Python is the base programming language which is used to write the code. Python. Python consist of multiple libraries which are used in this research for the output of the research

B. Classification

Classification is a way to extricate data from data sets. This is done by separating the data into groups based on some characters. The idea is to arise a model which can execute the classifying process by training it on data items. The model should then be able to classify unlabeled data with sufficient accuracy. There are many different models that are used for classification, e.g. neural network.

C. Artifical Neural Network

Machine learning is a lea in computer aided-learning aiming to replicate human knowledge progression. Artificial neural network
(ANN) is an expert learning method where the structure of the human brain is the stimulus.
The artificial neural network (ANN) is a network built of a number of interconnected neurons. The neurons are simple processing units that change their internal state, or activation, based on the current input and produces an output that depends on both the input and current activation. The ANN is constructed by having a large number of these neurons working in parallel and connecting some neurons to others through weighted connections, creating a weighted and directed network of different layers. It is by adjusting these weighted connections and the internal activations of the neurons the ANN can be improved, or trained. Usually the network cycle through a set of training data sufficiently many times, until the weights have been adjusted enough to produce the desired output.

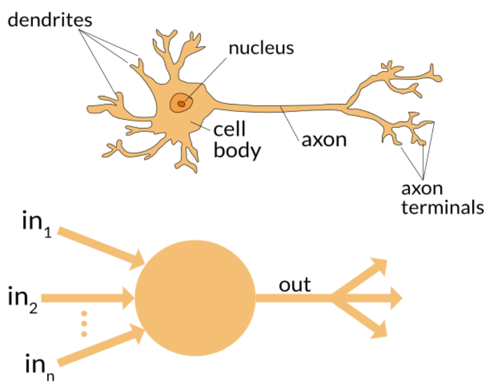


Fig 2: A comparison between a biological and an artificial neuron

A common way of learning for a neural network is the process of back propagation. This is a method of dynamic adjustment based on providing feedback to the network, initiated from a difference between the desired output and the current output. The weights of the interconnected neurons are adjusted depending on the degree they contribute to the error and this process is repeated in cycles until the network achieves a desired accuracy of classification. In car damage investigator, all the modules are trained with the help of the artificial neural network. some line is missing.

D. Convolutional Neural Network

CNNs are hierarchal models whose convolutional layers alternate with sub-sampling layers, reminiscent of simple and complex cells in the primary visual cortex [6]. The Network architecture consists of three basic building blocks to be composed as needed. We have the convolutional layers, the max-pooling layers and the classification layers [5]. CNNs are among the most successful models for supervised image classification and set the state of the art in many benchmarks [7,8].
The convolutional layers work as a feature extractor, or a filter, and extract some sort of characteristic from the input data. Usually, one convolutional layer has several filters which are all applied in the same step, but extract different features. The size of the filter, or the kernel, depends on what the size of a specific feature is expected to be.
When a feature has been extracted from the image, we can reduce the special
size of the image. This will keep the information of which features are present and their relative positions, but in a lower resolution. This process is called subsampling and is done by a pooling layer. In this case we are using a max pooling layer, which is a common choice for convolutional neural networks. This specific king of pooling means that from the pooling kernel, only the pixel with the largest intensity value will be transferred into the subsampled image. We can see that for each similarly coloured two-by-two square, only the highest value has been transferred to the subsampled square.

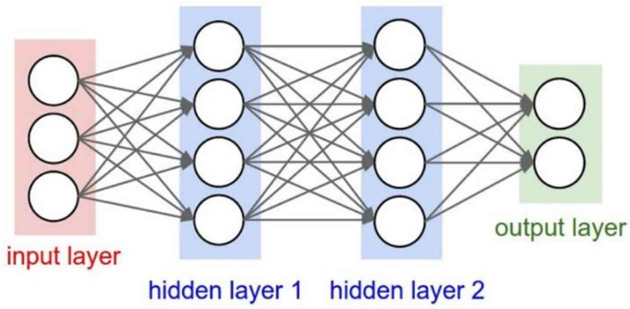


Fig 3: Convolutional neural network

E. Training a Network

CNN: s is trained using back propagation. In order to adjust the weights correctly, we need a sufficiently large set of training data. There is no clear formula for how big this data set should be, but one aspect that is important to consider is variance between classes. If the disparity within a class is big, the number of training data objects should be larger.
During the training process, for each *step*, one data object is run through the model and the weights are adjusted. When all training data has passed through the network once, one *epoch* is completed. The number of steps and epochs are important parts of the training process, as too few or too many can lead to under- or overfitting.
A model is overfitted if it is too well adapted to the training data but does not perform well in the general case. One possible cause of overfitting is if the classes in the training data are unbalanced. Underfitting occurs when the chosen model does not fit well with the data and causes "over generalization" by the model. One way to combat overfitting in neural networks is the use of so-called regularization.

F. The Result Neural Network

Since we are using 2D images as data for the network, a CNN is our choice of neural network variant, as they are superior in that field. Also, CNN: s is usually simple to use, as they have fewer parameters than other kinds of ANN: s and they are usually easy to train.
We chose a relatively simple structure of our CNN, with five hidden layers. Two convolutional layers exist interspersed through two max-pooling layers the final layer before the output is a dense and copiously associated layer, condensing the individual weights of the neurons in the network into network predictions.

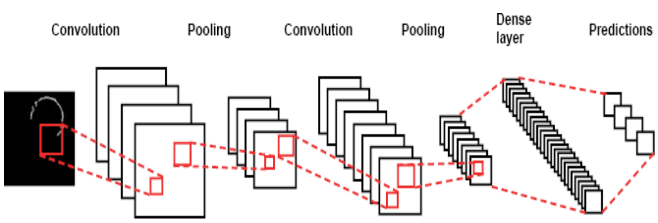


Fig 4: the setup of neural network

V. EXPERIMENTAL SETUP

In this research, our portal works by using five different modules (layers) in tandem. Each layer is responsible for judging a unique attribute. The user
is first greeted on the upload page. After uploading an image here, the image is passed on to the layers for analysis.

- UPLOAD IMAGE:

This will be the first page that a user sees. There is a place for the user to upload an image to the server. After that is done, the other modules will sequentially analyze the image and determine the type and extent of damage, if any.

- 1st MODULE-

The first module will analyze the image and judge whether the image received by it actually features a vehicle or not. If the picture does contain a vehicle, the image will be dropped, and not passed on to the subsequent layers.

- 2nd MODULE-

The second module will ascertain whether the car in image is actually damaged or not. Depending upon its decision, the image may either be dropped, or it may be passed on to the next layer.

- 3rd MODULE-

The third module judges whether the damage being displayed has been inflicted on the front, side, or the rear of the vehicle.

- 4th MODULE-

This module assigns a severity score to the damage out of the following three possible ones: Minor, Moderate, Severe.

- 5th MODULE-

This module is responsible to combine all the module explained above and produces the final result which is to be displayed to the end user.

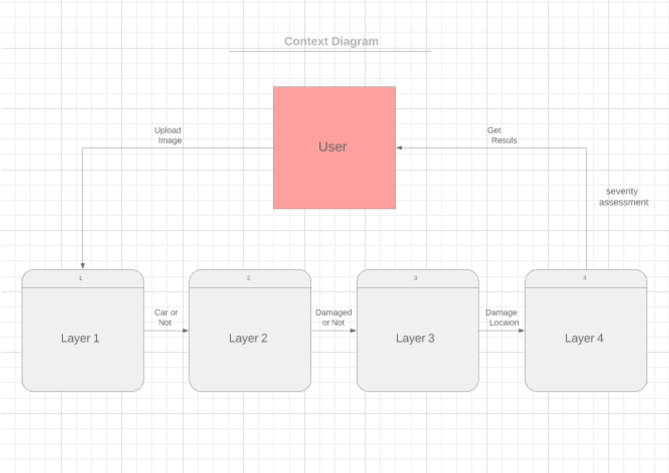


Fig 5: Layers in model

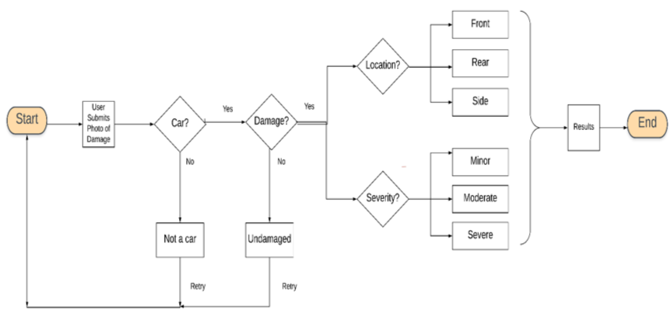
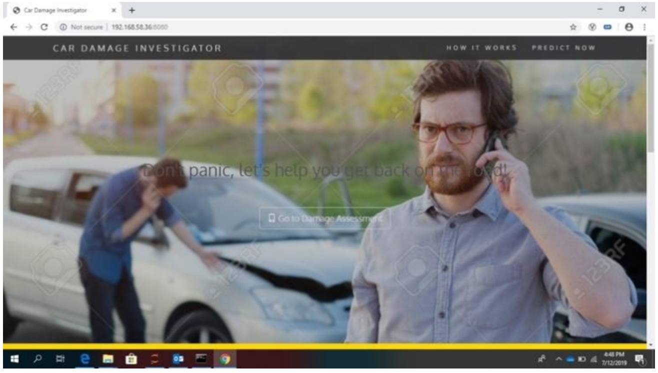


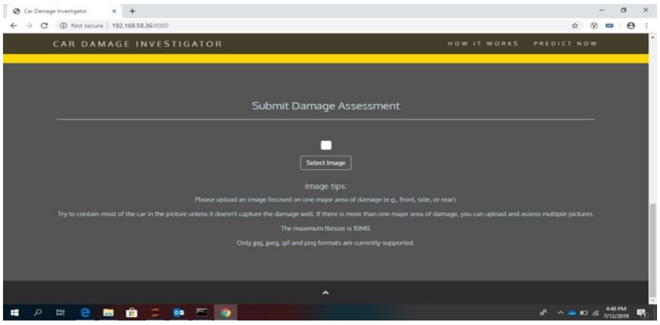
Fig 6: Flow chart of preventing car damage

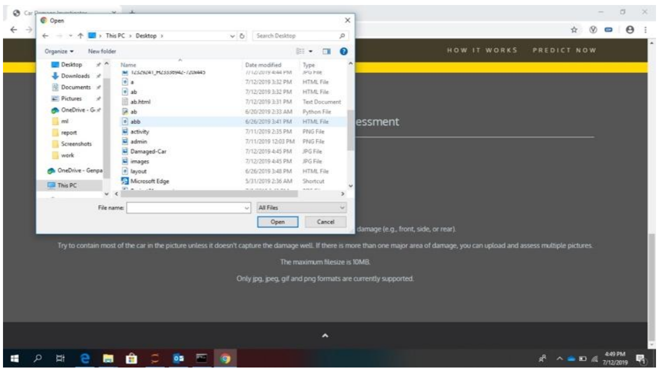
VI. . CONCLUSION

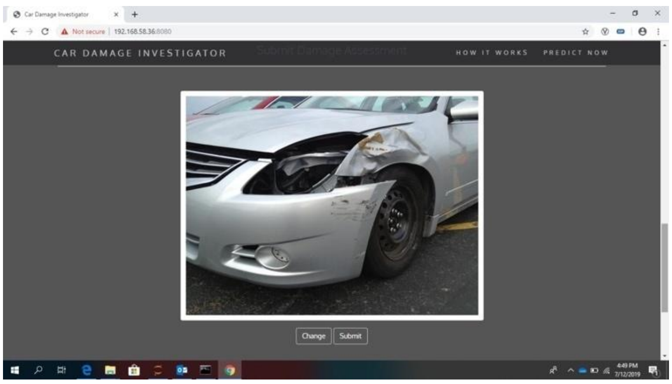
In this paper, we projected a hierarchical learning-based elucidation for car damage assistance. While there was no openly accessible dataset, we crafted a new dataset by gathering images from web and manually annotating them.

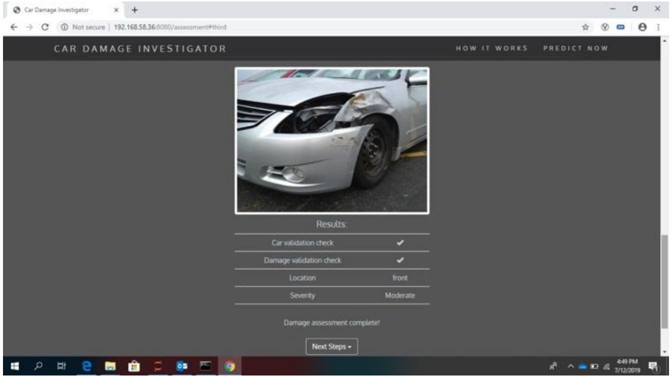
The learning models were able to achieve satisfactory results with a theoretical accuracy (based on the test cases) of about 88% and with similar results in the real world.
Most of the failures that the model did face were encountered in the second model i.e. the damage detection phase of the analysis. This mainly occurred due to the irregular shadows on the vehicle although more in-depth testing is still recommended. But the good thing was that there were not a lot of false positive results and the damage localization results were also highly accurate.











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