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# Damage Assessment of a vehicle and Insurance Reclaim.

Vaibhav Agarwal[1], Utsav Khandelwal[2], Shivam Kumar[3], Raja Kumar[4], Shilpa M[5]

*[1234]Student [BE], Department of Computer Science and Engineering, Dayananda Sagar Academy of Technology and Management (DSATM), Bengaluru, Karnataka, India.*

*[5]Assistant professor, Department of Computer Science and Engineering, Dayananda Sagar Academy of Technology and Management, (DSATM), Bengaluru, Karnataka, India*

*Abstract*— **By reducing loss adjustment costs, improvements in the First Notice of Loss and the speed with which claims are examined and evaluated might save a lot of money in the automobile insurance claims process. Car damage is automatically identified and classified using advanced picture analysis and pattern recognition technology. A technique that compares before-and-after-accident car images to automatically detect the damaged location.**

***Keywords — Convolution Neural Network, Deep Learning, Image classification, R-CNN and object detection.***

## I. INTRODUCTION

In today's world, it can observed that the number of vehicles we use is quickly expanding; let's agree that there isn't a single street without a car. As a result, an increase in the number of automobiles on the road may lead to an increase in the percentage of accidents occurring nearby; additionally, the number of accidents occurring nearby would be significant; the accidents would not be particularly serious, but the automobile would be damaged, prompting people to file insurance claims.

The whole idea focuses on this question: how can a customer claim insurance more quickly? To keep the procedure quiet, a machine learning model is developed that utilizes image processing to categorize the photographs and calculate the percentage of damage to the car. The user will be able to get payment based on the model's outcomes. Because the ML model would be exclusively responsible for this procedure, it would be faster than the manual approach.

Analyze the damage in a fraction of the time it takes people and with minimal human interaction.

## II. LITERATURE SURVEY

Li Ying & Dorai Chitra, 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.

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.

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.

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-ResnetV2** 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.e., **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.

## III. METHODOLOGY

To begin, it gathers the photographs of one's damaged automotive, which then feed into the machine learning model, which uses image processing to identify the elements of the image, and then uses image processing to analyses the percentage of damage to the automobile.

The next it divides the photographs into two categories, as illustrated in the block diagram: replace and repair. If the damage percentage exceeds, say, 80%, the damaged part must be replaced, however if the damage percentage is less than 80%, it computes the compensation amount depending on the damaged percentage. Create a thorough report based on our examination of the vehicle and use it to file a claim with the insurance provider for payment.

## IV. PROPOSED SYSTEM

In proposed system firstly, it collects the pictures of one's damaged automobile, later use these pictures to feed into our ML model that makes use of image processing to identify the details of the image, using Image processing it analyses the percentage of damage of the automobile.

Next, it segregates the pictures based on 2 factors which are replace and repair. i.e. if the damage percentage exceeds say 80% then the damaged part has to be replaced, whereas in the other case "Replace" even in this case it calculates the reimbursement amount based on its damaged percentage.

Then at last it generates a detailed report on analysis of the automobile and use this to claim one's reimbursement with the insurance company.

## V. IMPLEMENTATION

The analysis of car damage model accepts an input image from an user in JPEG format and processes it across different stages, the project is divided into 2 phases, to identify the damaged car that is, if the car is damaged or not, and then to find the location of damage like front, rear or back. The analysis can be achieved using steps that include image classification and object detection.

In image classification, it processes and classify the image provided by the user into either damaged car or a whole car i.e., undamaged or completely fine. Whereas, object detection and image localization come into picture to help us identify the location of the damage. It can predict the location along with the class for each object using Object Detection.

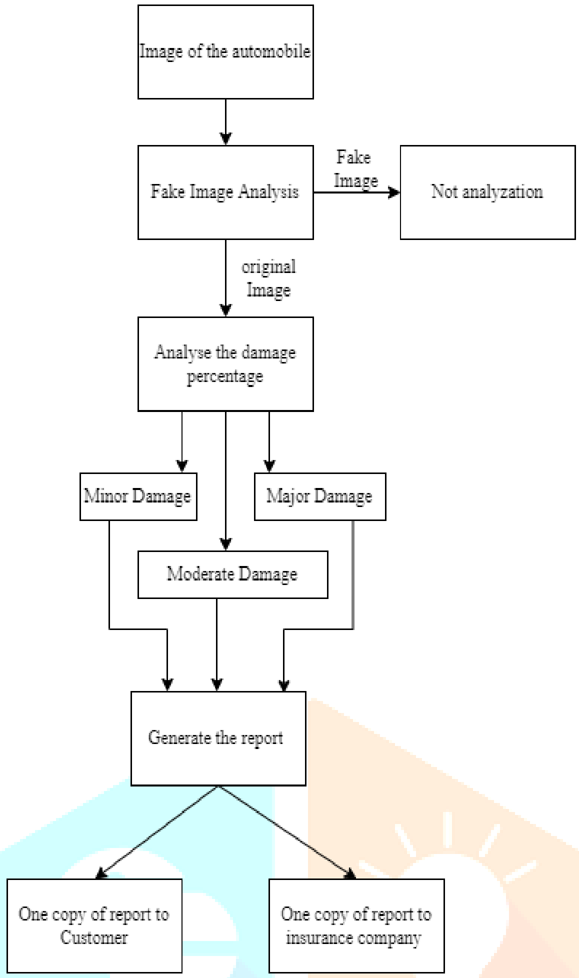


Fig: Flow Diagram The CNN is

divided into
1. Convolutional layer to flattening. Where, the input image goes through convolution, max - pooling, densing and flattening.

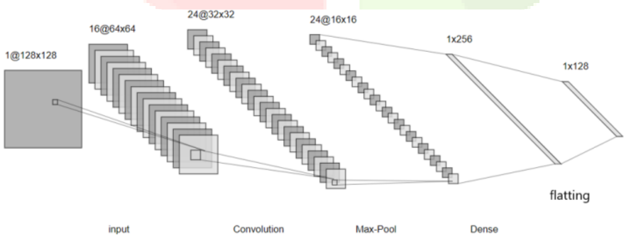


Fig1: Input to Flattening

2. Image classification using a fully convoluted neural network. This network consists of an input layer at the start and fully connected layers that are hidden layers, activation functions and output layer.

Each of the connections has weights, which assists in the calculation of the image as either whole or damaged car.

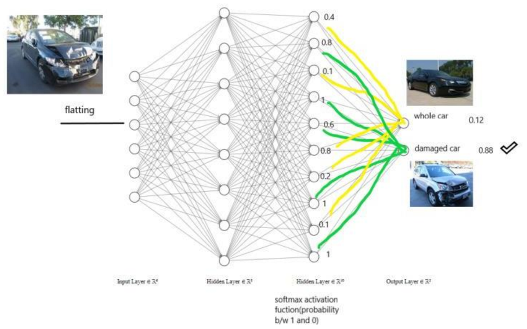


Fig 2: Image Classifier Using a Fully Connected NN

## VI. ADVANTAGES

1. It can categorize the proportion of damaged parts and determine whether they need to be replaced or repaired.

2. It aids the user in expediting the process of filing an insurance claim for his vehicle.

3. Get a report with the vehicle's damage analysis created for you. To get compensation, submit the created report. Process that saves time and money.

## VII. CONCLUSION AND FUTURE WORK

In this work of Damage analysis of a vehicle in general and insurance reclaim, a system has been designed using CNN and image classification which takes the input from a user as an image to test the severity of damage, which happens in a sequence of two steps. First being the image classification, here the input provided by the user is processed by the neural network to identify the car that is if the car is damaged or not. and later on the second step, the flattened input obtained as the output in step 1 is applied for object detection to identify the region and severity of damage, where region might be rear, front or side and severity is divided into minor, moderate and major. The R-CNN network identifies the severity of damage and a report is filed and sent to the user and the insurance firm.

The major drawback of the proposed model is that it only identifies the physical visible damage and not of the internal or the interior damage.

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