



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

# IJRSET

International Journal of Innovative Research in  
**SCIENCE | ENGINEERING | TECHNOLOGY**



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 12, Special Issue 2, April 2023

**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA

 9940 572 462

 6381 907 438

 [ijirset@gmail.com](mailto:ijirset@gmail.com)

 [www.ijirset.com](http://www.ijirset.com)

# Assessing Car Damage with Convolutional Neural Network

Varaprasad Seepana<sup>1</sup>, V.Santhosh<sup>2</sup>, Dr. S. Bangaru Kamatchi ME,Ph.D<sup>3</sup>

Student, Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, Tamil Nadu, India<sup>1</sup>

Student, Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, Tamil Nadu, India<sup>2</sup>

Associate Professor, Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, Tamil Nadu, India<sup>3</sup>

**ABSTRACT:** Visual image classification is a research area that involves both computer vision and machine learning. The task of visually classifying an object consists in assigning an object to a category, or set of categories the object belongs to. Traditionally, visual classification tasks are performed using a two layered system, made up of a first layer featuring an out-of-the-shelf feature extractor and detector, and a second classifier layer. In most recent years, convolutional neural networks have been shown to outperform such previously used systems. Cars have a paramount role in today's world, and being able to automatically classify damages in cars is of great interest specially to the car insurance industry. Car insurance companies deal with car inspections on a daily basis. Such inspections are a manual, lengthy and sometimes faulty processes. Processes that bring costs and inconveniences to costumers and insurance companies alike. Even though the total replacement of such manual inspection processes might still be far away, developing systems to aid, accelerate or enhance the process might be possible with today's technology.

**KEYWORDS:** Machine Learning, Data Science, phishing website,

## I. INTRODUCTION

Insurance is a very old industry and it has been quite resistant to change until recently. Manual validation of large-scale claims is not sufficiently quick in meeting dealing with large numbers of insurance claims. Claim amounts are determined by the type of damage and the affected part of the vehicle and an automated car insurance claim processing system - that efficiently detects and estimates damages - could be of great help. Automatic damage assessment employing analysis of images has proved to be fast and efficient, and will improve further as more and more data is collected. Deep learning enables us to automatically detect scratches, teeth, rust, and breakages, to determine the affected part of the vehicle and to quantify the severity of the damage. After processing, reports can be generated with a list of damages and an estimate of the cost of repair.

Ability to detect damages in dataset taken cars is a subset of image classification because, at its most fundamental level, identifying claims in images entails categorising an image into a particular type as well as collection of classes. There has been a great deal of research on image classification, but there haven't been many works on car visual damage detection. Nonetheless, and be capable of detecting car damage automatically is a research topic with numerous practical uses. Automobile insurance companies deal with car accidents on a daily basis. Cars are frequently required to be serviced for damage, which is problematic for clients as well as extremely expensive for companies. As a result, it's critical to be able to automate car damage detection, making it easy for customers and affordable.

## II. LITERATURE REVIEW

[1] Deep learning is an efficient method used for classification. Kalpesh Patil, et. al. in [1] have used the concept of deep learning in order to classify car damage. The model used is trained on CNN directly. The preprocessing includes the steps of domain-specific pre-training followed by fine-tuning. The paper has conducted a combined and separate

study of Transfer Learning and Ensemble Learning. The research has a setback of unavailability of a proper dataset which has resulted in creation of dataset by annotating images. The use of Convolution Autoencoder based pre-training followed by supervised fine-tuning and transfer learning is a novelty factor of this research.

Deep learning methodology can also be used for detecting presence or absence of damage and conducting further analysis. The researchers in

[2] have applied this in the field of automotives. In this paper, CNN is used for object recognition. The task of classification has been performed on Damaged Vehicle dataset. Mask RCNN is used for segmenting, decomposing and sub-dividing the various instances of Machine Learning. The scope of research is limited to a particular dataset. Extensive research on new data can be performed for testing the quality of the model. Yet the fact that it is an automated system that can classify the damaged vehicle and predict how the damage has occurred remains a unique factor of this research.

The concept of faster R-CNN can be helpful for real-time object detection with Region Proposal Networks. This concept is implemented in

[3] RPN (Region Proposal Network) is trained end-to-end to generate high-quality region proposals, which are used by Fast R-CNN for detection. RPN and Fast R-CNN are merged into a single network by sharing their convolutional features using neural networks with attention mechanisms. The RPN component is essentially used for the unified network to focus on a particular object. The research does not include exploitation and preprocessing on the data. This process could have been used to improve results. The research has built a unified, deep learning based object detection system to run at near real-time frame rates.

Computer Vision Technology can be used for assessment of damage to an object. Xianglei Zhu, et. al. in

[4] have developed an unified intelligent framework based on this concept. This paper uses RetinaNet algorithm to identify damaged parts. The accuracy with this algorithm is improved. Mask R-CNN is adopted for the identification of vehicle parts, the damaged parts are determined by the method of sampling, and the time complexity is greatly reduced. The accuracy achieved in this research can be improved in order to get better results. A combination of characteristics of vehicle damage data and suitable data can further strengthen this system. The research has successfully reduced time complexity in damage detection and the use of Retina Net gives good accuracy in damage detection.

The use of Improved Mask RCNN can be used for vehicle damage detection. In

[5] this approach is followed using Segmentation algorithm. A deep learning approach is used to detect vehicle-damage for compensation problem in traffic accidents. The algorithm has achieved good detection results in different scenarios. Regardless of the strength of the light, the damaged area of multiple cars, or a scene with an overly high exposure, the fitting effect is better and the robustness is strong. The limitation of this research lies in the mask instance segmentation. In many cases the obvious damage is not considered and segmented leading to inaccurate results. This research contributes to detection of damage of vehicles in a more efficient method through improved Mask algorithm.

Convolutional Neural Network (CNN) is a widely used algorithm for the purpose of classification problems. This method is used by Jeffrey de Deijn in [6]). The research was able to detect car damage with fairly accurate results. The type, location and size of damage is detected with moderate accuracy. The addition of Ensemble learning could have further improved the results from this research. The use of ConvNets to detect car damage detection and transfer learning are the novelty factors of this research.

[7] Now days claiming and settlement of vehicle insurance is done through online, where customers are allowed to upload the image of damaged vehicle taken using their mobile phones and request for claim. However there can be chance of repeated claim for same case which can be loss for insurance company. So the main objective is to develop an Anti-Fraud checking system to process the request and speed up the insurance claim process. YOLO detector is used as object detection framework. YOLO detects the damage on vehicle by learning features though regression in 4 coordinates. To extract local features, pre-trained VGG16 object recognition model is employed as a feature extractor. Global deep features and color histogram are present in Global feature. [8] In this paper the authors have suggested an automated system that can classify the damaged vehicle and predict how the damage has occurred. Convolution Neural Network (CNN) can be used for understanding, detecting and analyzing various classes of damage in the minor and

major parts of car. The damages can be of any types like bumper dent, door dent, glass shatter, head lamp broken, tail lamp broken, scratch and smash. CNN is used for object recognition task, in the proposed system it is being applied in the specific context of car damage recognition. Classification task is done on Damaged Vehicle dataset. This allows us to separate different objects and give bounding boxes, classes and masks. Once after locating bounding boxes, it can be colored and individually extract the features.

[9] Due to the development of deep learning, in recent years, the field of computer vision grows rapidly. A large amount of computer vision technologies have been applied in actual problems. At present, the industry of vehicle damage assessment requires a lot of manpower, and new automatic intelligent damage assessment technology can greatly reduce industrial costs. In this paper, a framework of intelligent vehicle damage assessment algorithm based on object detection technology and image classification technology is proposed. This algorithm can automatically identify the damage position, type and degree according to photos provided by users, so as to offer appropriate maintenance price and reach the accuracy that can meet actual application requirements.

[10] Traffic congestion due to vehicular accidents seriously affects normal travel, and accurate and effective mitigating measures and methods must be studied. To resolve traffic accident compensation problems quickly, a vehicle-damage-detection segmentation algorithm based on transfer learning and an improved mask regional convolutional neural network (Mask RCNN) is proposed in this paper. The experiment first collects car damage pictures for preprocessing and uses Labelme to make data set labels, which are divided into training sets and test sets. The residual network (ResNet) is optimized, and feature extraction is performed in combination with Feature Pyramid Network (FPN). Then, the proportion and threshold of the Anchor in the region proposal network (RPN) are adjusted. The spatial information of the feature map is preserved by bilinear interpolation in ROIAlign, and different weights are introduced in the loss function for different-scale targets. Finally, the results of self-made dedicated dataset training and testing show that the improved Mask RCNN has better Average Precision (AP) value, detection accuracy and masking accuracy, and improves the efficiency of solving traffic accident compensation problems.

### III. PROPOSED SYSTEM

A very well-known technique which has worked effectively in case of small labelled data is transfer learning. A network which is trained on a source task is used as a feature extractor for target task. There are many CNN models trained on ImageNet which are available publicly such as VGG-16, VGG-19, Inception, Resnet. Transferable feature representation learned by CNN minimizes the effect of over-fitting in case of small, labelled set.

For the implementation of this paper 4 algorithms were considered, VGG16, VGG19, Resnet50, Inception V3. VGG16 being effective in terms of its object detection(car) capability and classification (severity and location) because of its simple linear architecture and hence compatibility with the required use case. Hence VGG16 model was best suitable for implementation.

The most complex challenge is reducing model training time. Performing image classification tasks with a traditional CNN model and identifying the optimal weights for the network over several forward and backward iterations might take a long time. Using GPUs, this process could take days or even weeks to finish. Fortunately, using pre-trained CNN models that have been previously trained on big benchmark datasets like the ImageNet dataset, the model training effort can be decreased. Through transfer learning, weights can be freely extracted and their designs can be used for other particular tasks.

### IV. DESCRIPTION OF THE PROPOSED MODEL/SYSTEM

#### MODULE 1 - DATA COLLECTION AND PREPROCESSING

Data Processing is the task of converting data from a given form to a much more usable and desired form i.e. making it more meaningful and informative. Using Machine Learning algorithms, mathematical modeling, and statistical knowledge, this entire process can be automated. The output of this complete process can be in any desired form like graphs, videos, charts, tables, images, and many more, depending on the task we are performing and the requirements of the machine.

The performance and reliability of the models depend upon the dataset used for training. The dataset must contain realistic car damage images. The dataset for car images were collected from a website like Kaggle, a few of the images from Google and other images are collected from Indian traffic management database..

The dataset images are collected from online sources making noisy and low-quality images. The final dataset had about 7000 images. The dataset used for the classification model is preprocessed before it is fed to the model to improve accuracy and increase robustness. The model accepts input in image and video format. The video is divided into frames and the captured frames are stored as images. After all the images are collected, the preprocessing process starts with removal of unwanted car images that are not needed by the system. This step is necessary as the model would work only on a certain set of images in which cars can be identified, classified and so can be the severity of damage. It is followed by removal of noise, unwanted elements from th dataset images. There is also a chance that there are images in the database which are out of focus or we can say the blurred images. It is necessary to remove them as such images provide no actual information to they system and it is necessary to remove them. The next step includes annotating all the images in the dataset and labelling the bounding boxes with the labels damaged or not damaged. The images are also labelled according to the class of the damage level as well as damage position.

### Image Pre-processing

After the collection of images of car damage, we performed the pre-processing of the collected image dataset. During pre-processing of the dataset, the following various operations were performed on the images.

#### Types of Image:

- Binary Image
- Black and White Image
- 8-bit color format
- 16-bit color format

#### Resizing of images

- First, We will resize all images to same size.
- It will help to reduce computization power.
- The cropped images are resized to 224X224 Pixel, which is the input size required for our pretrained network.

#### Zooming

Image zooming means converting the image into a magnified image. The zoomed version of thermal images can be used for augmentation as they represent the case when images are taken from a close distance from a car

#### Rotation

Rotation of an image means changing the position of an object about a pivot point at some angle. Image of a damaged car or undamaged car when rotated, will still look like a damaged or undamaged car and would represent the case as if the picture was taken from a different angle.

#### Salt and pepper noise

Salt and pepper noise is added to an image by randomly changing intensities of some of the pixels of an image to 1 and some other to 0. Salt and pepper noise can represent a case where images were collected on a dusty day, or when the camera has dust on it.

## MODULE 2 - LABELLING AND CLASSIFICATION OF DATA

The images of the first dataset are annotated before loading them into the framework. Image annotation is the process of labeling the objects to be detected. The software used to label the data is called “LabelIng”, an abbreviation of Label Image. The labeling process can be done by drawing a bounding box around the damaged sections of the car.

The position of each damaged part is then converted into a text file with the coordinates of the bounding box. The next step includes annotating all the images in the dataset and labelling the bounding boxes with the labels damaged or not damaged. The images are also labelled according to the class of the damage level as well as damage position.

## MODULE 3 - CNN CLASSIFICATION

CNN or ConvNets is one of the deep learning algorithms, designed to extract features of images which help in classifying images. The CNN architecture with different layers is shown and the same is discussed below.

### Introduction to the network

Neural networks are mathematical model designed to loosely resemble the human brain. Convolution neural network (CNN) is one of the different types of neural network. CNN specializes in image processing and can be used for image classification, segmentation, object detection etc. Fig. 3 shows a schematic of a simple CNN, which classifies an input image into different category of vehicle present in it

It consists of different categories of layers such as convolution layer, pooling layer, activation layer, etc. Convolutional layer The major part of this layer is carried out by a kernel or filter, which is imposed number of times on the image based on stride length. The kernel is moved over an image to extract the features like color, edges and gradients. The kernel travels through the entire image to extract the features.

### Pooling Layer

The Pooling layer is responsible for reducing the spatial size of the Convolved Feature. This is to decrease the computational power required to process the data through dimensionality reduction. Furthermore, it is useful for extracting dominant features which are rotational and positional invariant, thus maintaining the process of effectively training of the model.

It is used to extract features that are invariant to rotation and position. Pooling can be categorised into two types i.e.

1. Max Pooling
2. Avg Pooling.

After the convolution and pooling layer, the model is enabled to understand and extract features from an image. Max Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel.

Max Pooling also performs as a Noise Suppressant. It discards the noisy activations altogether and also performs denoising along with dimensionality reduction. On the other hand, Average Pooling simply performs dimensionality reduction as a noise suppressing mechanism. Hence, we can say that Max Pooling performs a lot better than Average Pooling.

The Convolutional Layer and the Pooling Layer, together form the i-th layer of a Convolutional Neural Network. Depending on the complexities in the images, the number of such layers may be increased for capturing low-levels details even further, but at the cost of more computational power. After going through the above process, we have successfully enabled the model to understand the features. Moving on, we are going to flatten the final output and feed it to a regular Neural Network for classification purposes.

### Creating a RESNET Model

Also, these networks have performed fairly in various deep learning competitions with very less error percentage. They also solve the problem generally observed in large networks that is with increase in depth of networks, saturation and degradation in accuracy start taking place. We have tried to employ the best practices for training the models. We have used cyclic learning rates that change their values cyclically between epochs and differential learning rates that change their values according to layers such that the training rate varies layer-wise as initial layers usually represent primitive features and inner layers represent high-level features. This helps in improving the accuracy greatly and reducing overfitting if any.

### Creating a 3 Level Prediction Model

CNN is used as the backbone of our system. We create a 3-step prediction model.

- Creating a model for checking ID - damaged or not
- Creating model for damage level prediction
- Creating model for damage position

Setting up Learning rate and optimizer

- The model uses binary cross-entropy as the loss function which is a logarithmic loss function.
- Adam optimizer with various parameters like learning rate, decay etc. has been used for optimization.

### Training Model

Training procedure includes adaptive moment estimation (Adam) optimizer that uses exponential weighted moving averaging to find the momentum and the second moment of the gradient. Similarly, different variations of learning rate (LR) has been experimented and 0.001 is found effective with batch size of 64 for the given input frames. Because, if it is very large, optimization diverges, and if it is very small, it takes extended time to train or end up with a trivial outcome. Moreover, activation function ReLU makes model training computationally effective because, the gradient in the positive interval is always 1.

Hence, parameters are not accurately initialized, the sigmoid function might get a gradient of nearly 0, and the model cannot be efficiently trained. Activation score in transitional layers may vary from the input to the output, over time due to the updation in the model's parameters and through nodes in the same layer. This accumulation in the activation distribution can delay the convergence of the network that too may lead to alterations in the LRs for every layer which is computationally expensive. Thus, normalizing the activations of every node through batch normalization has been applied to handle with the mentioned problem and it assists the model to converge at the early stages. Padding and stride are kept at unit movement and Softmax function is utilized in final layer.

The dataset was split into training, validation and test sets in the ratio of 70:20:10. The images were resized to  $224 \times 224$  dimensions. The modified network has been trained for 10 epochs using batch size of 64 using cyclic learning rate of 0.2. During training of the modified network, discriminative layer learning was used. Initially, the model was trained by keeping initial layers of the model unchanged i.e. no change in values of pre-trained network parameters. Afterwards, model was trained by unfreezing all the layers of the network i.e. parameters values of all layers were changed.

## V. RESULTS

Machine learning algorithms, such as the random forest algorithm or the support vector machine (SVM), are used to identify and distinguish phishing websites from legitimate ones. Good accuracy in detecting Phishing attacks has been observed

## VI. CONCLUSION

All models are assessed using validation accuracy and loss metrics. The basis for algorithms used lies in Convolutional Neural Networks, customized to optimize accuracy. Each approach is analyzed and varying degrees of accuracy were achieved across different models deployed ranging from 68% to 87%. Accuracy as high as 87.9% was obtained during the course of experiments. Each algorithm has several parameters that can be tested with different values to increase their accuracy. Static analysis has also proven to be safer and free from the overhead of execution time



## REFERENCES

- [1] A. Alswailem, B. Alabdullah, N. Alrumayh and A. Alsedrani, "Detecting Phishing Websites Using Machine Learning," 2019 2nd International Conference on Computer Applications & Information Security (ICCAIS), 2019.
- [2] M. Korkmaz, O. K. Sahingoz and B. Diri, "Detection of Phishing Websites by Using Machine Learning-Based URL Analysis," 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT), 2020.
- [3] M. H. Alkawaz, S. J. Steven and A. I. Hajamydeen, "Detecting Phishing Website Using Machine Learning," 2020 16th IEEE International Colloquium on Signal Processing & Its Applications (CSPA), 2020.
- [4] A. Odeh, I. Keshta and E. Abdelfattah, "Machine Learning Techniques for Detection of Website Phishing: A Review for Promises and Challenges," 2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC), 2021.
- [5] V. Patil, P. Thakkar, C. Shah, T. Bhat and S. P. Godse, "Detection and Prevention of Phishing Websites Using Machine Learning Approach," 2018 Fourth International Conference on Computing Communication Control and Automation (IC3CAA), 2018.
- [6] A. Razaque, M. B. H. Frej, D. Sabyrov, A. Shaikhyn, F. Amsaad and A. Oun, "Detection of Phishing Websites using Machine Learning," 2020 IEEE Cloud Summit, 2020.
- [7] M. M. Vilas, K. P. Ghansham, S.P. Jaypralash and P. Shila, "Detection of Phishing Website Using Machine Learning Approach," 2019 4th International Conference on Electrical, Electronics, Communication, Computer Technologies and Optimization Techniques (ICEECCOT), 2019.
- [8] M. Rastogi, A. Chhetri, D. K. Singh and G. Rajan V, "Survey on Detection and Prevention of Phishing Websites using Machine Learning," 2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), 2021.
- [9] A. Lakshmanarao, P. S. P. Rao and M. M. B. Krishna, "Phishing website detection using novel machine learning fusion approach," 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS), 2021.
- [10] W. Bai, "Phishing Website Detection Based on Machine Learning Algorithm," 2020 International Conference on Computing and Data Science (CDS), 2020.





**SJIF: 8.423**



INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INTERNATIONAL CENTRE



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 **9940 572 462**  **6381 907 438**  **ijirset@gmail.com**



[www.ijirset.com](http://www.ijirset.com)

Scan to save the contact details