# Automated Classification of "Bad Images" by Means of Machine Learning for Improved Analysis of Vehicle Undercarriages

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## ABSTRACT

This research focuses on the development of a vehicle undercarriage image quality machine learning model. The model returns the quality of the image across several categories which are used for classifying image defects. Through analysis of 1M+ images taken with a proprietary Virtual Lift™ imaging system [1], a list of image issues, defects, and causes were identified and classified. An image dataset incorporating all issues / defects was then created and labeled for training and validating a neural network. The deep convolutional neural network, a ResNet 34, classified the undercarriage images with a micro-average RoC area under the curve of 0.90. An ensemble was created from both the image quality model and an object detection model to increase overall performance of the object detection model. Applications expand to driving image data quality upstream at the time of image capture by providing real time feedback to the end user and as a second check to results from an automated imaging platform.

***Keywords***: bad image detection, image quality identification, data analysis, machine learning, classification

## 1 INTRODUCTION

The condition of an automobile's undercarriage is a significant indicator of its purchase price, overall condition, safety, and future length of service [3]. It can provide insights on upgrades or problems associated with the vehicle such as an aftermarket modification or improper repairs, damaged / missing components, or major rust. For evaluation however, proper analysis is often difficult to obtain. Traditional processes often require a trained professional and the use of a physical vehicle lift, inhibiting buyers' ability to effectively estimate a used vehicle's value. This is especially true when evaluating vehicles listed on online auction platforms, where physical inspections are limited or impractical. ACV Auctions, an online wholesale automotive marketplace that specializes in providing a detailed and transparent assessment of vehicles listed on its auction platform, has developed a solution to this problem. Their solution is their proprietary Virtual Lift imaging system, the industry's first mobile vehicle undercarriage imaging tool (Figure 1). The lightweight, low-profile device utilizes ACV's proprietary mobile hardware and software technology to provide a full bumper-to-bumper view and image of the vehicle's undercarriage in less than one minute [2]. A Virtual Lift image is produced and displayed for each vehicle sold on their platform and is a key feature of what makes their platform unique in vehicle condition transparency.

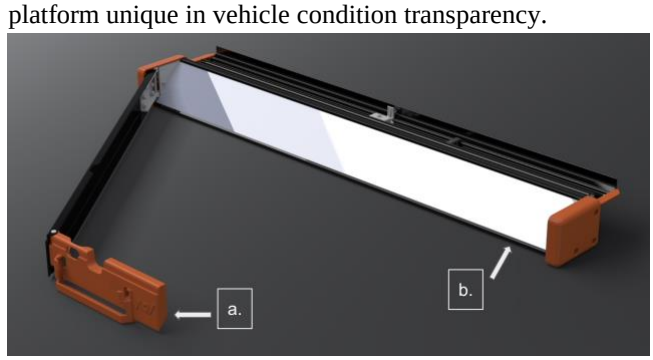


Figure 1. Image of a Virtual Lift (a) mobile phone / camera holder (b) reflective surface pointed up at vehicle undercarriage.

The Virtual Lift requires proper use of the physical system as well as manual cropping of the image size to produce a quality image. Improper use of the system or poor cropping of the image produces a defective image, inhibiting one's ability to properly assess a vehicle's undercarriage. For proper assessment, a high-quality photo which includes adequate lighting, high resolution, and full end-to-end display of the undercarriage is required. This work outlines the identification of the resulting defects, their causes, and the creation of a system that autonomously identifies / classifies those "bad" images produced.

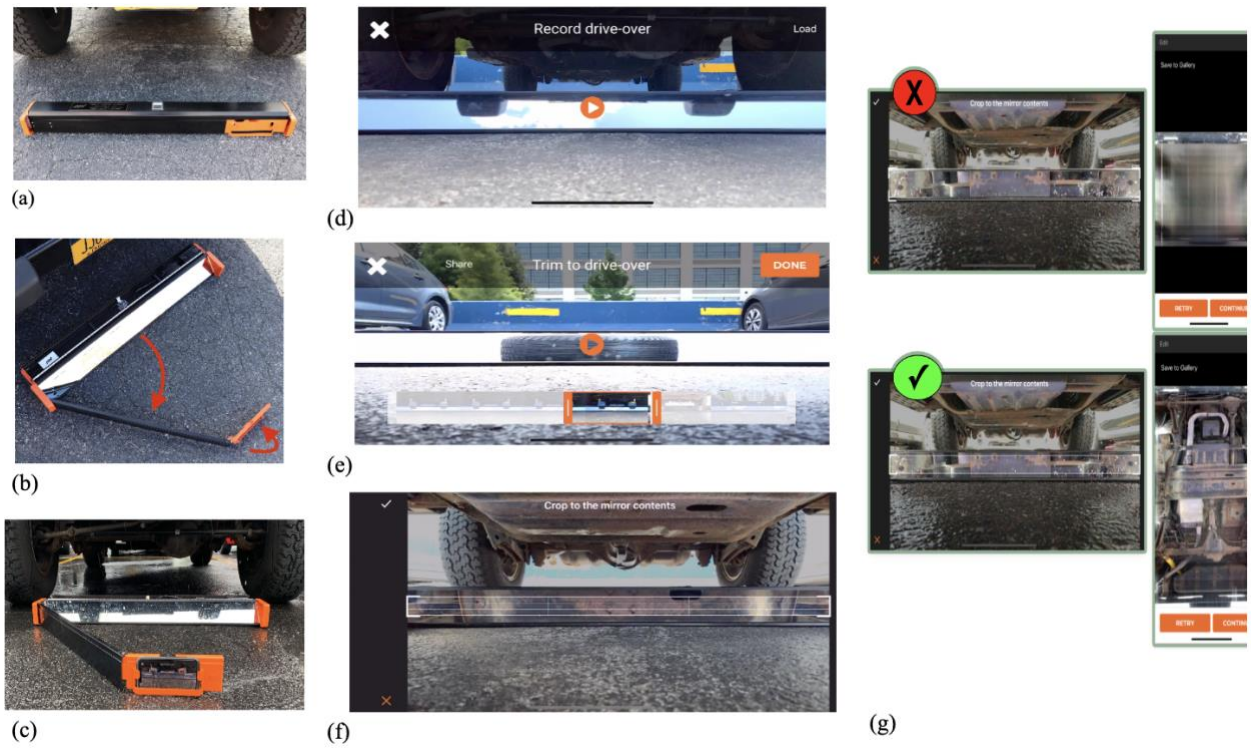


Figure 2. Flow of Virtual Lift system use. (a) Place Virtual Lift in front of vehicle, (b) open Virtual Lift, (c) place mobile phone / camera in holder and open Virtual Lift app, (d) press record drive over and drive over Virtual Lift with vehicle, (e) manually trim length of Virtual Lift recording including only the recording of the undercarriage, (f) crop camera focus on mirror only, (g) if properly cropped and trimmed the recording is stitched together into a high-resolution photo of the vehicle's undercarriage bumper to bumper. Improper Cropping results in a defective / extremely low-quality image output.

## 2 METHODS

The Virtual Lift imaging hardware system utilizes a mobile camera pointed at a reflective surface to image the underside of a vehicle [1]. Following capture of the image, users must crop the image on their mobile camera to include only the vehicle's undercarriage. The step-by-step process in using the Virtual Lift can be seen in Figure 2. Through human operating error, images which contain defects or issues are often generated preventing proper assessment of the vehicle's undercarriage. In an attempt to push image data quality upstream and acquire more usable photos for vehicle assessment, classification of the resulting images and their defects was conducted. Eight main defects were identified and categorized. Figure 3 provides an overview of the defects identified resulting from user error during the image collection process. Utilizing the Computer Vision Annotation Tool (CVAT), 1100 undercarriage images were labeled with the corresponding eight tags (Figure 4). With a labeled dataset, a machine learning model was trained to identify if an image was usable (Defect free) for proper undercarriage assessment and to identify the root cause of the problem.

The deep neural network used for classification is a ResNet-34 [6] with ImageNet [5] pre-trained weight initialization. The fully connected layer is modified for 8 output classes. We use adaptive average pooling to train on images with a resolution of (650, 224) and the image colors are normalized by the mean and standard deviation of the dataset. We use binary cross entropy with logit loss to perform multi-label classification, since each image can have any number of defects present. The model is trained with an ADAM [4] optimizer and a learning rate of 0.0001 for only 10 epochs.

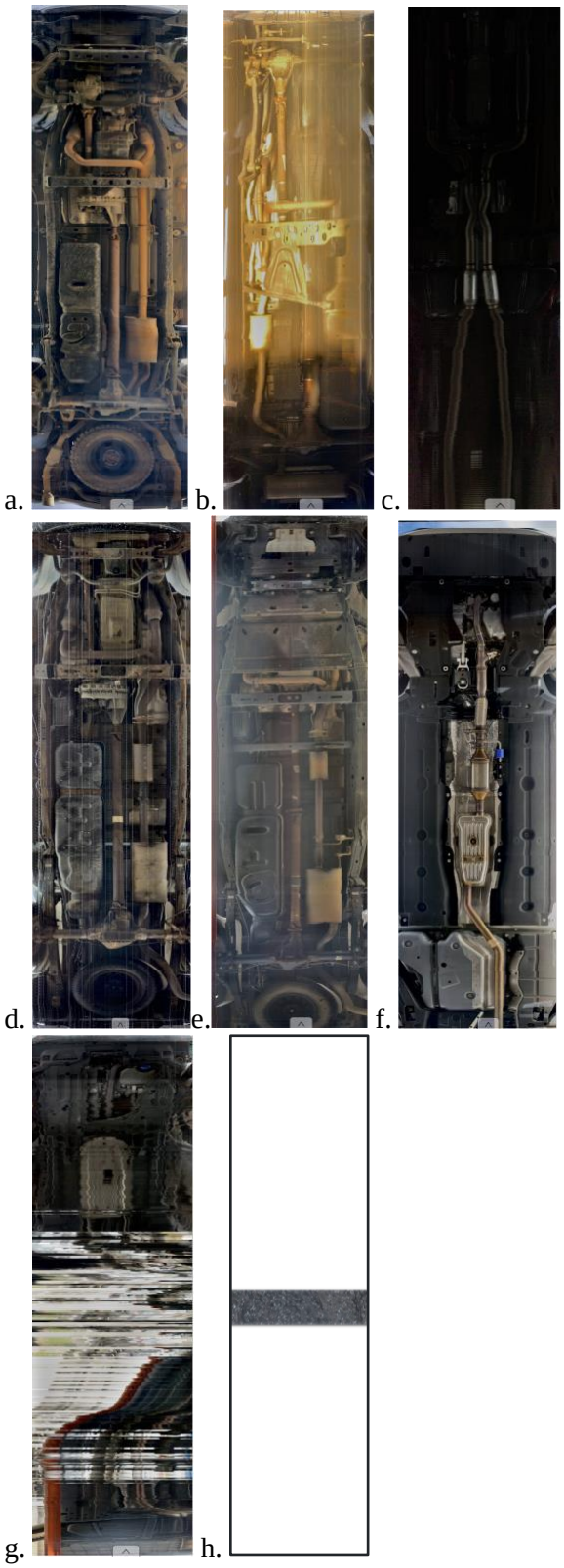


Figure 3. (a) Usable / quality photo which includes adequate lighting, high resolution, and full end-to-end display of the undercarriage. (b) Haze / glare caused by light reflecting off of the mirror. (c) Dark image resulting from poor lighting of the undercarriage. (d) Has lines / stripes down the image caused by a dirty mirror. (e) Has an orange line on the side of the image, resulting from poor image cropping. (f) Section of the undercarriage is missing, caused by poor trimming of the image. (g) Insufficient detail, which appears in the reconstruction as a choppy elongated image. (h) is a small image of only the mirror, which is the result of having a recording issue.

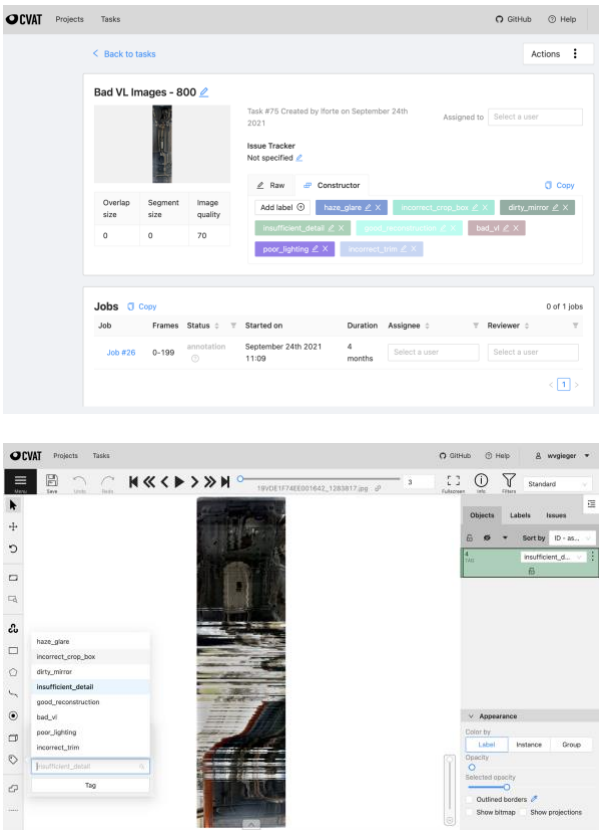


Figure 4. Labeling Image Process. (Top) Images are uploaded to CVAT and label tags are created for each subset of images (Bottom) images are individually tagged / labeled

## 3 EXPERIMENTS AND RESULTS

To test our machine learning model's ability to effectively identify and classify defective virtual lift images, we created and used a validation test set to do so. We labeled a set of 220 images which included a fairly even distribution of all eight image classes. Per a validation image set, these images were not used to train the model. This set would only be used to validate whether or not the model correctly identified the images' classes after making its predictions / classifications. We then tested our machine learning models ability to classify each image in the set and their class. As a result, the ResNet achieved a micro-average RoC AUC score

of 0.90 with some classes achieving as high as 0.99 AUC (Figure 5). The RoC is produced by calculating and plotting the true positive rate against the false positive rate for a single classifier at each threshold. This result showed the model has an effective ability to classify and identify "bad" Virtual Lift images.

Classes that achieved above .99 AUC can be assumed to have had a sufficient number of labeled images to train the model. For improvement in the model's ability to classify all other classes to a higher AUC, more images can be labeled to train the model.

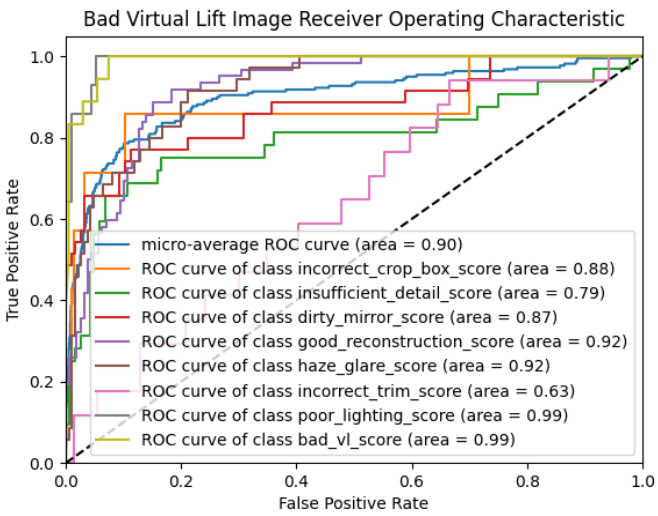


Figure 5. Receiver operating characteristic graph showing performance scores of our model on each image class type. (Class 0) Incorrect Crop Box (Class 1) Insufficient Detail (Class 2) Dirty Mirror (Class 3) Good Reconstruction (Class 4) Haze Glare (Class 5) Incorrect Trim (Class 6) Poor Lighting (Class 7) Bad VL

## 4. CONCLUSION

The research and development shown in this work establishes a method / system that identifies and classifies defective or "bad" images produced by a proprietary Virtual Lift imaging system. These methods / systems show capability to be integrated into the image collection process to provide real time user feedback and suggestions to improve data capture quality. Ensuring usable data as an end result, as well as faster improvement in a user's ability to optimize the system and produce the required images efficiently. This project's application of the system was to the automotive industry, where the undercarriage of a vehicle is a significant indicator of its purchase price, condition, safety, and future longevity. For proper assessment, a high-quality photo which includes adequate lighting, high resolution, and full end-to-end display of the undercarriage is required. The system developed ensures this outcome. In turn guaranteeing ACV Auctions and its customers the ability to properly assess each vehicle on their platform to its entirety.

Further, this model is now used as an ensemble to filter bad Virtual Lift images across other machine learning models that use Virtual Lift images. Including a tailpipe emissions equipment detection model and a rust detection model. The "bad" image detection model provides great improvement in the performance of these separate models.

## REFERENCES


[1] ACV Auctions Inc. (2021). vehicle undercarriage imaging system (10,893,213). U.S. Patent Office. https://uspto.report/patent/grant/10,893,213

[2] "ACV Auctions Unveils Virtual Lift™," *ACV Auctions*. [Online].Available:https://www.acvauctions.com/blog/acv-auctions-unveils-virtual-lift.[Accessed: 10-Apr-2022].

[3] Burski, Bartłomiej, Piotr Czajka, and Piotr Garbacz. "Hybrid vision method for vehicle undercarriage diagnostics." Problemy Eksploatacji (2014).

[4] D. P. Kingma J. Ba, 'Adam: A method for stochastic optimization', arXiv preprint arXiv:1412. 6980, 2014.

[5] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, L. Fei-Fei, 'Imagenet: A large-scale hierarchical image database', 2009 IEEE conference on computer vision and pattern recognition, 2009,. 248–255.

[6] K. He, X. Zhang, S. Ren, J. Sun, 'Deep residual learning for image recognition', Proceedings of the IEEE conference on computer vision and pattern recognition, 2016,. 770–778.