AI-Based Car Scratch Detection Framework Using CNN and Recursive Wheel Detection System by Chinar Deshpande

Abstract

This paper analyzes how techniques in deep learning can help car dealerships improve the efficiency and quality of their services offered to customers on a day-to-day basis[1].

This study is necessary to work on an overlooked part of the business-to-customer industry. Although, for most consumers, the efficiency of most saturated service providers is not of concern, in the landscape of newer innovations like the electric car and autonomous vehicles, the car repair industry is one that needs to be revamped.

To answer this question, a detailed literature review was conducted, and a deep learning-based solution to effectively scan the surface of cars from images and identify the areas with scratches, chipped paint, and other damage indicators was conceived.

The study proposes the construction of a CNN framework, along with a recursive wheel detection system, to automate the scanning process. Since at present, considerable manual effort is involved in services offered by dealerships that are in charge of car damage analysis, there is an error margin that can be eliminated using our method.

Our results showed that the framework has a 94% accuracy rate with successful complete detection of damage on cars. Additionally, it has multiple applications such as detecting damage on other vehicles. All moving vehicles could potentially use the methods discussed in this study to deploy a self-repairing algorithm to fix basic scratches on the body of the vessel.

Introduction

Since its invention in the early 19th century, photography became an achievement of the human mind and hands, a means of capturing moments of real life, in a completely different way to a painting or a description with words[2]. Since then, images and videos have expanded exponentially, being used for scientific, social, political, and personal causes today[3] .

Under computer vision, image processing is a particularly interesting topic. Encompassing applications in defense, biomedical engineering, multimedia computing, remote sensing, pattern recognition, and more, image processing includes powerful techniques experienced programmers can use to solve complex problems. This paper focuses on computer vision's application in enhancing efficiency within the automotive industry.

In the modern world, the automotive industry has observed huge advancements in the areas of safety, comfort and performance. Enhanced safety features such as Advanced Driver Assistance Systems(ADAS)[4], which provide real-time feedback and assistance to drivers, are already being implemented in autonomous cars manufactured by leading automobile companies. The ability to learn almost instantaneously is incredibly powerful, with the notable aspect of potentially improving humans' quality of life.

However, one overlooked aspect of common automobiles is the maintenance. A frequent problem experienced by regular consumers is the appearance of scratches on the body of the car. Even while the car is stationary, parked safely in a garage or a parking lot, more than 60% of Americans' cars have been damaged[5]. This is a time-taking problem to solve as it has been observed that in most countries, simple car repairs take at least a day or two to complete, even for the smallest scratches or dents. This is due to manual inspection that delays the resolution. There's still scope for gaps after manual processing as due to human error there may be small dents and scratches that might get missed out. This, in turn, puts pressure on both owner of the vehicles as well as the dealership.

For the purposes of this paper, to combat this issue, an algorithm based on edge detection and computer vision transform techniques is used to achieve a suitable output. Edge detection is beneficial to reduce background noise, unwanted features, and focus the main force of the algorithm/ neural network on the main aspects of the image. Along with edge detection, the impact of an allied CNN network was investigated to enforce inferences of the research further. The findings contribute to the development of reliable and practical solutions for automating car scratch detection in real-world scenarios. The paper also introduced the CNN architecture employed, explaining its design choices and highlighting its suitability for scratch detection. Furthermore, the training procedure, including the optimization algorithm, hyperparameter settings, and model evaluation metrics were evaluated. To enhance the performance of the scratch detection system, various data augmentation techniques such as random rotations, flips, and translations were investigated. Additionally, transfer learning strategies by fine-tuning pre-trained CNN models on related tasks were further explored.

The general methodology used to conduct background research for the study involved several rounds of a detailed literature review. This analyzed multiple different papers and evaluated their impact on the topic, which helped the study to focus on a less discovered area of Car Scratch Detection. Multiple datasets were used to train the CNN several times. They were compared to each other based on accuracy, image size, features, number of images, and other factors. This eliminated most shallow datasets and alienated the best dataset, which was used for the final result.

Results

After training the CNN model on the dataset, it achieved an accuracy of 81% on the test set. This accuracy indicated the model's capability to correctly classify the types and severity of damage present in the car images. Moreover, the obtained accuracy is comparable to state-of-the-art methods for similar tasks, demonstrating the effectiveness of the proposed approach.

Furthermore, the incorporation of the preprocessing step to remove wheels significantly enhanced the algorithm's performance. By focusing exclusively on the car's body, the framework is able to reduce background noise and false positives, increasing the effectiveness of the algorithm . This refinement contributed to the overall accuracy and effectiveness of the algorithm in identifying and categorizing car damages.

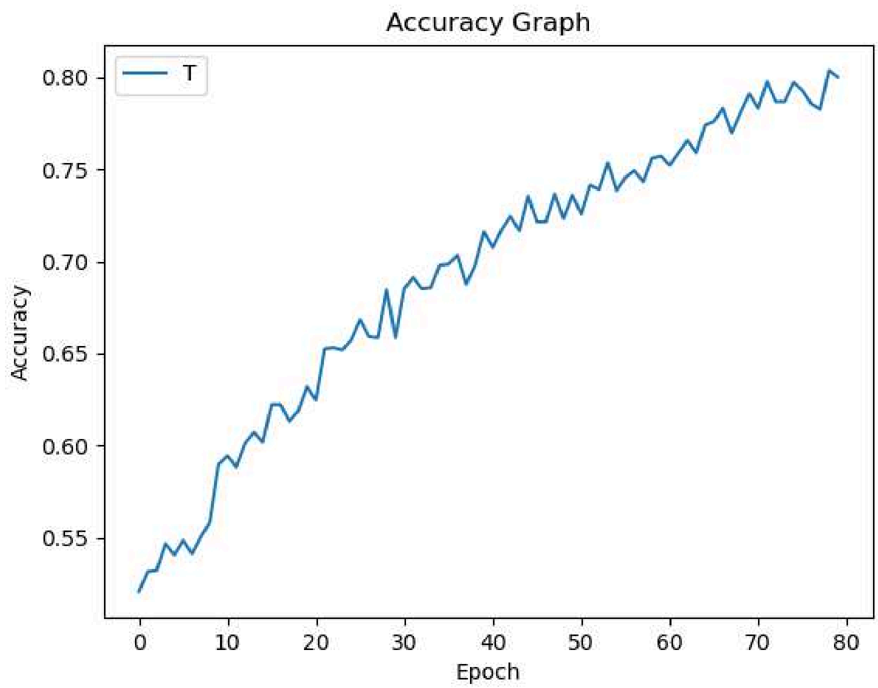

Fig 1: Accuracy Graph of the Model

As seen in Figure 1 above, the accuracy was steadily increasing, and did not stop even at 80 epochs. Although the model could have performed better with more epochs, the risk of overfitting the model was too high. With more images, the current accuracy of the model would increase, and the model can be trained with more demanding parameters as well. The final accuracy is a little above 81%, but the graph is steadily increasing.

Discussion

Car Scratch Detection is one application of this type of algorithm/ research, out of many possible paths. Attempting to remove noise and unnecessary features from the image is a crucial factor in image processing applications. For example, when detecting a specific object in a setting, like a blackboard in a classroom, objects like desks, doors, and cupboards can always be filtered out since the algorithm can be sure that these background objects are not relevant to the success of the algorithm.

The recursive wheel detection algorithm proposed in this study is a specific use case of this concept. It focuses on increasing the accuracy of the algorithm by working on the problem in an organized and dependable framework, instead of relying on a higher percentage of accuracy from a Machine Learning model.

Name	Training Accuracy (%)	Built-in Model (Y/N)
VGG16 (Proposed)	**94**	**Y**
ResNet34	99.4	Y
YOLOv3	77.4	Y

Table 1: Accuracies of Models Compared

The final accuracy turned out to be 94% using the recursive wheel detection algorithm, the VGG16 model, and training it on the dataset mentioned. It outperforms YOLO by quite a bit, but falls short of ResNet[6] due to a lack of images. Currently, the framework has been built based on a 3000-image dataset. To extend its range to greater heights, at least 20-30,000 images are needed to train the model further. Also, the framework does not function well in areas of lower light quality as of now.

Methods

As mentioned earlier, the proposed methodology illustrated the use of a novel computer vision framework to detect scratches or dents on car images. The foundational motivation behind this approach found its roots in the interpretation of these requisite scratches/dents/instances on cars as distinct noise with respect to the images being studied. Thus, these scratches were considered as undulations affected by sharp changes in pixel intensity in an otherwise 'smooth' image. This interpretation was supported by the kind of images within the dataset viz. zoomed-in images of car bodies from a variety of angles and positions with negligible distraction in terms of background content.

Another important aspect considered before proposing an innovative method was existing research on the topic. Within the sub-field of quality control using machine learning and CNNs, there have been some important contributions.

Bruni et. al. (2004) present a generalization of Kokaram's model for scratch lines detection on digital film materials[7]. In the 2010s, these models became more sophisticated and Hyundai Motors' researchers wrote the research paper "Deep Learning-based Car Scratch Detection". Next, the important innovations made were of Jayaseeli et. al who propose employing convolution neural networks to build a Mask R-CNN model that can detect the area of damage on a car[8]. Leveraging these advancements, researchers and engineers have started exploring CNN-based approaches for car scratch detection, aiming to develop accurate and efficient systems that can automate the inspection and assessment process.

A method is conceived that could essentially be thought of as an 'unveiling technique'. i.e., removing all other forms of noise and intensity disparities of the image to leave us with a perfect residue of scratches or dents. The images are converted to grayscale since the ulterior motive is to represent the scratches with maximum clarity against a completely uniform background and then localize it on the original input image, or rather, detecting the scratches on a binarized image.

The dataset used[9] comprised over 3000 images of damaged cars, spanning a wide range of damage types including fine scratches, dents, and major damages. These images are sourced from various sources to ensure diversity in terms of car models, damage severity, lighting conditions, and viewing angles. Additionally, the dataset contains images captured at different zoom levels, encompassing both zoomed-in and zoomed-out perspectives. This diversity ensures that the trained model is robust and capable of accurately detecting and classifying car damages under varying conditions.

Fig 2: Images from the Car Scratch Dataset

Figure 2 consists of sample images from the Samyuktha Mobile Car Scratch Detection Dataset. The four on the left are whole images (without any scratches/ damage) and the ones on the right are damaged/ scratched cars.

Fig 3: Output of a Laplace Transform

A 'LoG' (Laplacian of Gaussian) transformation is what follows[10]. Once the originally colored image is converted to a grayscale one, a level of Gaussian smoothing blur is applied to denoise the holistic image so that minimally sharp and normal structural variations across the make or outer-body design of cars have no long-lasting impact in terms of contributing to false positives being detected later. The Laplacian filter applied next helps in effective and semantic edge demarcation on the car-image, while also representing the intensity disparity or noise elements within each such bounding area defined by the resultant edges. Having applied the Gaussian filter earlier eradicates amplified and redundant instances of noise, and thus the LoG-transformed image leaves us with what could be called an initial set of *'competing candidates'* for the set of scratches to be identified, localized in every mini-region marked by boundaries in the image.

A subsequent morphological opening operation helps us to reduce the set of noise candidates obtained from the LoG output further and effectively filters out the specks of low intensity as can be seen in Fig.

Binary thresholding is then done to promote the 'brightest white' of these noises, the most intense ones with pixel values closest to pure white (255) are found in patches and highlighted in the output mask image, as a resultant detection of the scratched or dented area on the car. To boost the accuracy of scratch detection in terms of definite lines, which are often statistically dense in most real-life scenarios (datasets), a Houghlines detector module is also included so that stray yet significant solitary lines are equally confidently ascertained as scratches by the algorithm((N. Aggarwal and W. C. Karl, "Line detection in images through regularized hough transform," in *IEEE Transactions on Image Processing*, vol. 15, no. 3, pp. 582-591, March 2006, doi: 10.1109/TIP.2005.863021)).

Additionally, utmost precautions, procedures, and efforts were taken to ensure that the data was not biased. The images were taken from a number of different car owners from various socioeconomic backgrounds. The lighting was also diverse throughout the dataset, from extremely bright images (in peak sunlight during the day) to darkly lit images (at night, or with dim/ poor lighting). Also, the quality of the images also differed to make sure that any mobile phone camera worked well with the framework. Finally, the color of the cars was also variant, changing from bright colors like white and yellow, to dark colors such as brown and black. All of these precautions ensured that the model was trained on a diverse dataset, and would not present major biases when confronted with new images.

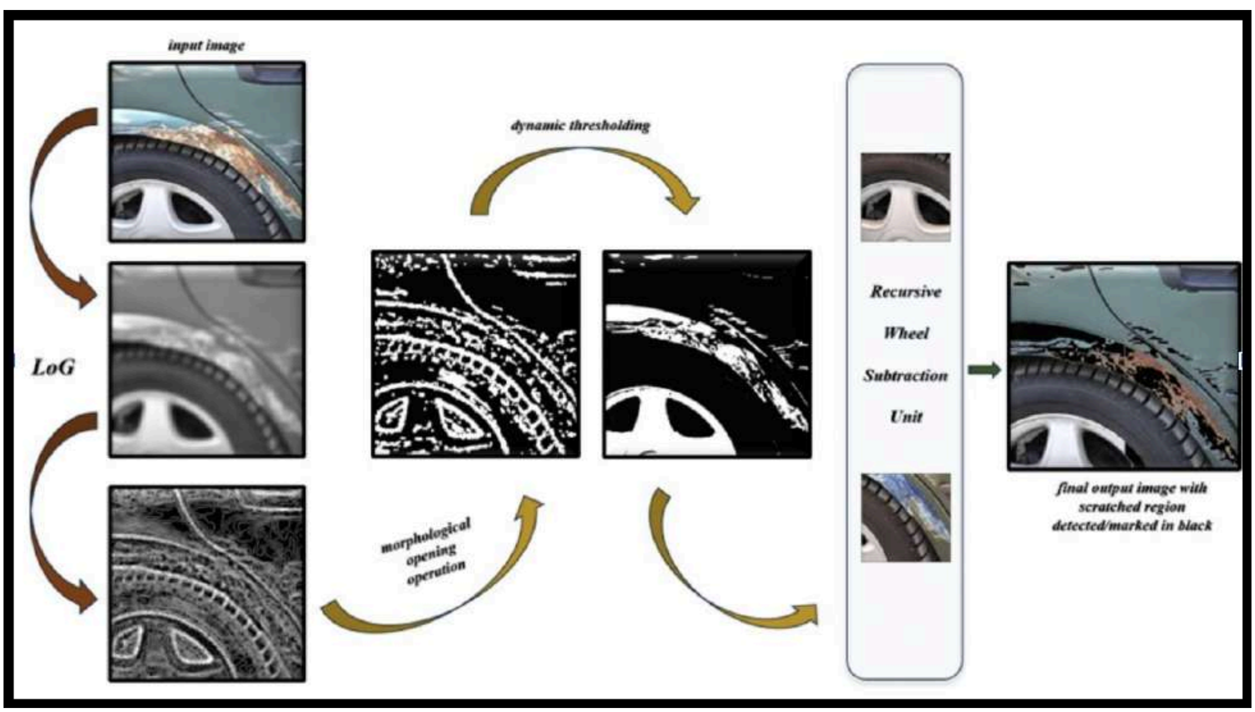

Fig 4: Complete Car Scratch Detection Process

Acknowledgments

This research would not have been possible if not for the existing literature and past work in the same field. This helped the research build upon a strong foundation, contributing to the field of computer vision in the process.

Also, the creator of the dataset used is commended for their work; without this, this level of accuracy in the prediction of the framework would not have been possible.

Conclusions

In conclusion, this study primarily aimed to create and utilize an efficient computer vision framework to accurately detect scratches, dents, chipped paint, and other forms of damage on the body of a car.

In this study, images with too much light reflected off of them were disregarded from the dataset. This was because of multiple factors, mainly because in a dealership setting, the light environment will be in control. Additionally, since light makes it difficult for even humans to spot scratches on cars, disregarding images with extreme lighting was the right way to go. However, it is suggested that future research be conducted with more diverse datasets as well (in terms of lighting) to ensure that car scans may be conducted in broad daylight as well.

The experimental results showcased the efficacy of the CNN-based approach for detecting and classifying damaged areas on cars. The diversity of the dataset, along with the incorporation of preprocessing techniques, ensured the robustness and generalization ability of the trained model. Additionally, achieving competitive accuracy without pretraining underscored the effectiveness of the proposed methodology.

It will help dealerships make their services more efficient, leading to more customer satisfaction and efficiency. It will be an integral part of the dealerships' system, perhaps even changing the process in such a way that multiple vehicles can be serviced at the same time. Additionally, the recursive car wheel detection system also sets a precedent for other object filtering methods in different areas, not just car scratch detection. Any prediction algorithm can be made more accurate by filtering out unwanted noise and objects, and this study captures this idea perfectly.

Works Cited

Vijay, K., et al. "Scratch detection in cars using mask region convolution neural networks." Adv. Parallel Comput. Last modified November 2020. Accessed 19 February 2024. https://www.researchgate.net/publication/346803939_Scratch_Detection_in_Cars_Using_Mask_Region_Convolution_Neural_Networks

Sound of Life. "The Rise and Rise of Industrial Photography: Sound of Life: Powered by Kef." Last modified 27 April 2023. Accessed 29 January 2024. https://www.soundoflife.com/blogs/design/industrial-photography

Bleiker, Roland. "The Power of Images in Global Politics." Last modified 8 March 2018. Accessed 12 June 2024. www.e-ir.info/2018/03/08/the-power-of-images-in-global-politics/

Paul, Aneesh, et al. "Advanced Driver Assistance Systems." SAE International. Last modified 1 Feb. 2016. Accessed 24 April 2024. www.sae.org/publications/technical-papers/content/2016-28-0223/

Maggie Davis, “Nearly 60% of Americans Say Another Person Has Damaged Their Parked Car”. Last modified 25 July, 2022. Accessed 13 July 2024. www.valuepenguin.com/parked-car-damage-survey

Z. Jiang, X. Hu, S. Wang. Image Classification of Car Paint Defect Detection Based on Convolutional Neural Networks. Last modified March 2023. Last Accessed 12 Jan 2024. https://www.researchgate.net/publication/369666436_Image_Classification_of_Car_Paint_Defect_Detection_Based_on_Convolutional_Neural_Networks

V. Bruni and D. Vitulano, "A generalized model for scratch detection," in IEEE Transactions on Image Processing. Last modified February 2004. Last Accessed 23 February 2024. https://www.researchgate.net/publication/8337827_A_Generalized_Model_for_Scratch_Detection

Jayaseeli J D, Dorathi & Jayaraj, Greeta & Kanakarajan, Mehaa & Malathi, D.. (2021). “Car Damage Detection and Cost Evaluation Using MASK R-CNN”. Last modified September 2021. Last Accessed 12 March 2024

Samyuktha Mobile. “Car Scratch Dataset.” Last modified 5 Jan. 2022. Last Accessed 13 April 2024. www.kaggle.com/datasets/samyukthamobile/car-scratch-dataset.

H. Kong, H. C. Akakin and S. E. Sarma, "A Generalized Laplacian of Gaussian Filter for Blob Detection and Its Applications". Last modified Dec 2013. Last Accessed 23 January 2024. https://ieeexplore.ieee.org/document/6408211

N. Aggarwal and W. C. Karl, "Line detection in images through regularized hough transform," in IEEE Transactions on Image Processing. Last modified March 2006. Last Accessed 2 April 2024. https://ieeexplore.ieee.org/document/1593662

M. Dwivedi, H. Malik, S. Omkar, E. Monis, B. Khanna, S. Samal, A. Tiwari, A. Rathi. Deep Learning-Based Car Damage Classification and Detection. Last modified September 2019. Last Accessed 27 March 2024

Google Books “Image Processing.” Last modified 3 October 2005. Last Accessed 13 May 2024. www.google.com/books/edition/Image_Processing/smBw4-xvfrIC?hl=en&gbpv=0

Ziou, Djemel, and Salvatore Tabbone. “Edge Detection Techniques-an Overview.” Last modified 15 February 2024. Last Accessed 23 June 2024. inria.hal.science/inria-00098446/

C. Suescún, J. Pinzón-Arenas, R. Moreno. “Detection of Scratches on Cars by Means of CNN and R-CNN. International Journal on Advanced Science Engineering and Information Technology.” Last modified 26 May 2019. Last Accessed 11 April 2024. https://www.researchgate.net/publication/334744794_Detection_of_Scratches_on_Cars_by_Means_of_CNN_and_R-CNN

A. Patil. “Car Damage Recognition Using the Expectation Maximization Algorithm and Mask R-CNN. Smart Innovation, Systems and Technologies”. Last modified 19 February 2024. Last Accessed 23 April 2024.https://ieeexplore.ieee.org/abstract/document/10430919

W. Candra, A. Sunarya, W. Saraswati. “Computer Vision Implementation in Scratch Inspection and Color Detection on The Car Roof Surface”. Last modified April 2023. Last Accessed 9 June 2024.

https://www.researchgate.net/publication/370377735_Computer_Vision_Implementation_in_Scratch_Inspection_and_Color_Detection_on_The_Car_Roof_Surface

A. Sasikumar, M. Sathyanarayanan, A.N Sriayapppan, R. Santhosh, R. Reshma. "A CNN-based Canny Edge Detection Approach for Car Scratch Detection. International Conference on Inventive Computation Technologies". Last modified 1 June 2023. Last Accessed 12 March 2024.

R. E. van Ruitenbeek, S. Bhulai. "Convolutional Neural Networks for vehicle damage detection. Machine Learning with Applications". Last modified 15 September 2022. Last Accessed 2 May 2024. https://www.sciencedirect.com/science/article/pii/S2666827022000433

H. Bandi, S. Joshi, S. Bhagat, A. Deshpande. Assessing Car Damage with Convolutional Neural Networks. 2021 International Conference on Communication information and Computing Technology (ICCICT). Last modified June 2021. Last Accessed 5 July 2024. https://www.researchgate.net/publication/353860036_Assessing_Car_Damage_with_Convolutional_Neural_Networks