

## Introduction

These days, Convolutional Neural Networks (CNNs) are heavily relied on. They are used in numerous applications, from scanning bank checks to crash avoidance on cars. On occasions, CNNs can encounter adverse conditions in the field that cause their performance to be degraded significantly. Often, the training process for CNNs is computationally expensive, making retraining to account for niche conditions undesirable. As an alternative to re-training, we explore algorithms to enhance an image before it is inferenced on. We will be focusing on two main algorithms, histogram equalization (HE) and Retinex that according to [1] make up 47% of research papers exploring image enhancement methods.

## Methodology

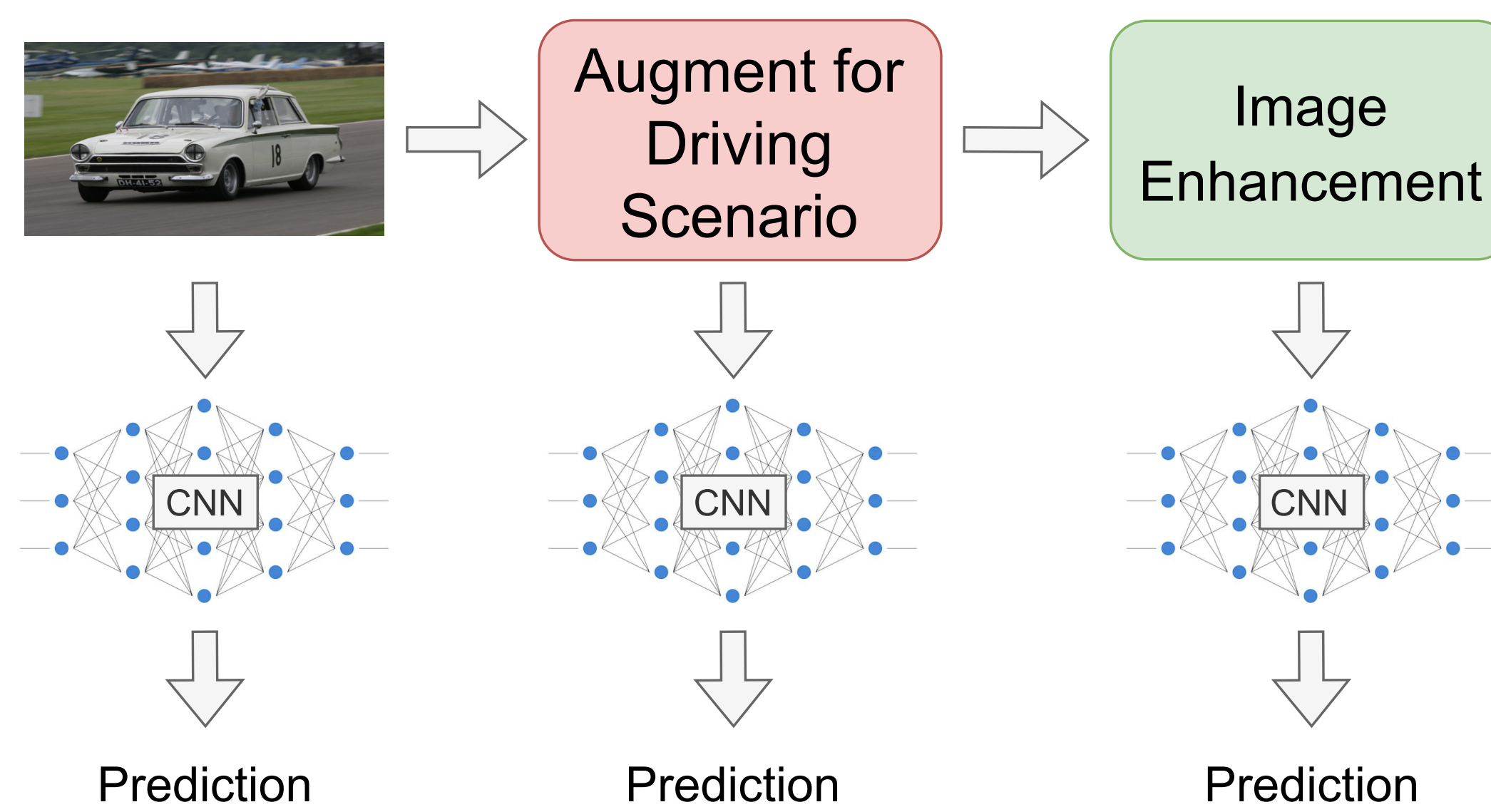


Figure 1. Methodology for evaluating effectiveness of histogram equalization and Retinex

OpenCV [2] is used to implement HE and [3] is used to implement Retinex. In order to effectively evaluate HE and Retinex, we need adverse images. For this, we elected to synthetically augment images to mimic adverse driving conditions. We will use four image augments to simulate the following adverse conditions: dark, over exposed, hazy/foggy, and dark & rainy, shown in Figure 2. Our testing methodology is shown in Figure 1. First, we evaluate two CNNs on validation datasets. For Resnet50, we are testing on the ImageNet validation set. For YOLOv8m we are testing on COCO2017 validation set. Second, we evaluate the CNNs on the augmented images. Last, we evaluate the CNNs on the augmented images with image enhancement applied.

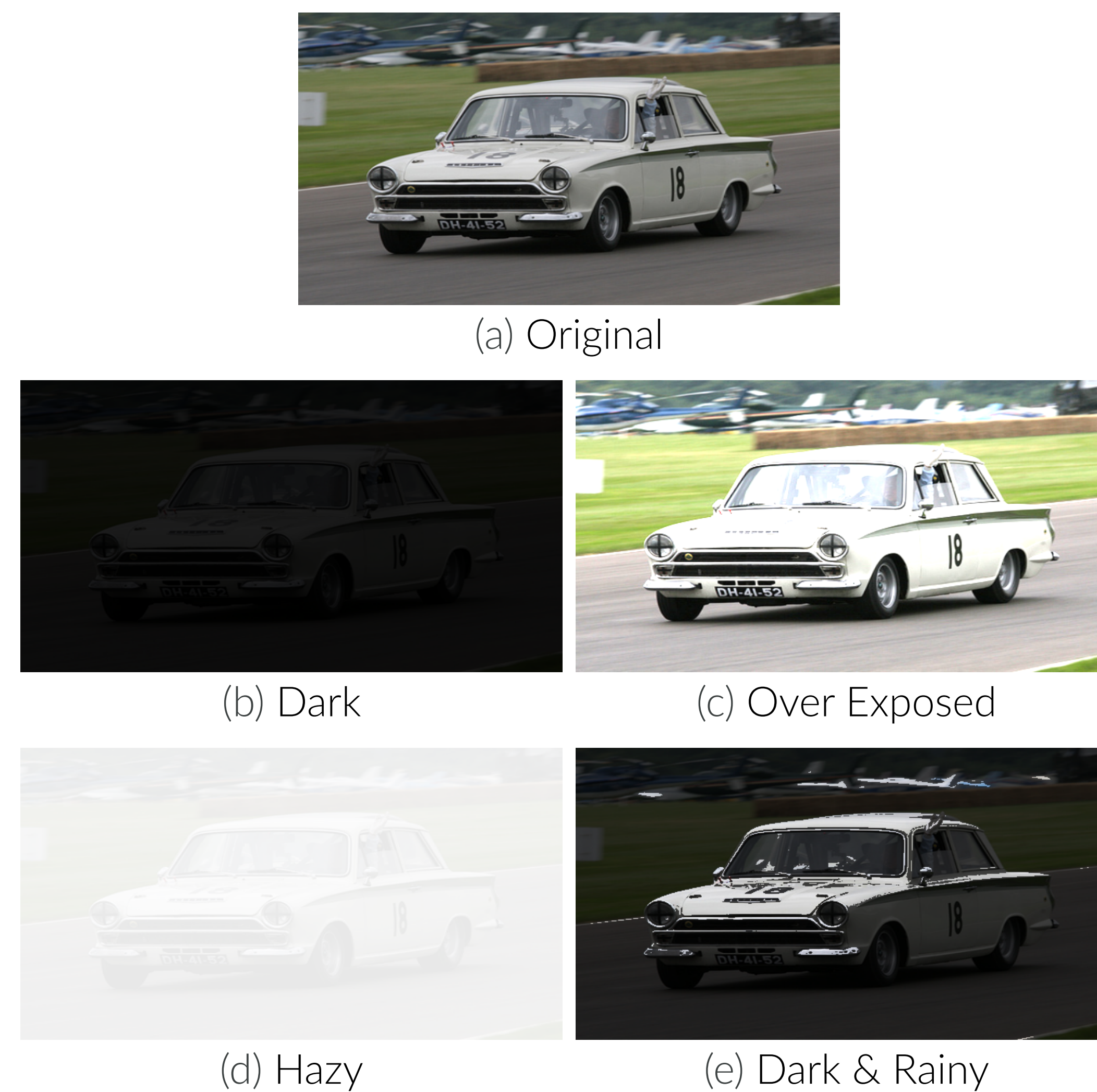


Figure 2. Example of image augments to simulate adverse driving conditions

In order to quantify the effectiveness of the image enhancements, we are using top-1 and top-5 accuracy for Resnet50 and mAP 50:95 for YOLOv8m. In addition, we are also measuring the average mean and standard deviation of the images.

## Results

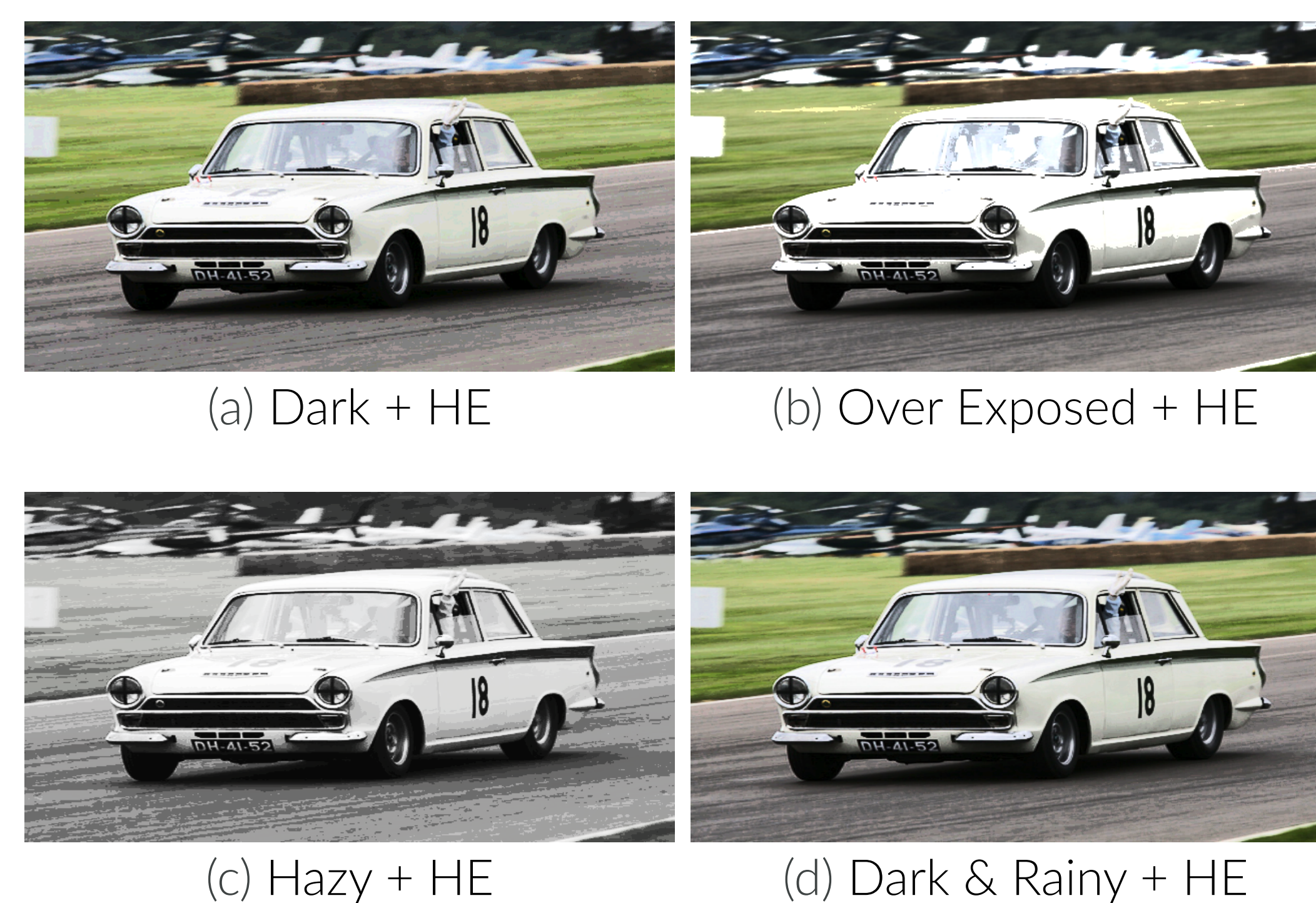


Figure 3. Images after applying the Histogram Equalization (HE) algorithm

In Figures 3 and 6 are examples of applying HE and Retinex to the augmented. The mean and standard deviation of ImageNet and COCO2017 have been averaged and are displayed in Figure 4.

Images Average Mean and Deviation

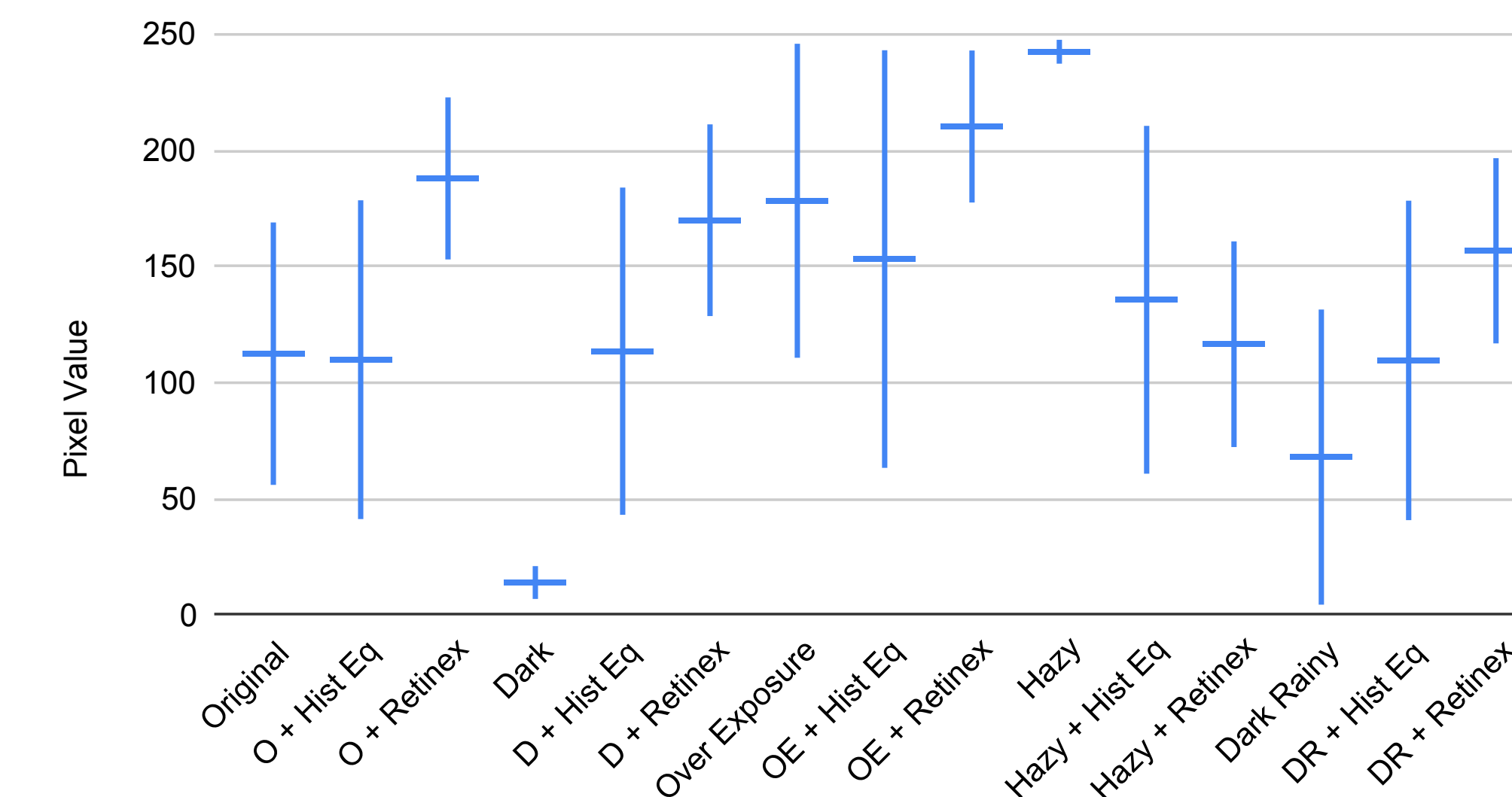


Figure 4. Mean and standard deviation of images. The horizontal lines represent the mean and the vertical line represents the standard deviation.

YOLOv8m mAP

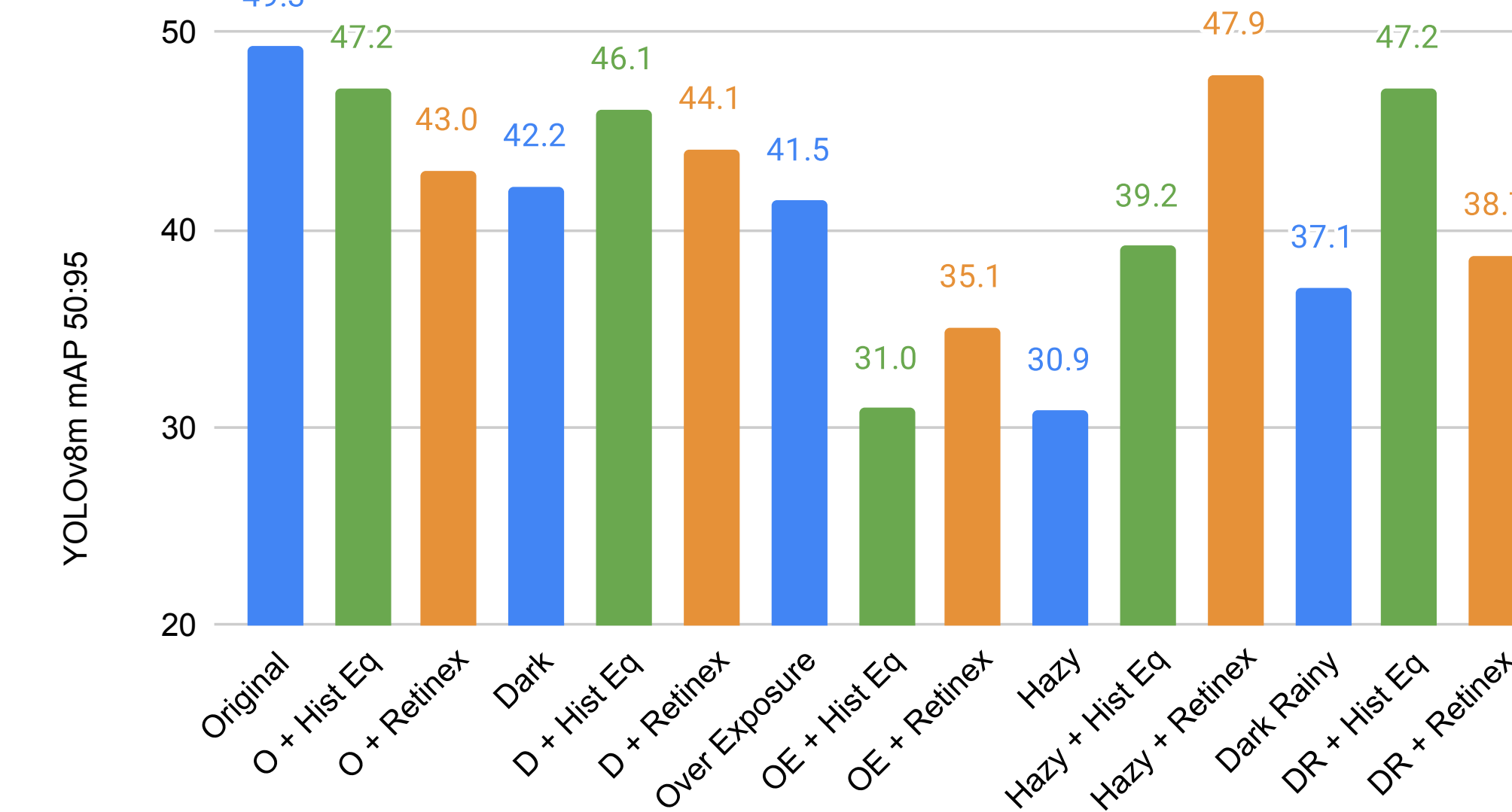


Figure 5. YOLOv8m mAP with and without image enhancements

In Figure 5 the results of YOLOv8m can be seen. For example, YOLOv8m has an mAP of 42.2 when inferencing on dark images, but after applying HE and Retinex the mAP is improved by 3.9 and 1.9 respectively. The change in performance of Resnet50 and YOLOv8m is shown in Figure 7. For Resnet50, the change in top-1 and top-5 accuracies have been averaged.

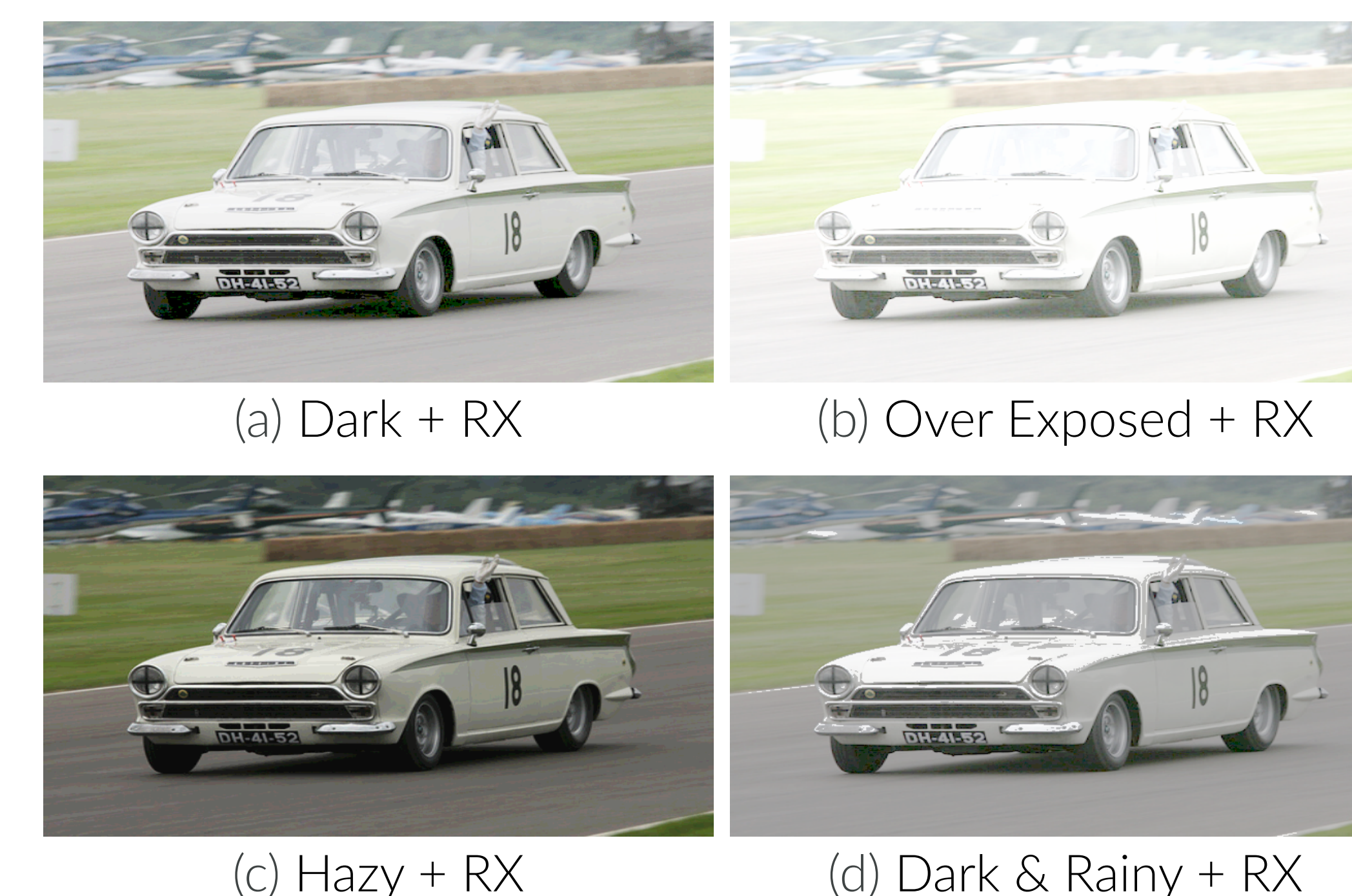


Figure 6. Images after applying the Retinex (RX) algorithm

Improved Accuracy and Improved mAP

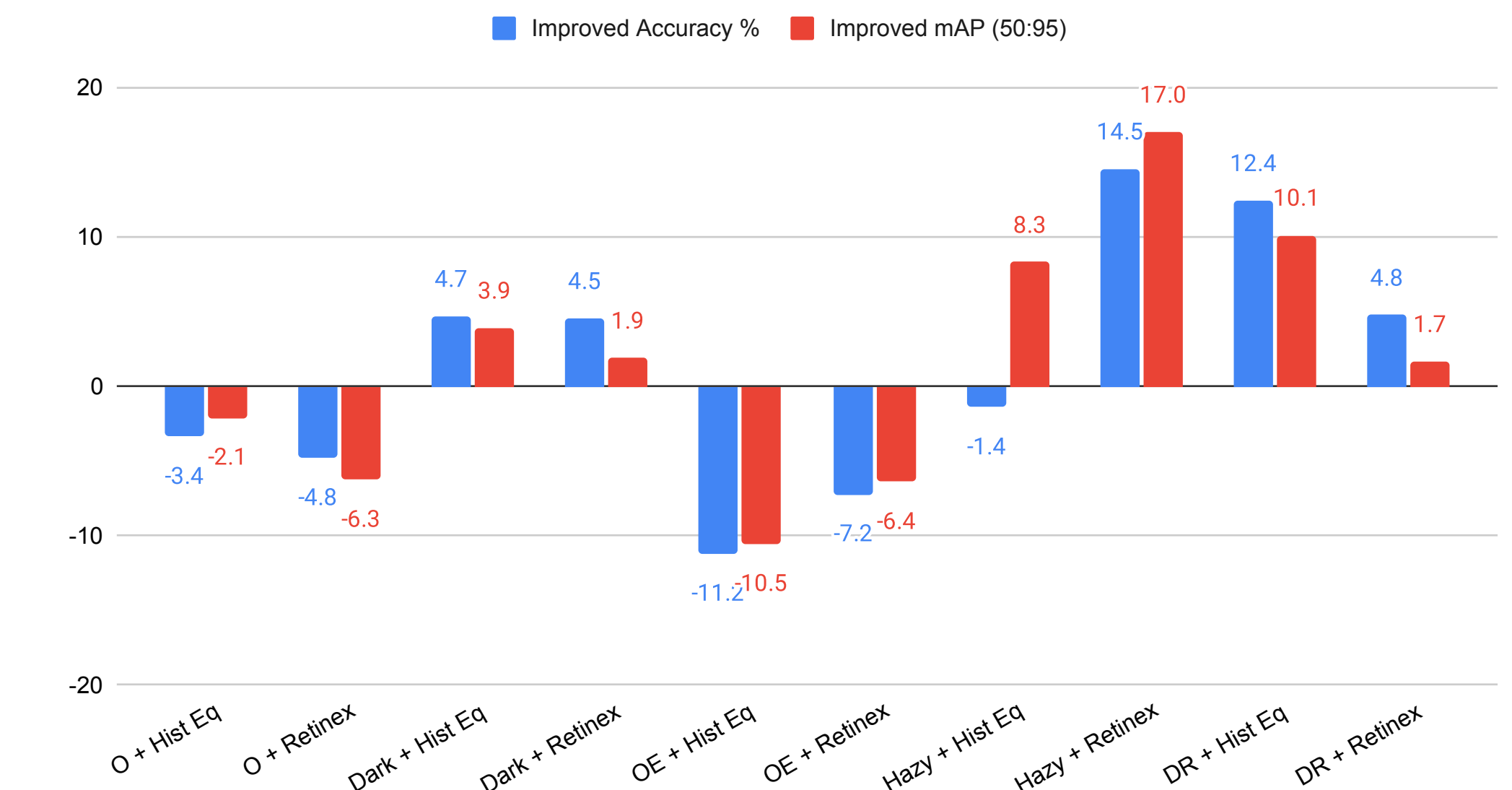


Figure 7. Change in accuracy and mAP with image enhancements applied.

## Discussion

As shown in Figure 7 when the image enhancements are applied to the original images they slightly degrade the performance. This is understandable as, the CNNs are optimized for the datasets they were trained on. HE and Retinex are able to improve the performance of the CNNs on adverse images in most cases. In general, HE is better at boosting contrast, while Retinex does a better job preserving color.

## Conclusion

In this work, we explored using image enhancements to improve the performance of CNNs inferencing on adverse images. We found that histogram equalization and Retinex both were able to improve the performance of Resnet50 and YOLOv8m. Neither algorithm is universally better, one scenario may benefit from one more than the better. In conclusion, to achieve optimal enhancement, an intelligent choice should be made of which algorithm is best to use.

## References

- [1] Y. Qi, Z. Yang, W. Sun, M. Lou, J. Lian, W. Zhao, X. Deng, and Y. Ma, "A comprehensive overview of image enhancement techniques," *Archives of Computational Methods in Engineering*, pp. 1–25, 2021.
- [2] "Opencv histogram equalization." [https://docs.opencv.org/3.4/d4/d1b/tutorial\\_histogram\\_equalization.html](https://docs.opencv.org/3.4/d4/d1b/tutorial_histogram_equalization.html).
- [3] Muggledy, "GitHub - muggledy/retinex: Retinex Algorithms: python code for MSRCR, MSRCP." <https://github.com/muggledy/retinex>.

## Acknowledgement

Special thanks to Dr. Talbert for prompting this inquiry. His machine learning class has been an excellent resource.