

Obstacle detection for BVLOS drones

For the TheBEAST project

Jan Moros Esteban

Supervisors: Maya Aghaei Gavari, Jaap Van de Loosdrecht

Summer 2021

Introduction

- New EU regulations allow Beyond the Visual Line Of Sight (BVLOS) drones
- This lead to the creation of the The BEAST project
- A submodule of it is Object avoidance for fail-safe landing
- This project's goal is to detect obstacles so they can be avoided during the fail-safe landing

Materials & Methods

- Dataset v1: 6 videos, of which 300 images are labeled
- Dataset v2: 8 videos, 423 labeled frames, split as 196 train, 64 valid., 63 test
- YOLOv3 [1] and YOLOv5 [2] architectures used
- Transfer learning from COCO pretrained weights

Abstract

With the introduction of new regulations in the European Union, the future of Beyond Visual Line Of Sight (BVLOS) drones is set to bloom. This led to the creation of the theBEAST project, which aims to create an autonomous security drone. This technical paper describes the first steps of a module within this project, which aims for detecting obstacles so they can be avoided in a fail-safe landing. An object detection method is used, and various experiments are held to maximize its performance. According to the results of the experiments, we conclude that although Object Detection is a promising approach to resolve this problem, more volume of data is required for potential usage in a real-life application.

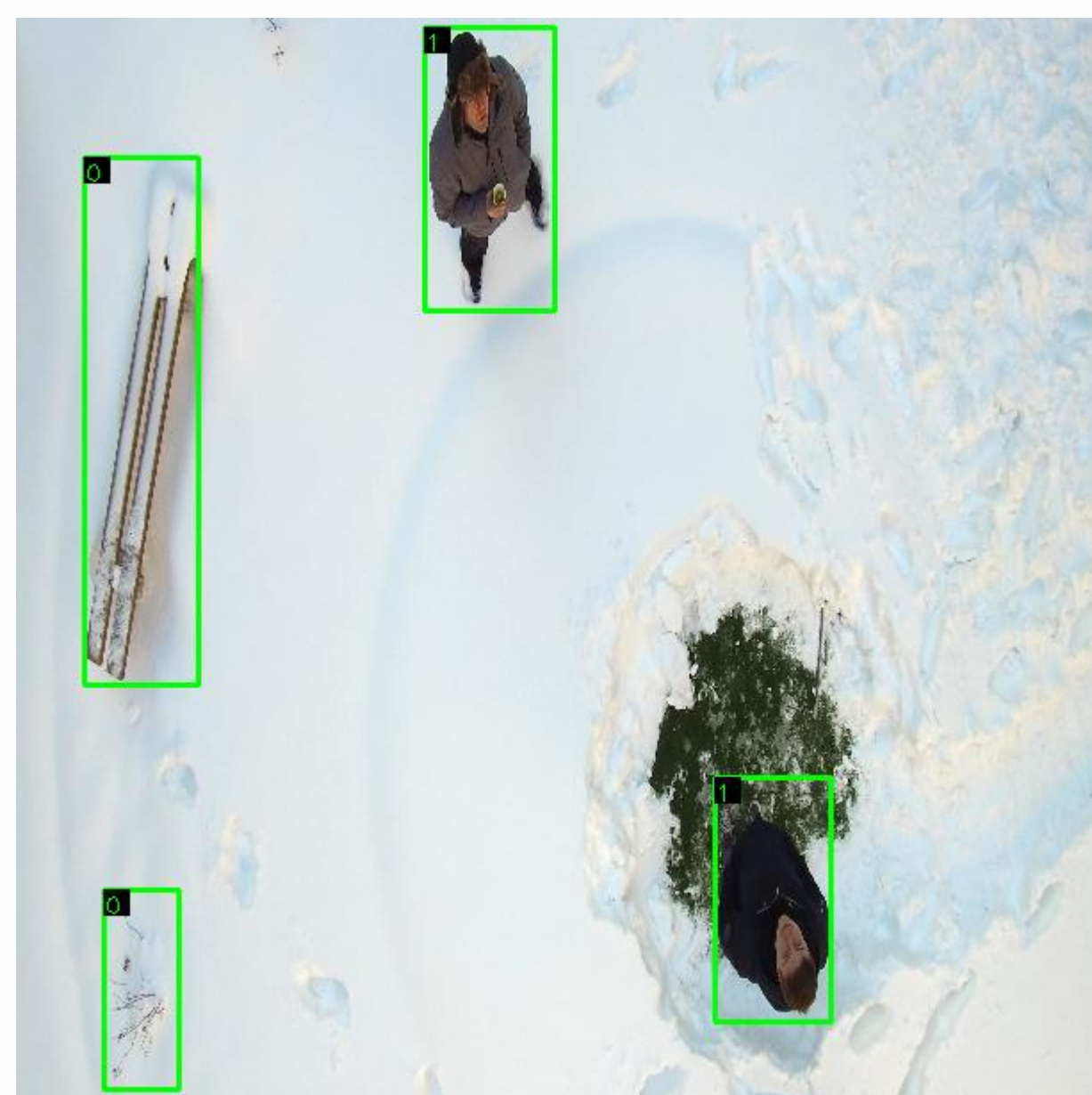


Figure 1. Sample image and labels from the dataset. The two classes present are visible. Those are Obstacle, represented by 0, and Person represented by 1.

Materials & Methods: Data Augmentation

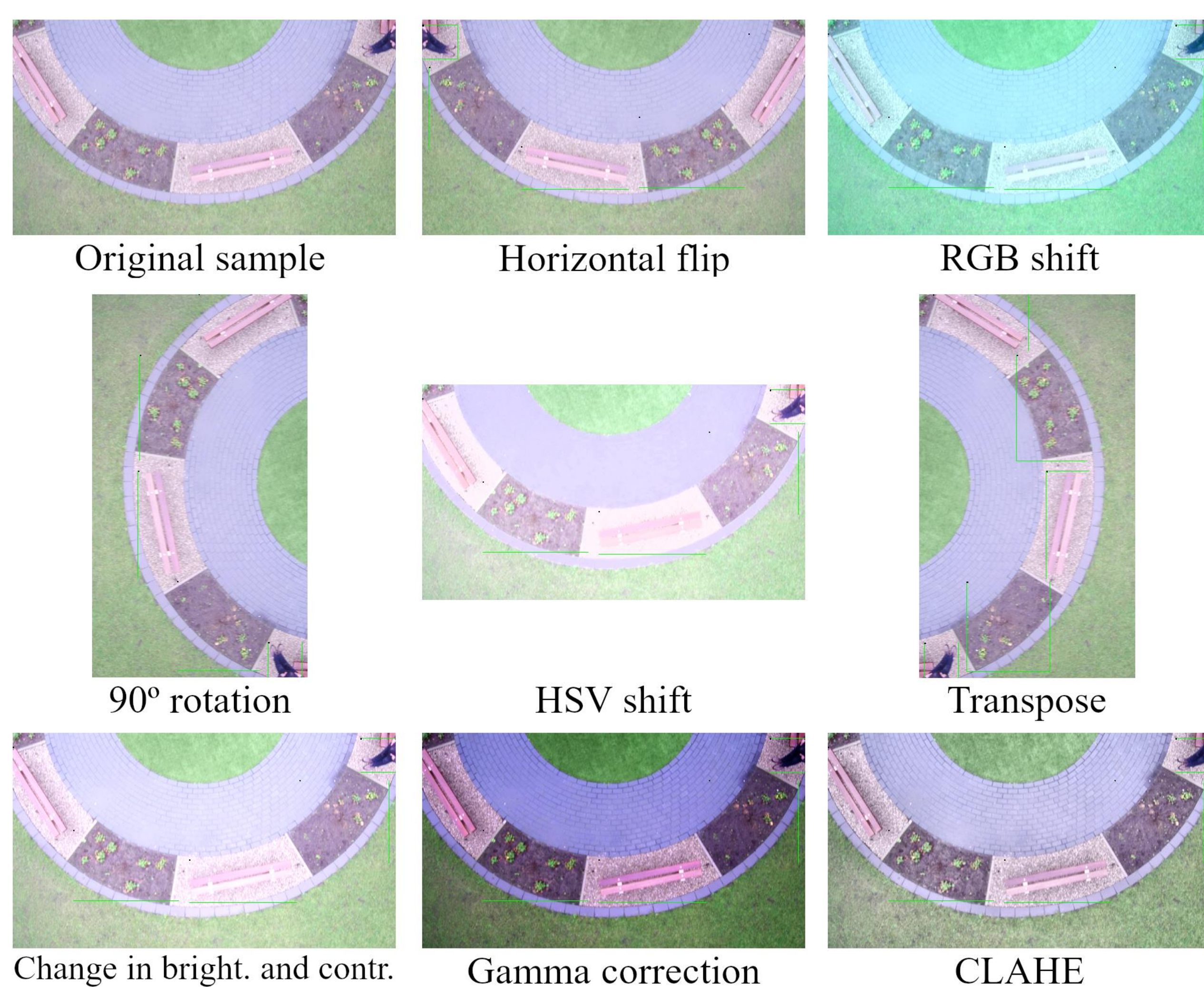


Figure 4. Examples of each augmentation, all applied to the same sample.

Acknowledgements

- This project is a collaboration with the Saxion university under the TheBEAST project.
- It is financially supported by the RAAK-mkb program.



computer vision
& data science



Experiments

We performed experiments on the following topics:

- Data augmentation
- YOLOv3 vs YOLOv5
- Dataset size: Dataset v1 is used throughout research, v2 arrived for these last experiments.

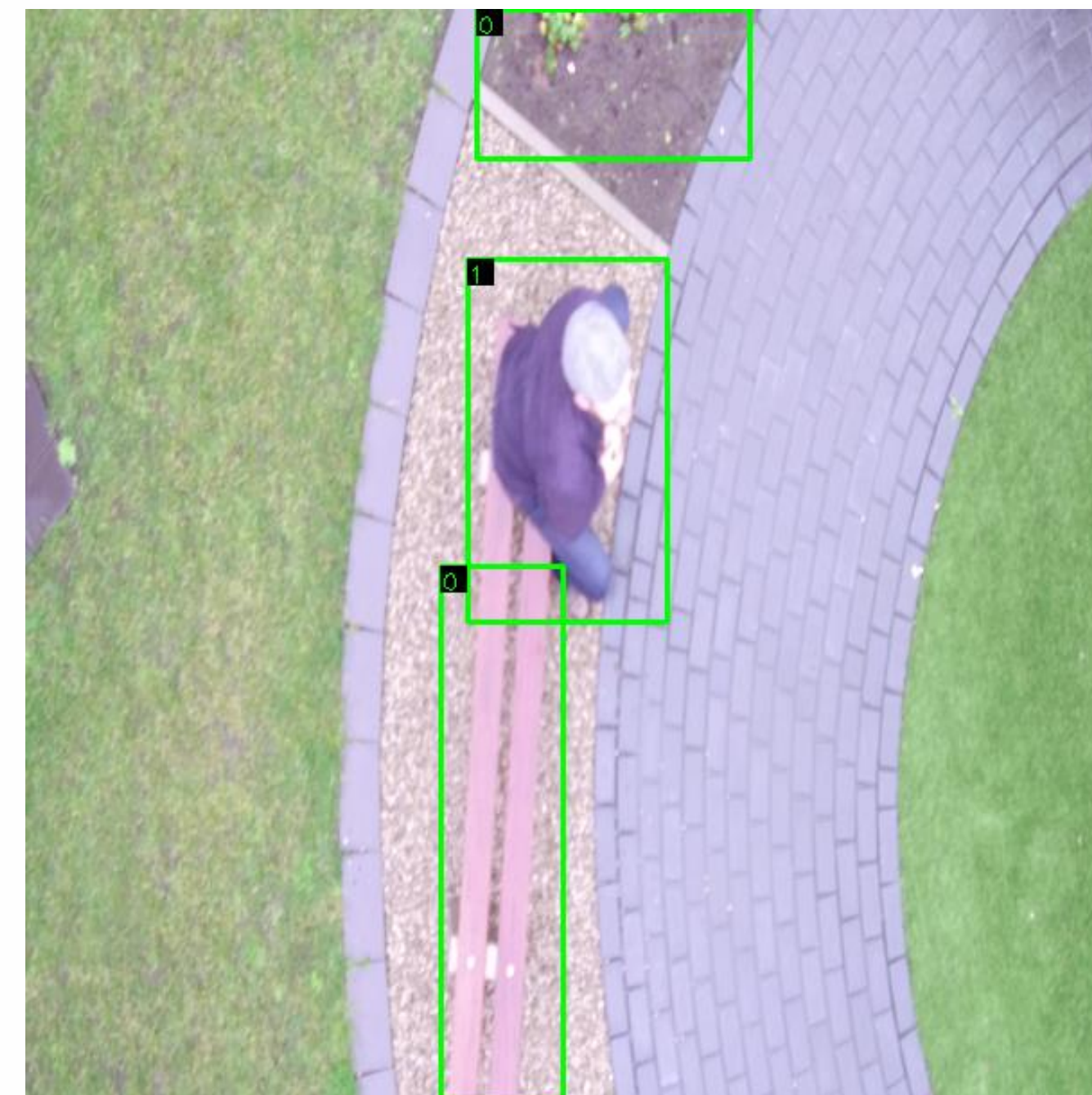


Figure 2. Another annotated sample from Dataset v1

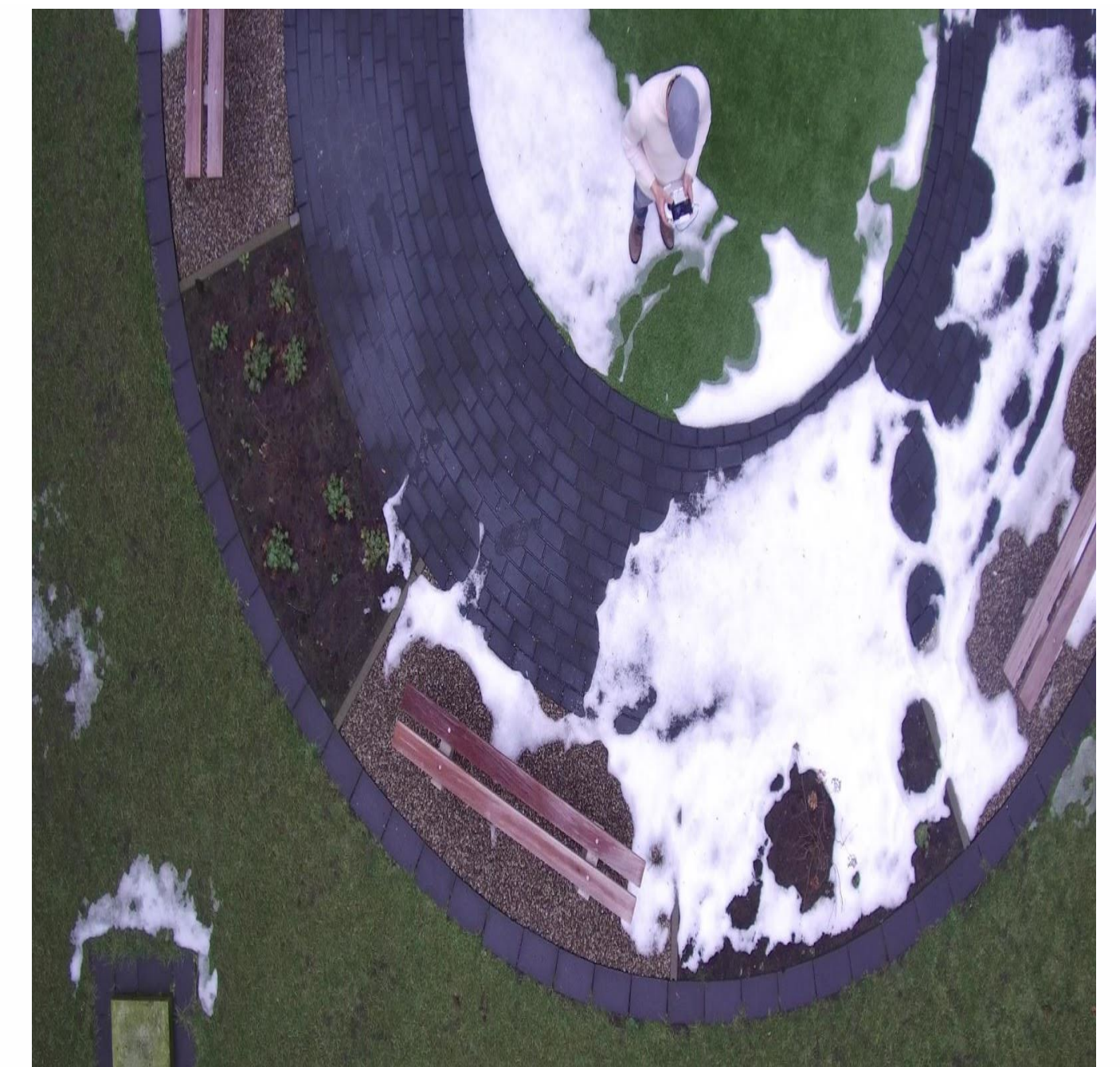


Figure 3. Sample from Dataset v2.

Results

- Comparison between data augmentations showcased in Figure 5. Horizontal flip, 90° rotation, Brightness and contrast changes, Gamma correction and CLAHE improve over the baseline.
- Larger YOLOv5 sizes have higher performance, but the small version is used because of its speed and small weight.
- YOLOv5s outperforms YOLOv3 on all situations.
- A combination of the best augmentations scores a higher mean mAP.
- The model does not generalize well enough with the initial dataset, but is consistent in detecting Persons.

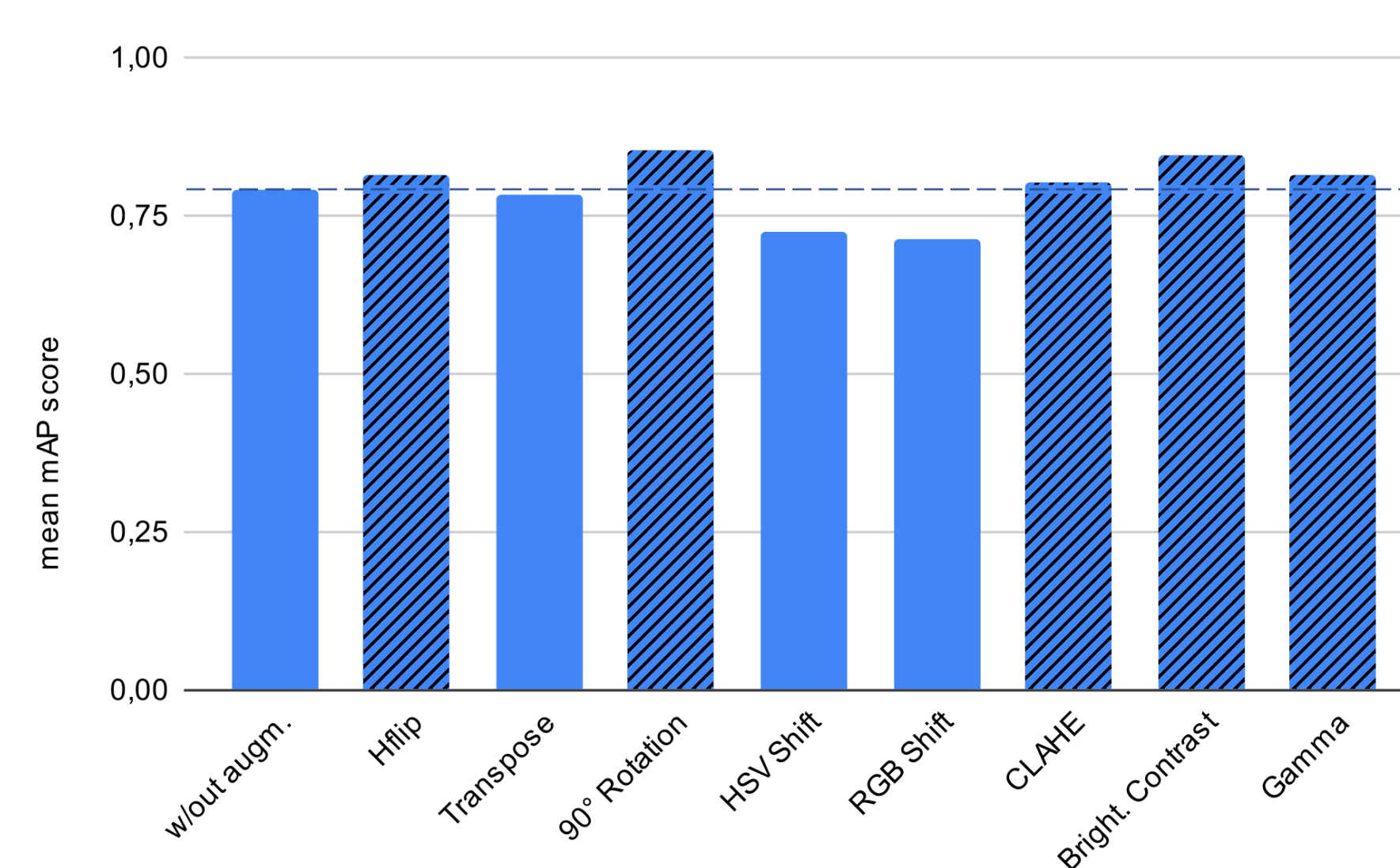


Figure 5. Bar plot comparing the mean mAP score of all augmentations.

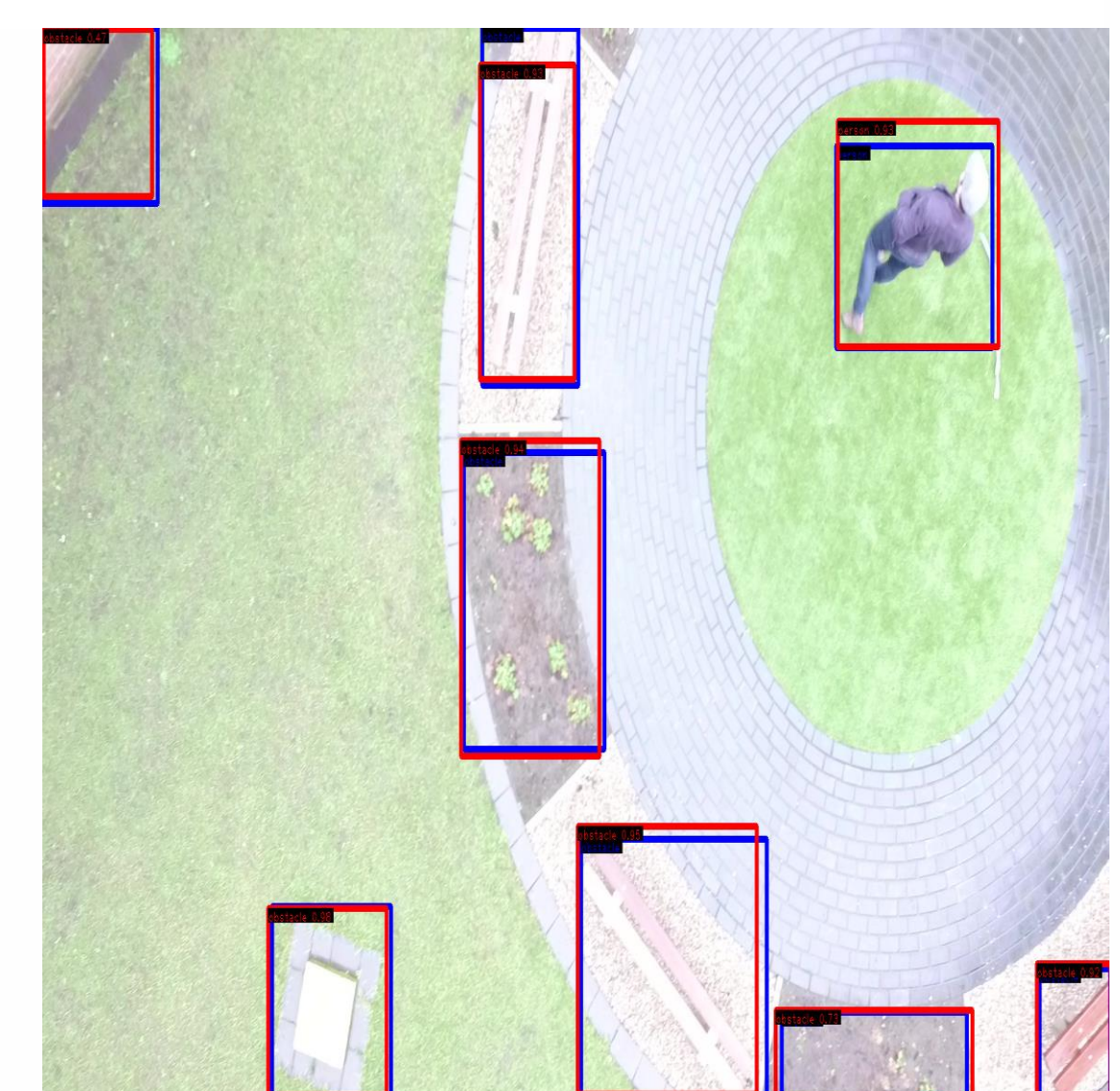


Figure 6. Example output of YOLOv5s trained with the combination of augmentations

Conclusions

- Object Detection with Deep learning is a suitable approach
- Data augmentation improves performance
 - Techniques displayed in Figure 5
 - Combination of Hflip, 90° rotation, Change in brightness & contrast and Gamma correction improves it even more
- YOLOv5 is proven to have a higher performance even in its small version
- Big limitation: size of the Dataset
- Complete and functional pipeline

References

- Joseph Redmon and Ali Farhadi. Yolov3: An incremental improvement, 2018. arXiv:1804.02767
- Glenn Jocher et al. ultralytics/yolov5: v4.0, January 2021. <https://github.com/ultralytics/yolov5>