

Drone Safe Space Landing Detection

The BEAST Project

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Introduction

- The regulations for civil drones usage were revised in the European Union, thus allowing more freedom for the use of Beyond Visual Line of Sight (BVLOS) UAVs for diverse purposes, according EASA[1]
- The current issue is that there is no reliable and fully accurate autonomous fail-safe landing system for unmanned aircraft operating beyond the visual line of flight.
- The main goal of this project is to detect and avoid hazardous impediments on the ground which might interfere with a safe landing maneuver performed by the BVLOS.
- This research paper will address the implementation of segmentation using the U-Net and U-Net++ architectures for fail-safe landing in drones operating BVLOS

Materials and Methods

- Aeroscapes dataset → 3269 RGB images, captured from an altitude range of 5 to 50 meters, having a resolution of 720px by 1280px
- The U-Net[2] and U-Net++ [3] architectures were used in this project
- Three compelling tiling methods → Fixed-, Random-, and Positive Tiling
- The metrics used are: IoU, F1 score, Precision and Recall

Abstract

This technical paper continues the work done for The BEAST project, which aims to create a failure-safe landing system for BLOVS UAVs, in order to achieve fully autonomous drones which comply with the European Union Aviation Safety Agency regulations. This research tackled a specific part of the project, which aims to find a suitable segmentation model which can detect and avoid ground obstacles in the scenario of an emergency landing performed by an unmanned aerial vehicle. A deep learning approach is used, involving two segmentation architectures, U-Net and U-Net++, supported by different experiments in order to improve the performance of these models and in the end determine the best performing architecture. From the results, was decided that using a segmentation approach is a suitable method to apply in this project, although a few limitations must be first settled in order to test this method in a real-life scenario.

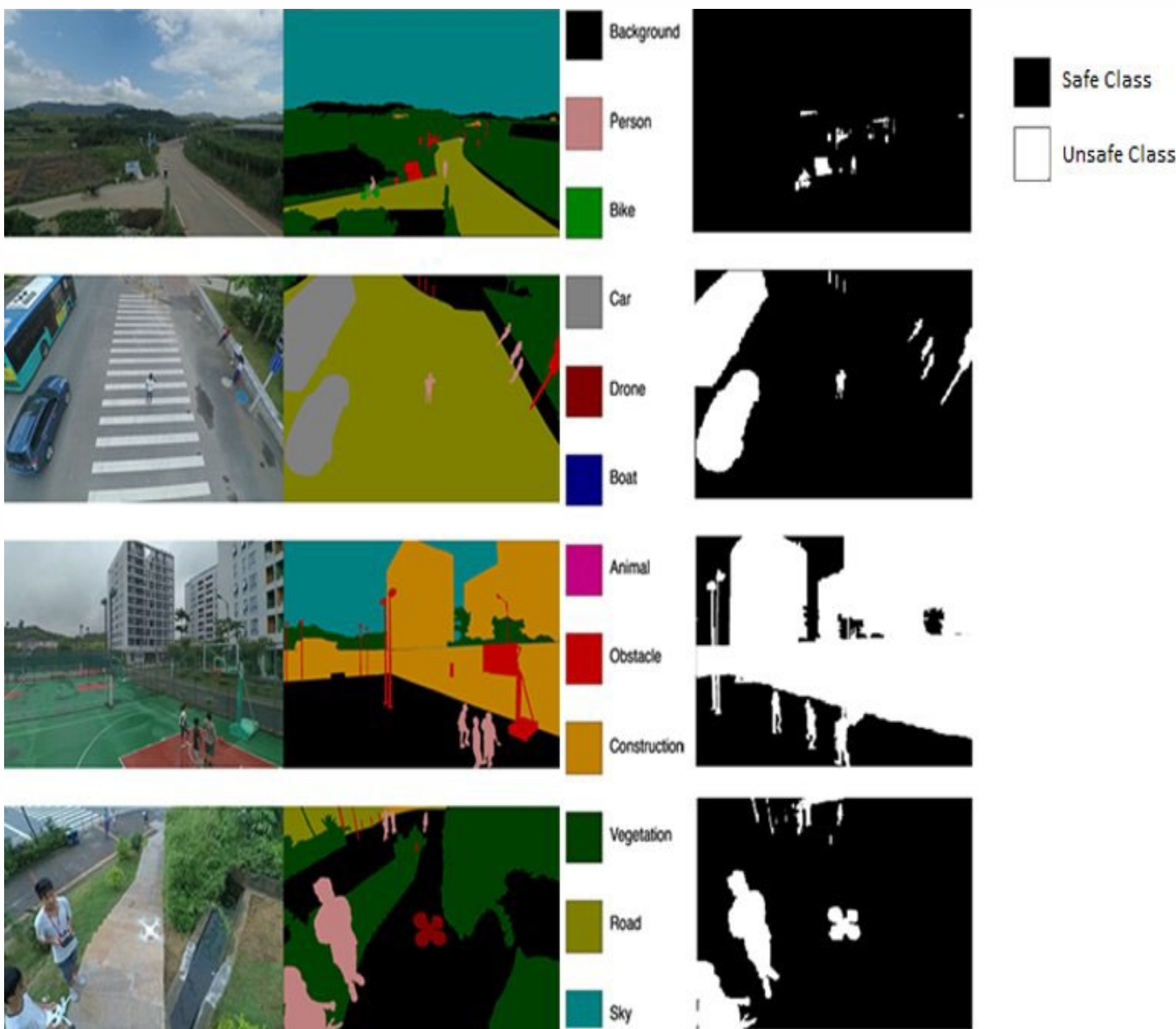


Figure 1. AeroScapes dataset



Figure 2. Fixed Tiling

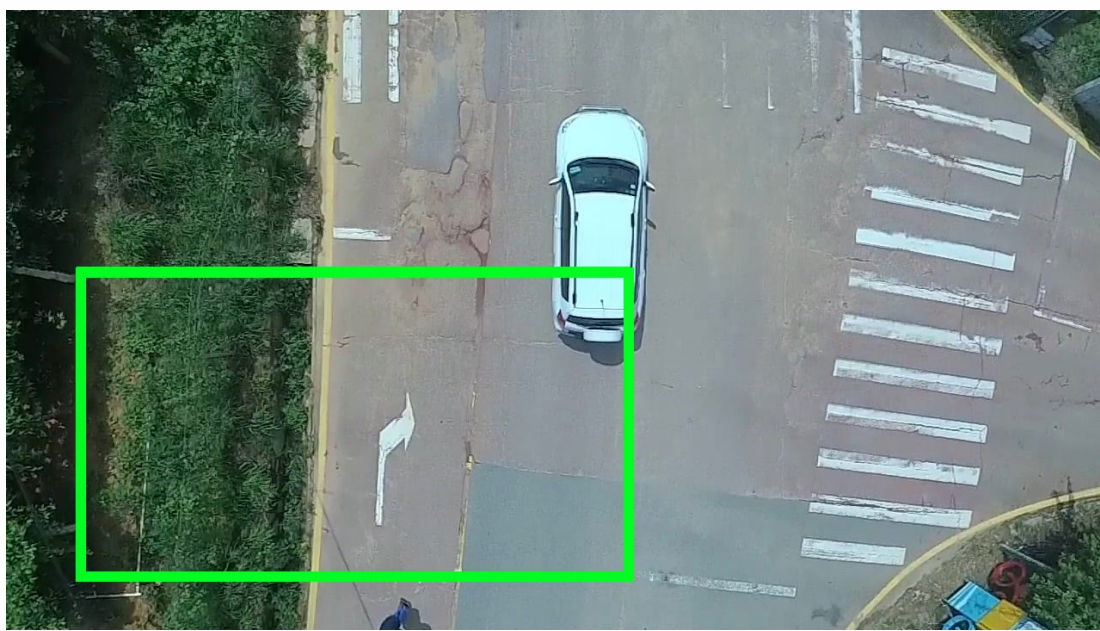


Figure 3. Random Tiling



Figure 5. Semantic Drone Dataset

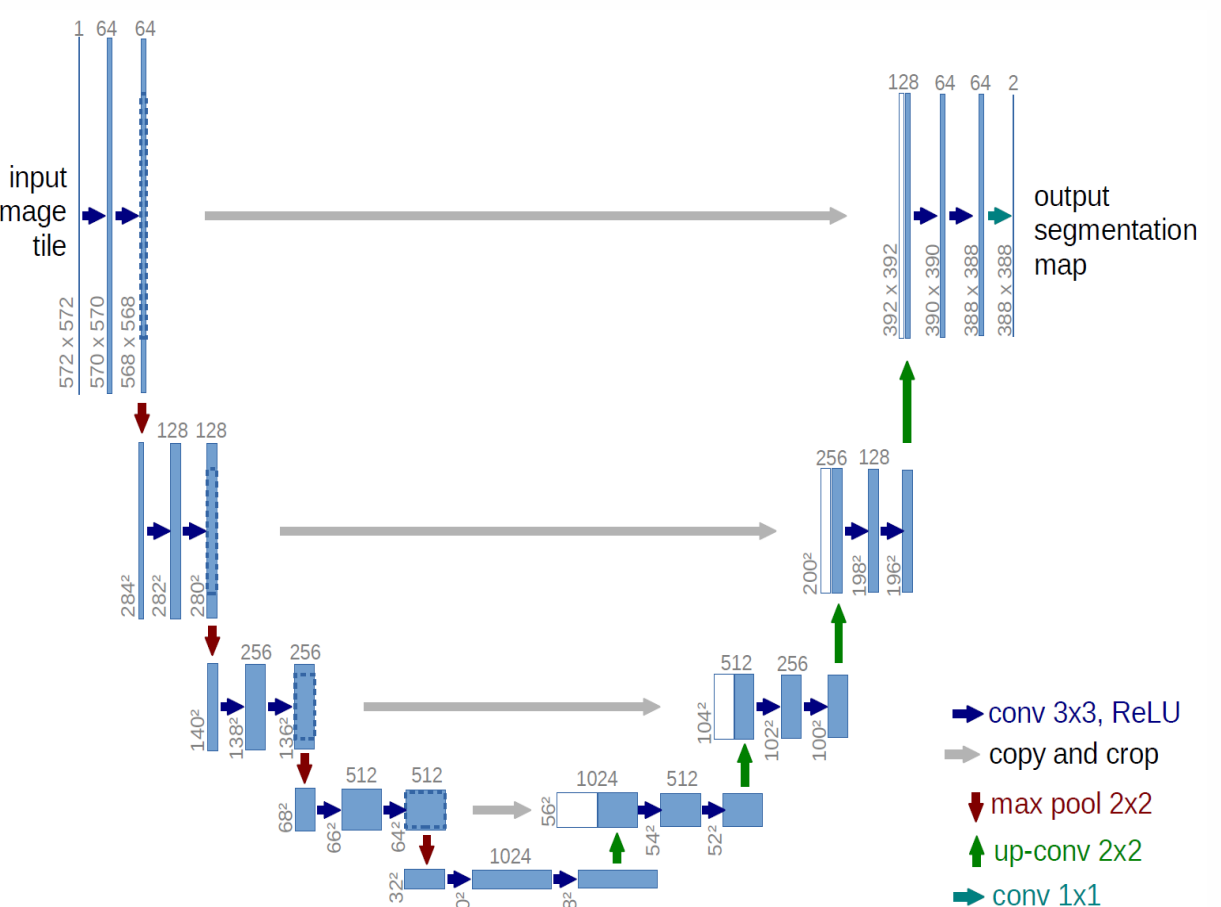


Figure 6. U-Net architecture

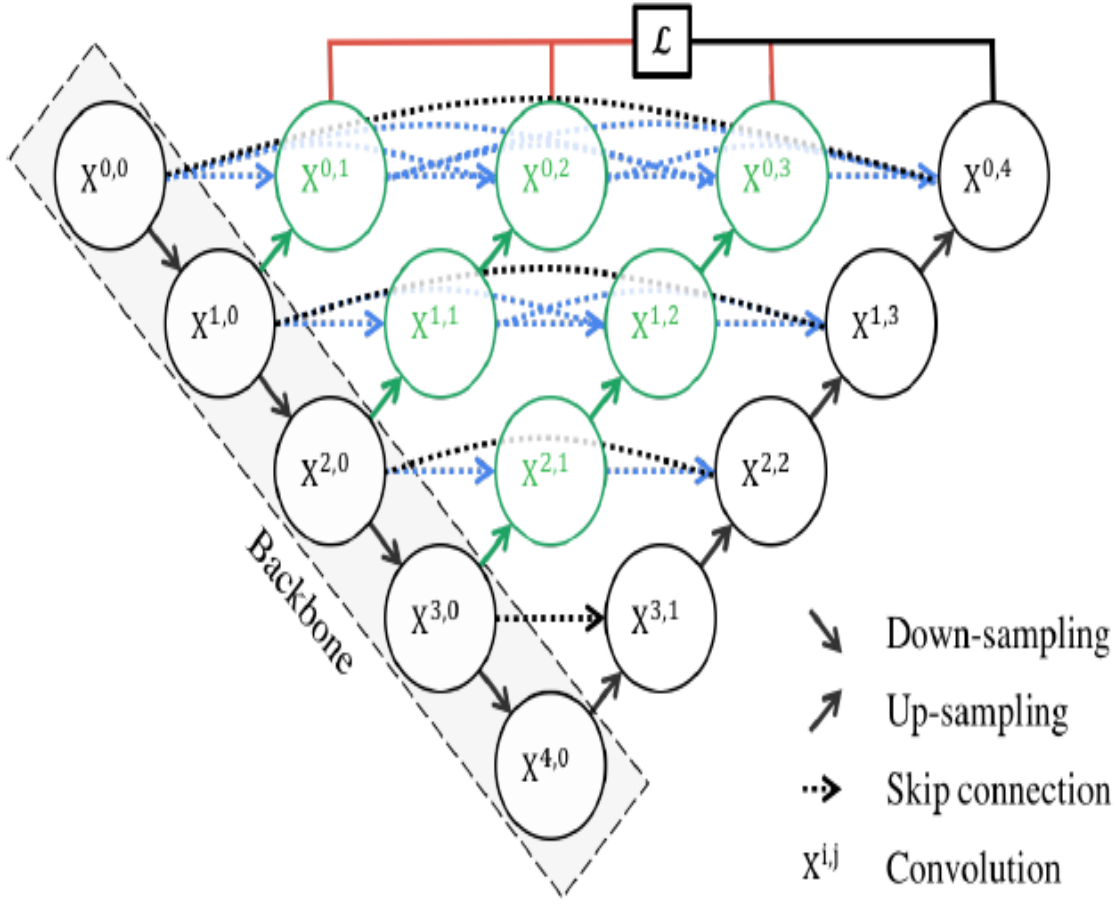


Figure 7. U-Net++ architecture

Experiments

The experiments were divided into the following sets:

- Tilling Method → None / Fixed Tiling / Random Tiling
- Optimizers → Adam, Adamax, AdamW, SGD, ASGD
- Learning Rate → 1e-3, 1e-4, 1e-5
- Data Augmentations → Gamma, Blur, Fog, Rain, Horizontal & Vertical Flip
- Model Architectures → U-Net, U-Net++
- Datasets → AeroScapes Dataset, Semantic Drone Dataset

Results

- Both Fixed- and Random Tiling improved the model, where Fixed Tiling yielded the best results.
- The comparison between the optimizers resulted in Adamax being the most suitable optimizer for this project
- Combining all the data augmentations resulted in the best performing model in this project
- U-Net++ was compared with U-Net model

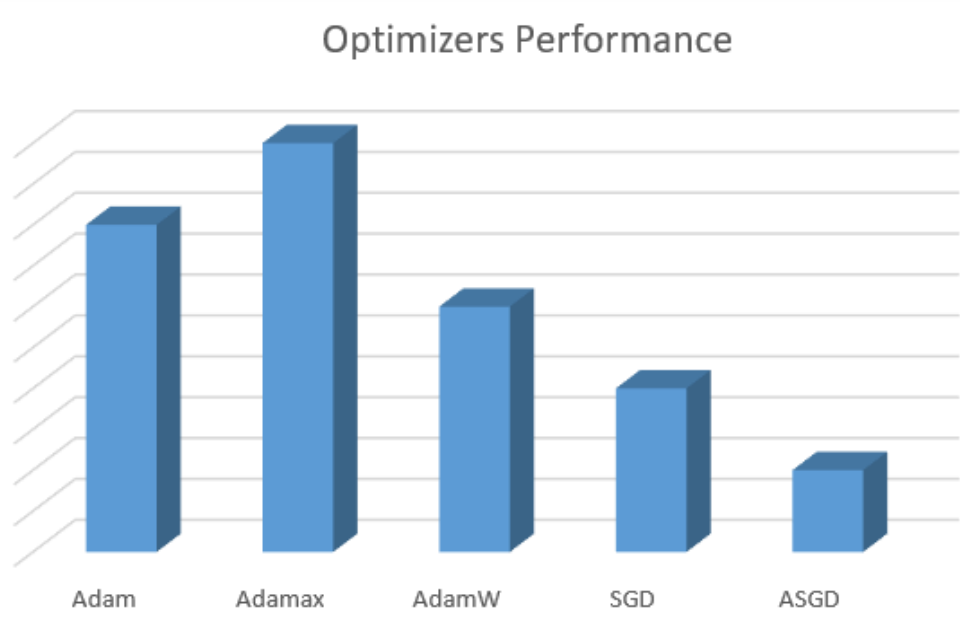


Figure 8. Optimizers Comparison

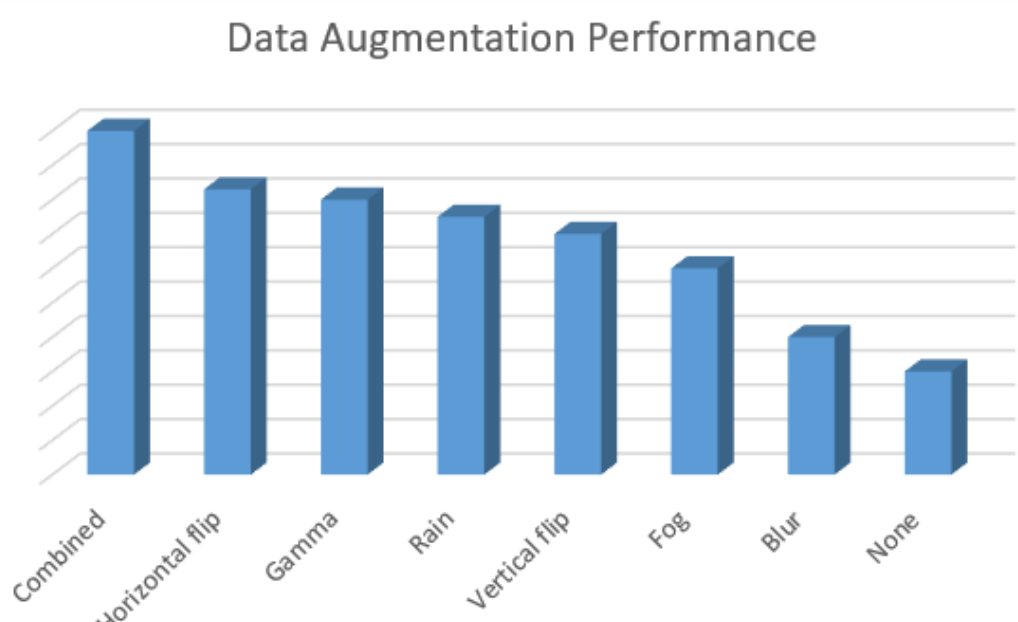


Figure 9. Data Augmentation Comparison

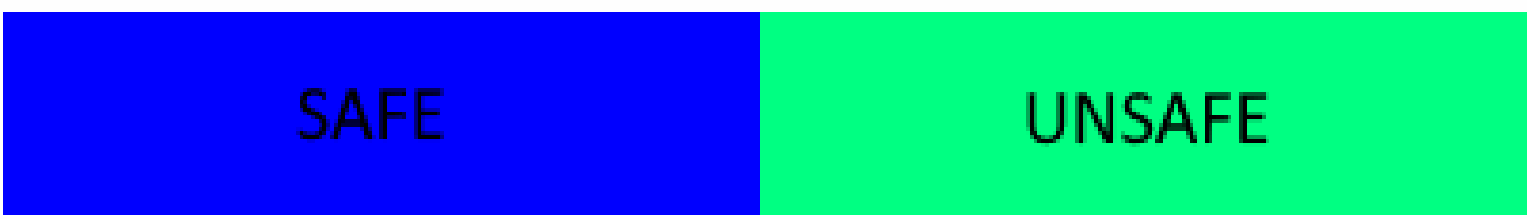


Figure 10. Legend : Segmentation classes

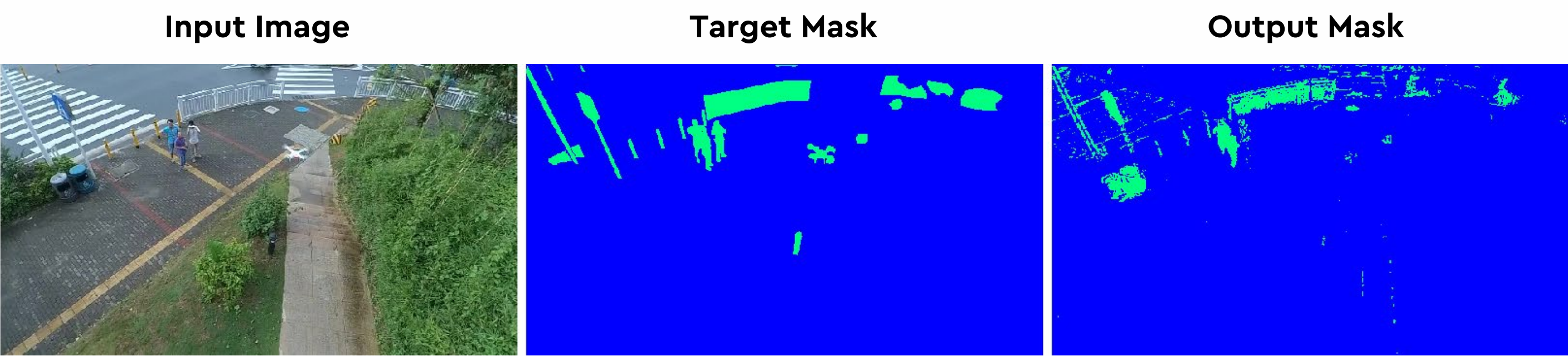


Figure 11. Project's Starting Point before Fine-Tuning

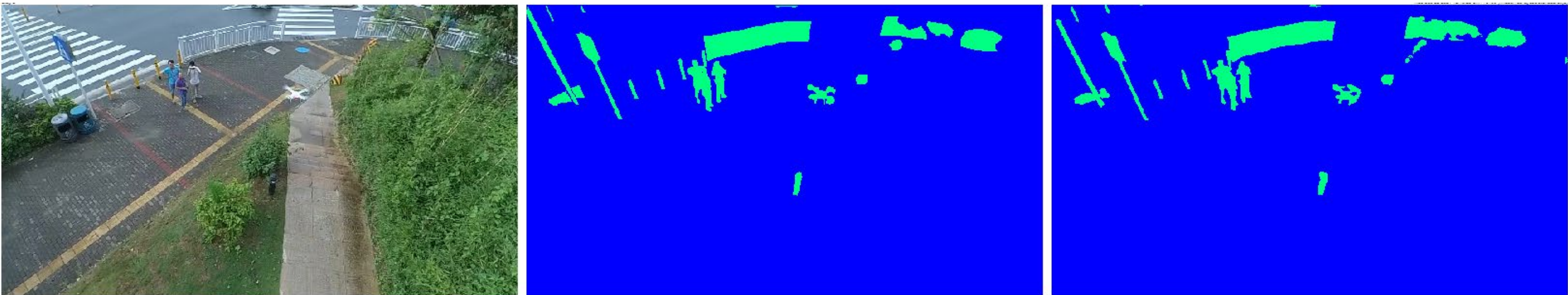


Figure 12. Best performing U-Net model

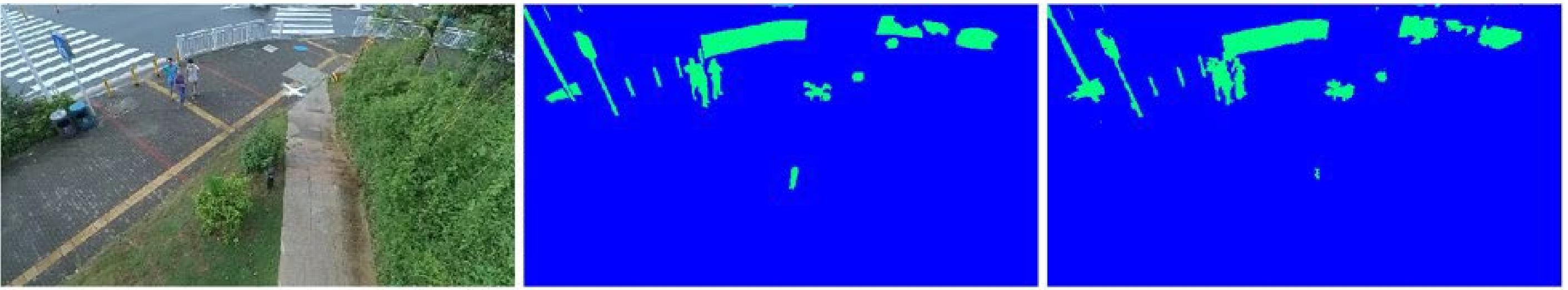


Figure 13. Best performing U-Net++ model

Conclusion

- Applying tiling and random tiling improved the model's performance
- The best performance was achieved when applying all augmentations to the dataset
- Using a segmentation algorithm was concluded to be a suitable approach for this project
- U-Net achieved higher performance than U-Net++

References

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- [3] Zongwei Zhou, Md Mahfuzur Rahman Siddiquee, Nima Tajbakhsh, and Jianming Liang. Unet++: A nested u-net architecture for medical image segmentation. In Deep learning in medical image analysis and multimodal learning for clinical decision support, pages 3–11. Springer, 2018.

Acknowledgements

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