Anomaly Detection for UAV Automatic Safe Landing

Jenny Nicolai, Master Computer Vision & Data Science
Supervisors: Maya Aghaei Gavari and Jaap van de Loosdrecht

Winter 2022

Introduction

- Drone industry is rapidly growing
- New regulations allow Beyond the Visual Line Of Sight (BVLOS) drones
- Anomaly detection for fail-safe landing

Abstract

This research revolves around anomaly detection to avoid obstacles for fail-safe landing, where the CutPaste anomaly detection framework is used. Various experiments try to maximize the model's performance, including choosing the tile size, hyperparameter tuning, and different data augmentation techniques. The best-performing model achieved an F1-score of 0.8036. Although anomaly detection looks like a suitable approach to resolve this problem, some limitations must be overcome before being used in a real-life application.

Materials and Methods

Dataset

- The AeroScapes semantic segmentation [1] dataset contains 3269 RGB images
- Ground-truth classes are converted to safe and unsafe
- Fixed tiling with converting the tiles to **normal** and **anomaly** classes

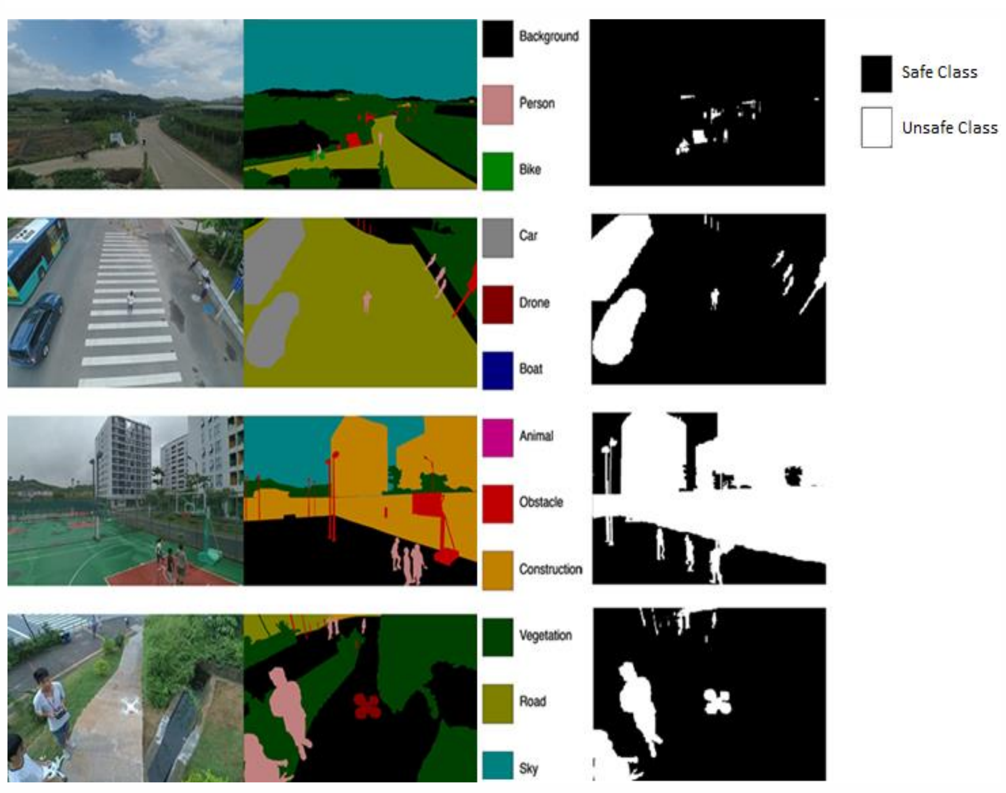

Figure 1. Some examples from the AeroScapes [1] dataset with corresponding ground-truth and converted masks

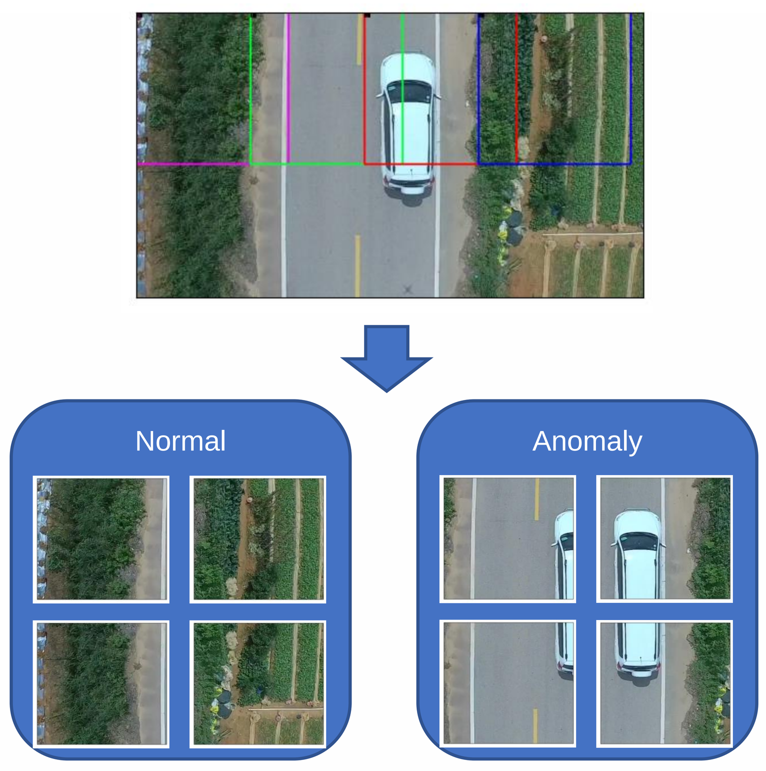

Figure 2. Example of tiling an image and converting it to normal and anomaly classes

CutPaste anomaly detection framework

- Self-supervised representation learning
- CutPaste alteration: Cut a random patch from the image and paste it randomly
- Aims to create irregular patterns on the normal data where the patterns resemble a possible anomaly
- Classify normal images from altered images

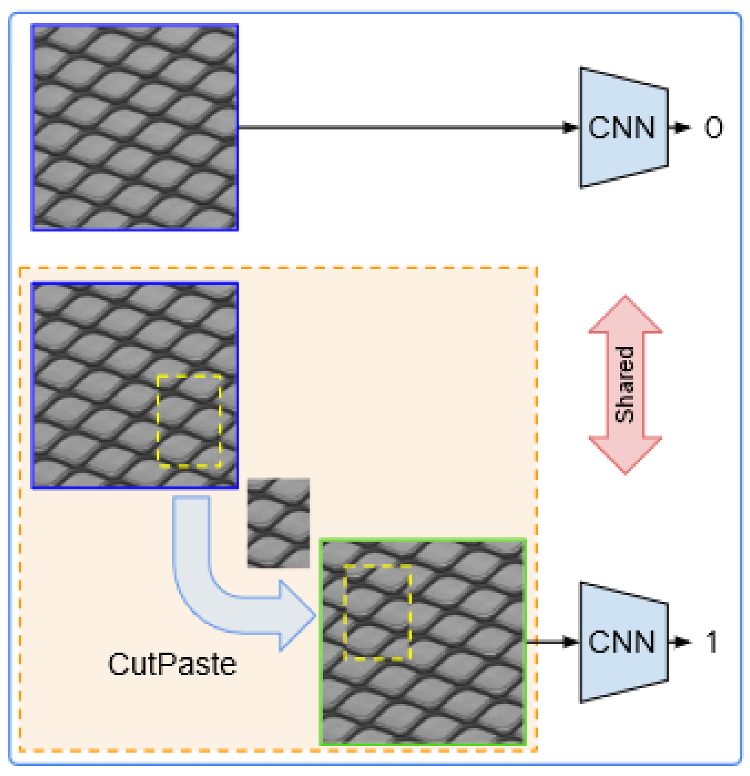

Figure 3. CutPaste self-supervised representation learning. Classification between normal and altered images [2]

CutPaste alteration variants

- In [2] Normal and Scar are introduced. Where Normal is a bigger patch, and Scar a smaller patch with rotation
- We propose Multiple: multiple random patches with different sizes and rotations are pasted back on the image

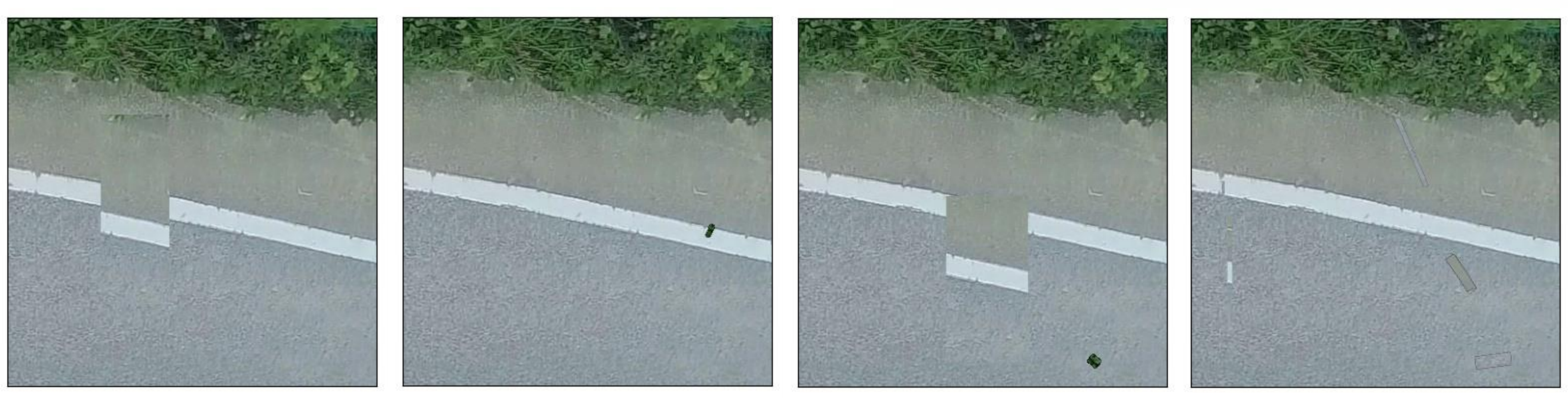

Figure 4. Example of an image with Normal, Scar, combination Normal & Scar, and Multiple alteration, respectively

Experiments

Different experiments are performed on the following topics:

- Different tile sizes
- CutPaste alteration
- CutPaste parameters
- Data augmentation

Results

- Tile size influences the performance of the model, where 384x384 yielded the best results
- In the comparison between the different CutPaste alterations performed Multiple best.
- The parameters, number of patches and patch size, have the highest F1 score where number of patches lies between 5-60 and the patch size is between 0.1-0.5%
- The model's performance improved with the sun flare augmentation.

Tile size	F1-score
128x128	0.5783
256x256	0.6786
384x384	**0.7260**

Alteration	F1-score
Normal	0.7260
Scar	0.7594
Normal & Scar (4-way)	0.7349
Normal & Scar (2-way)	0.7520
Multiple	**0.7597**

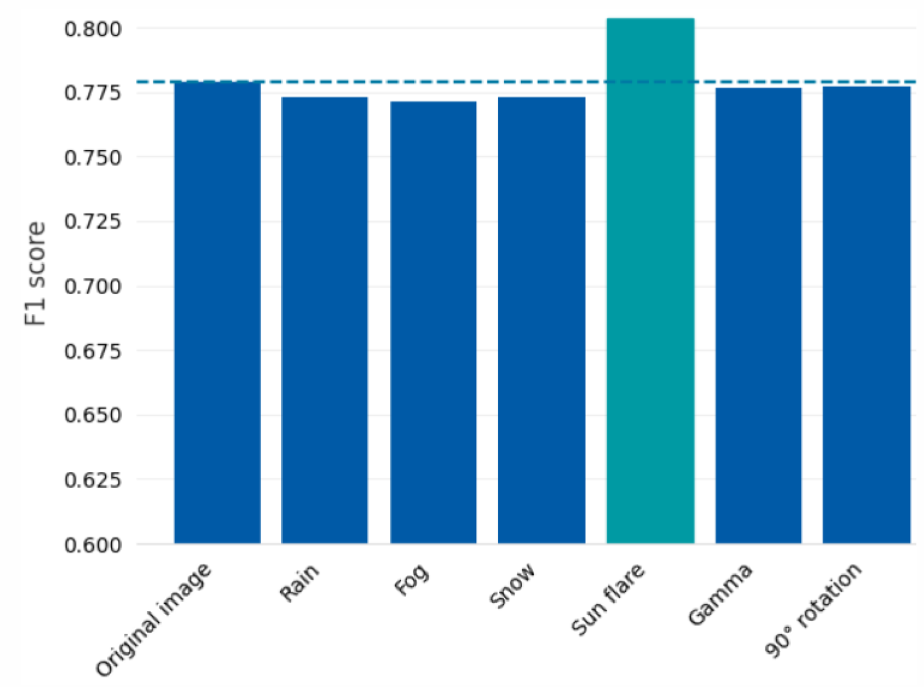

Figure 5. Data augmentation comparison

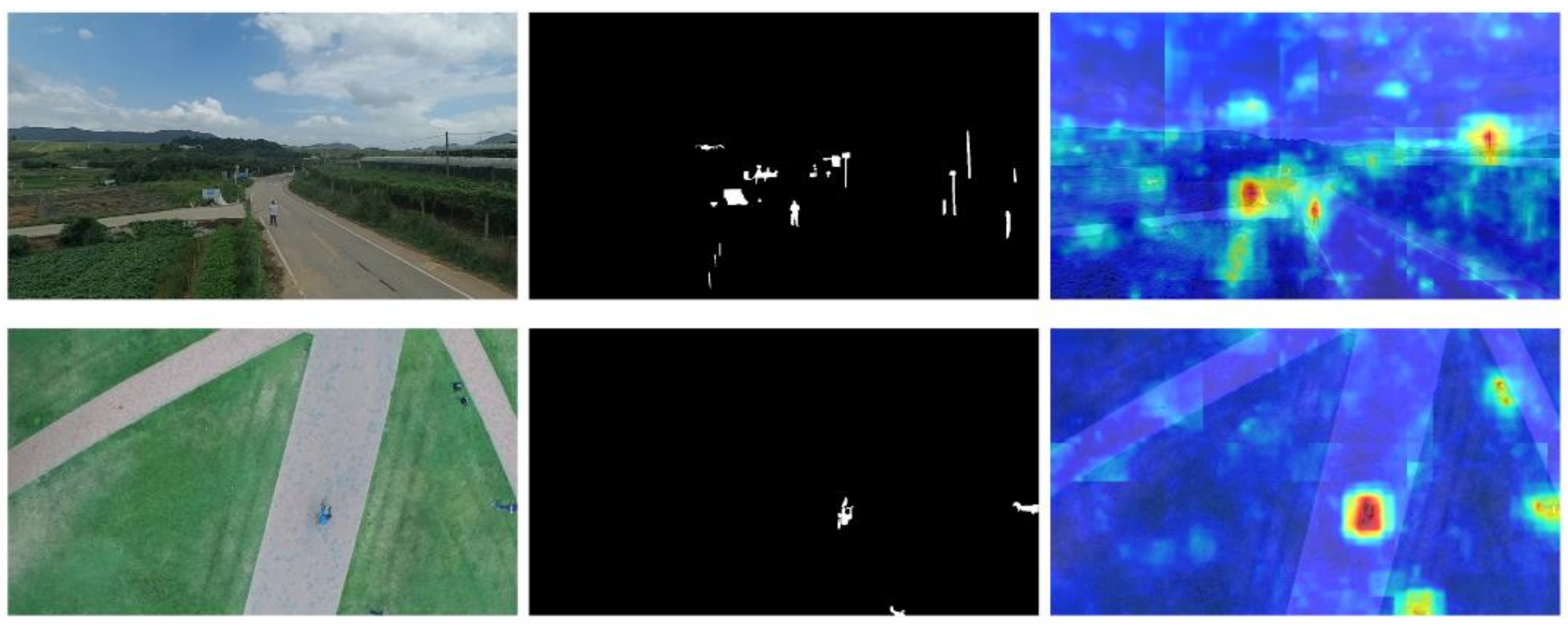

Figure 6. Visualization of the localization of the anomalies with a heatmap from the best performing model. The red/yellow zones indicate anomalous data and blue indicates normal data.

Conclusions

- Anomaly detection is a suitable approach for fail-safe landing
- Tile size influences the model's performance
- Our own CutPaste Multiple alteration outperforms the other alterations
- Data augmentation could improve the model if the proper augmentation is chosen

NHL STENDEN
computer vision & data science

Acknowledgements

This project is financially supported by Regieorgaan SIA (part of NWO) under the RAAK MKB project The BEAST

SIA Regieorgaan

References

[1] Ishan Nigam, Chen Huang, and Deva Ramanan. Ensemble knowledge transfer for semantic segmentation. In 2018 IEEE Winter Conference on Applications of Computer Vision (WACV), pages 1499–1508, 2018.

[2] Chun-Liang Li, Kihyuk Sohn, Jinsung Yoon, and Tomas Pfister. Cutpaste: Self-supervised learning for anomaly detection and localization. CoRR, abs/2104.04015, 2021.