Ortophoto mapping

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https://github.com/toomasherodes/orthophoto_mapping

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Introduction

In Estonia there are laws that permit/disallow building on private/public land. The buildings that need special permits need to be registered and documented in Land Cadastre (Ehitisregister) - that means that almost all big enough buildings are registered in Estonia. All registered objects are also mapped. This is all public information.

As our project we want to identify all man-made buildings from orthophotos with machine learning. Ideally also find all buildings that should be registered but are not.

Success criteria

We have built a machine learning model that can identify and report all man-made buildings on an orthophoto. We have analyzed the model and its results.

Methology

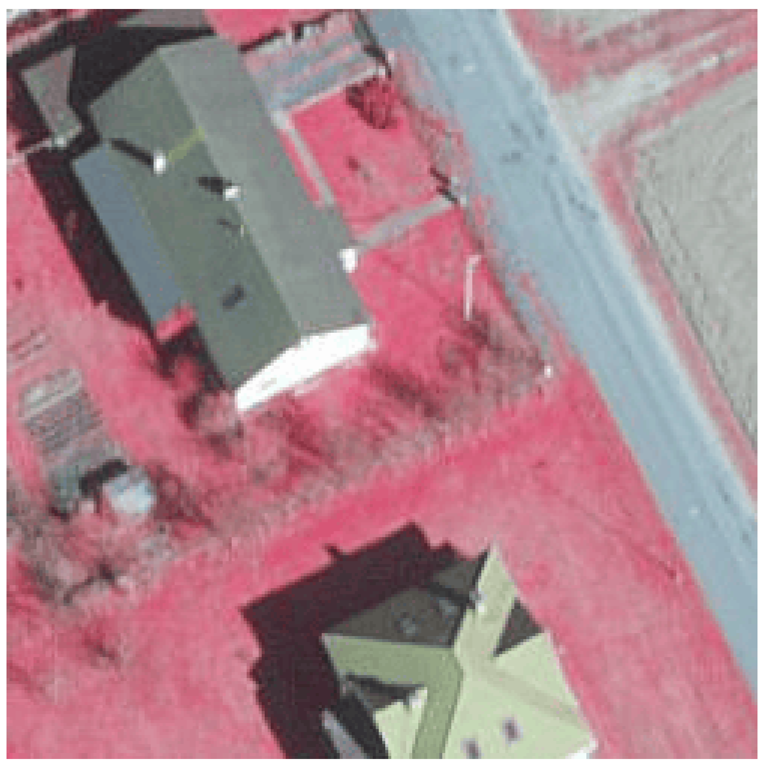
The model is trained on a DeepLabv3 model using our custom dataset. It uses atrous convolution for semantic image segmentation (1) - this is perfect for our defined criteria. We tried different weights for the segment classes and different learning rates. We also tried training it for different amounts of epochs - we concluded that it started overfitting very quickly, so we had to train it less for now. The input data is a 250x250px color-infrared orthophoto and the output is a segmented bitmap of where the model thinks the buildings lie. Using infrared photos makes it easier for the model to recognize man-made structures

source: https://arxiv.org/pdf/1706.05587

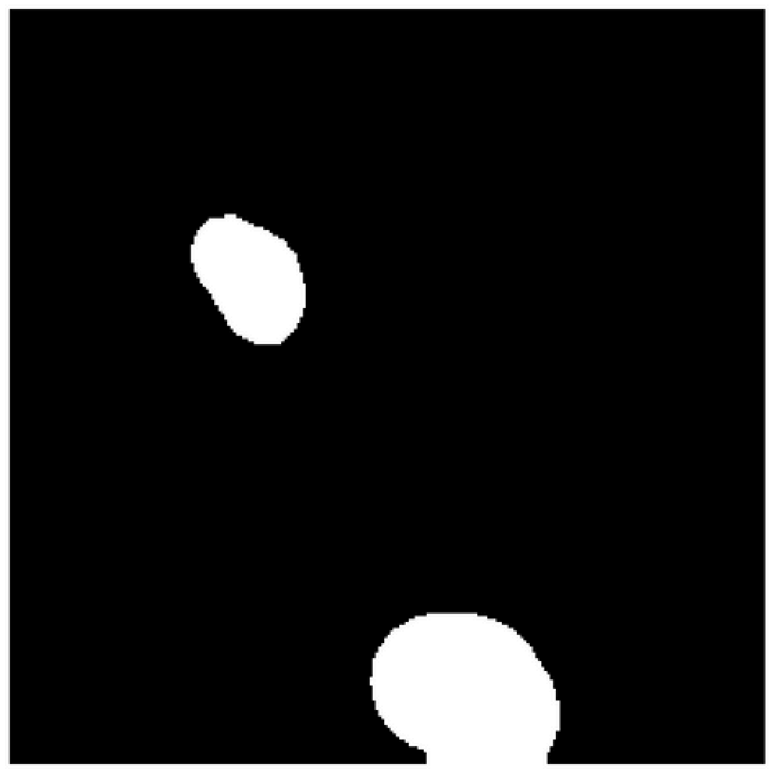
Objectives

- We gather data about registered buildings within a certain area (Tartu) from geoportaal.
- We clean the data, remove all unnecessary features.
- We gather ortophotos from a certain area (Tartu). Use them as training data, as we have the correct coordinates of all building corners.
- We build the model based on gathered data and test it
- We analyze the results

Results

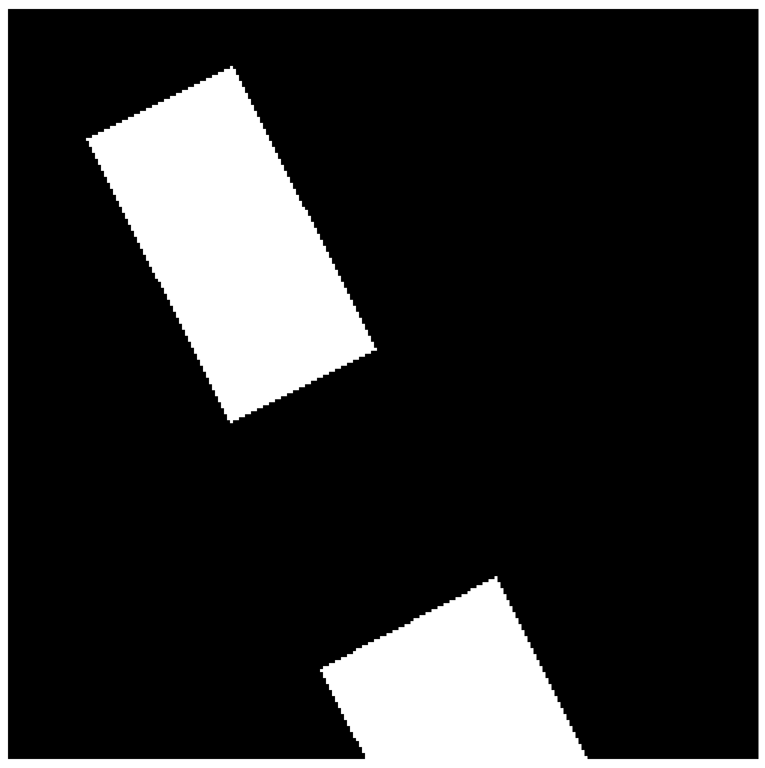


input image



model output

The trained model was capable of identifying buildings on an orthophoto. However, the detection accuracy was low and not all buildings were correctly identified, smaller houses mostly went undetected. Moreover, the buildings were never fully detected and the model was only capable of drawing a blob in the middle of the house. There were also a few cases of false positives, generally parking lots or roads that were identified as buildings.



ground truth

Analysis and conclusion

While the model did work, the results were not as good as we had hoped. The main issues were small houses not being detected and bigger houses only being detected by their centers. We concluded two main reasons for the model performance being underwhelming. The first one was quality of training data. The orthophotos were not perfectly orthogonal and were taken under a small angle. Because of that, the corners of buildings in our training data did not line up very well and training data quality suffered (as shown in the image). It was also difficult to manually adjust the buildings as the dataset was large. The second reason for the models poor performance was our lack of experience in choosing the correct model, adjusting it to our needs and picking the right parameters. We tested three different models and the DeepLabv3 model seemed to give the best results, but further work on the parameters could improve the models performance. In summary, the model works, but the accuracy is poor and it can therefore not be used for any real-world applications. The poor performance is caused both by low training data quality and lack of experience.