

Using SAR Data for the Detection of Waterlines With an Image-to-Image Network

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We introduce a new approach for a neural network for an automation of the detecting of waterlines on Sentinel-1A/B SAR imagery of intertidal flats. The neural network is designed as an image-to-image network, which enables the prediction of binary masks, segregating water from intertidal flats. Although a lack of labelled data impedes a validation of our results, the network already demonstrates its ability to substitute visual analyses of SAR images.

Background and Area of Interest



Fig 1: German North Sea coast, area of interest. Significant parts of the coastline show active morphodynamic processes within the tidal range.

Morphological changes such as erosion or even displacement of whole sandbanks is a common phenomenon on intertidal flats, as they are constantly exposed to strong tidal currents. Remote sensing data can be used to generate digital elevation models (DEMs) using the waterline method. Here, SAR sensors are particularly advantageous in that they are independent of cloud conditions, which is especially important given the usually high cloud coverage on the German North Sea coast. In addition, since the launch of the two Sentinel-1 satellites in 2014 and 2016, a very good temporal coverage of several SAR acquisitions per week is given.

DEM generation using remote sensing data is carried out manually or with algorithms that detect waterlines through a method called 'Edge Drawing' [1,2]. Subsequently, detected water lines are combined with tide gauges data to generate a three-dimensional DEM. A comparison of DEMs from different time periods reveals morphological changes, which are an important part of the monitoring of the Wadden Sea.

The SAR image contrast between exposed flats and open water, hence the applicability of such algorithms, depends on weather conditions, which is why a manual pre-selection of SAR data is required. In addition, a costly computation time for every image as well as sensible fine tuning constitute problems. To further automate the generation of DEMs, we replace the physical algorithm by an image-to-image network. Once trained on a suitable dataset, we expect this neural network to consume less computation resources and to be applicable to a broader set of SAR images.

Here, we present our proof of concept, which will be further refined using a larger set of reference data, eventually resulting in a convincing method that merges image fractions into a whole picture.

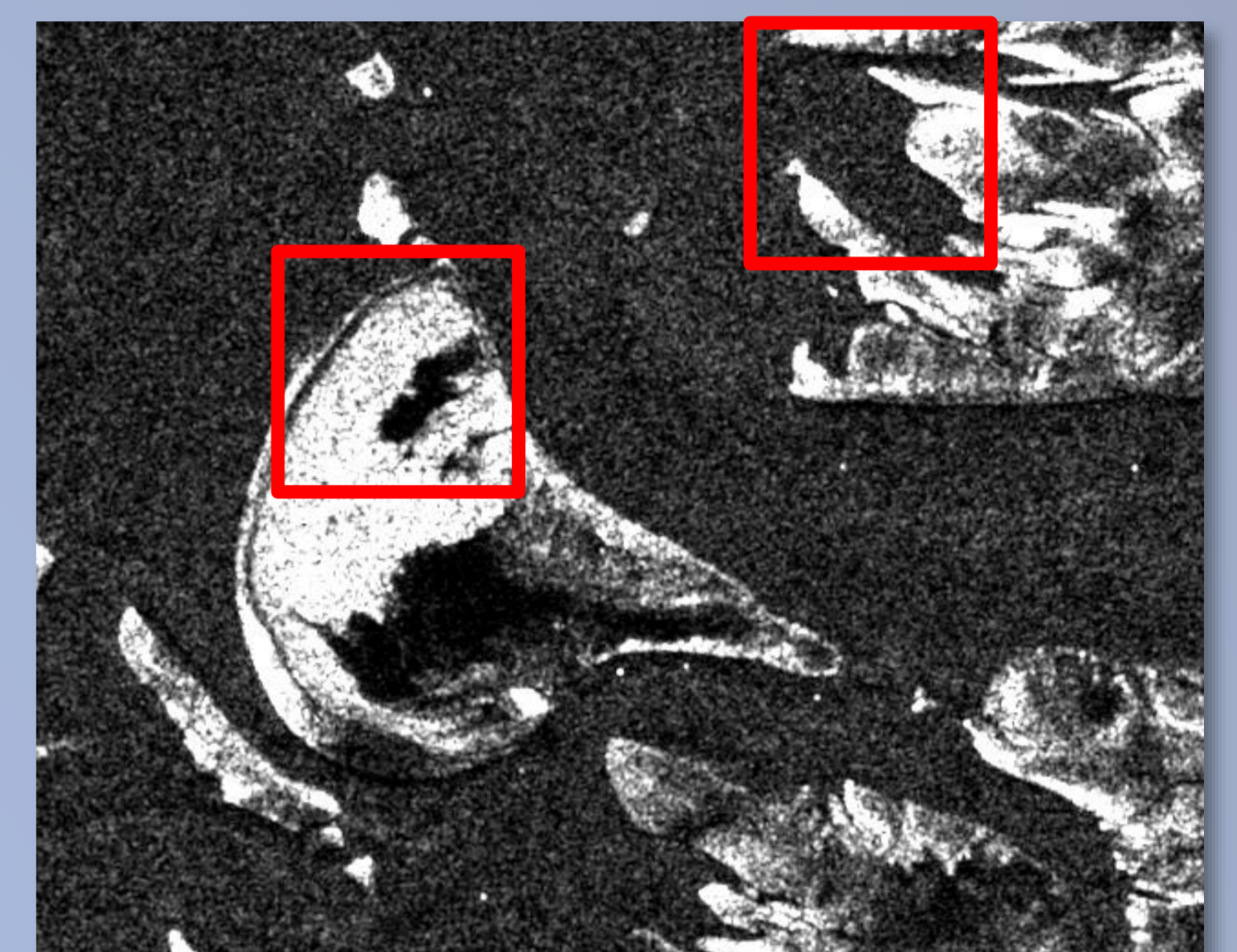


Fig 2: Excerpt of a SAR image (Sentinel 1A, 8 January 2020, 17:17 UTC) showing the island of Trischen and surrounding intertidal flats. Red squares indicate the image subsets used as input in Fig 3.

Image-to-Image Network

A neural network uses input data to create an output, whose type and size depend on its structure. In a training process, outputs of the network are compared to the 'exact' ground truth, i.e. labelled data that are based on the given input. The free parameters, or 'neurons', of the network are optimized towards a minimization of the loss between labelled data and network output. As a result, the network can make predictions for given inputs, due to its learning in the training process.

In the given problem, the network is supposed to segregate intertidal flats from open water. For this, a basic image-to-image network with >30.000 neurons was built. The targeted output is a mask of the input image, marking areas that are interpreted as land. As the size of a complete SAR image exceeds the capability of a simple image-to-image network, fragments of the SAR image with a size of 128 × 128 (~1 km × 1 km) are used as input.

Current State

The network requires a robust training dataset, which should contain fragments of SAR images of the area of interest, along with comparable coastlines. To increase the network's applicability, a wide range of tidal phases and weather conditions should be represented. The training dataset must contain labelled data, which have not been used previously. Due to that limitation, we based the network on a dataset of artificially generated data that mimic SAR images. Further, we refined the network using a small dataset, which was extracted from a single SAR image that was labelled manually.

The obtained results (Fig. 3b) do not always show satisfactory accuracies. However, training the network using the artificially generated dataset and applying it to test images reveals insightful results. E.g., for strong contrasts and large shapes an indicative predictability can be observed. Nonetheless, a significant part of the exposed flats as not detected as land, primarily when they show a similar image brightness as the open water. On the other hand, images consisting mostly of submerged areas exhibit comparably low predictabilities.

By further training of the model with fragmented SAR images, slight improvements were achieved (Fig. 3c). Waterlines with more complex shapes were derived more accurately and an overall 'clarification' (i.e., more coherent land areas) is visible. In addition, dry areas with a low brightness are detected more reliably. Submerged areas still show a low predictability.

Merging the fragments into a large mosaic of the test area (Fig. 4) demonstrates further inaccuracies of the network output. Note that, as the neural network processes the image fragments separately, strong differences (i.e., increased errors) can be observed at their interfaces. Due to the low predictability of submerged areas, the output mask shows significantly more exposed land than observed in nature. Hence, we conclude that at this stage, our neural network does not yet achieve trustworthy predictions.

Perspective

We have demonstrated that setting up a neural network to detect waterlines is a promising approach. At this point, no valid predictions can be achieved yet, mainly because of the above-mentioned limitations. The size of the dataset of SAR images is not sufficient to classify vast areas of the Wadden Sea with satisfactory accuracies, i.e., to allow for a wide applicability. A larger, more diverse dataset is expected to result in major improvements.

Note that the size of the input image may be critical, as in many cases it appears to be too small to allow the network to detect complete islands reliably. Our results further show that the network lacks a component to connect the generated masks reliably. While a solution could be to use input images at lower resolution, covering larger areas, this could only be done at the cost of a loss of small-scale information. As the implementation of a moving window, i.e. the use of overlapping input images, should limit these problems, the next stage of the development of our neural network will see a combination of both approaches into a two-stage network, which will combine the use of low-resolution imagery and a refinement process based on high-resolution images. This combination should ensure the detection of large-scale structures, while keeping the resolution of the result at a high level.

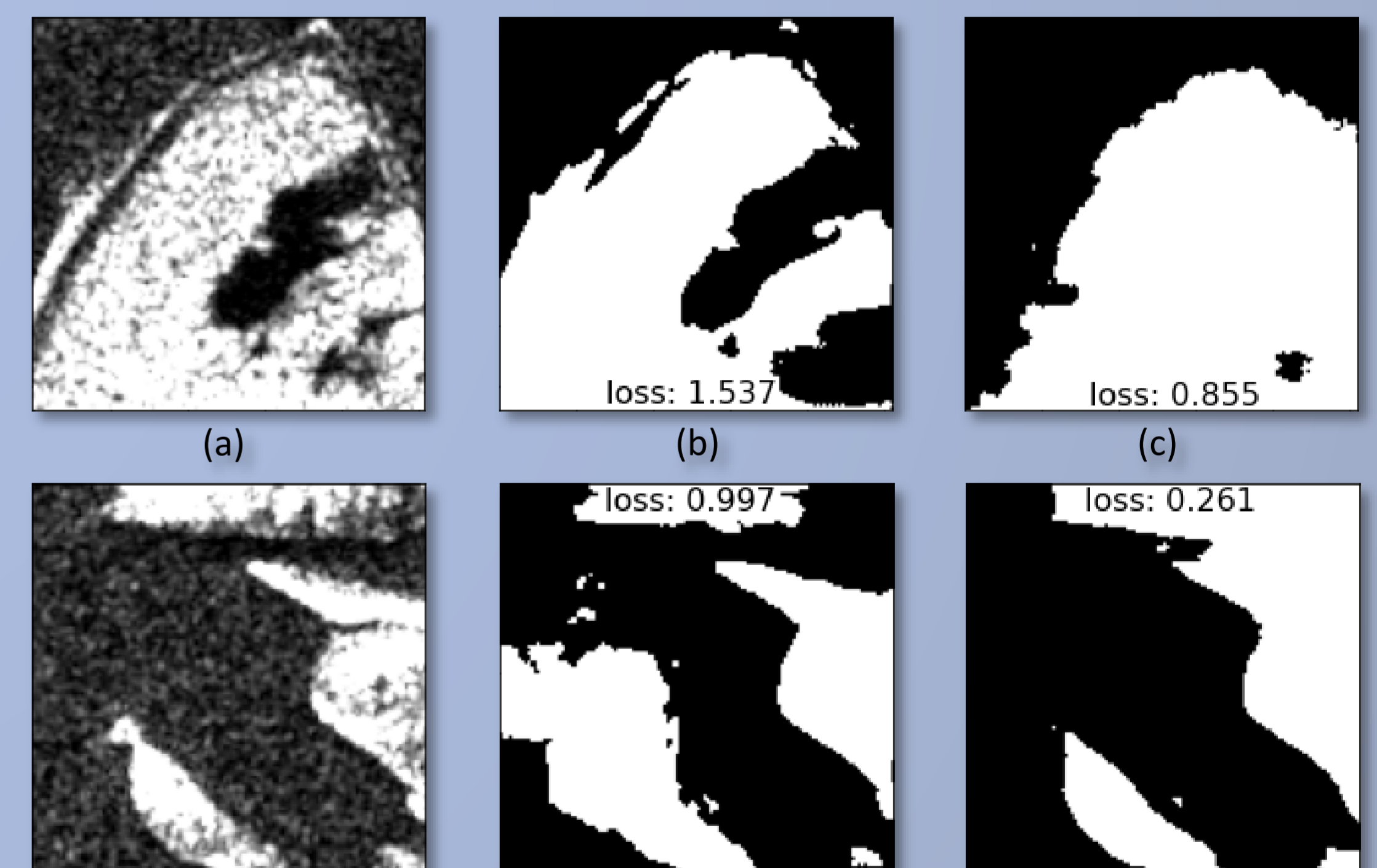


Fig 3: (a) Fragment of the area shown in Fig. 2, (b) mask predicted by the network after training with generated images, (c) mask predicted by the network after transfer learning with SAR images

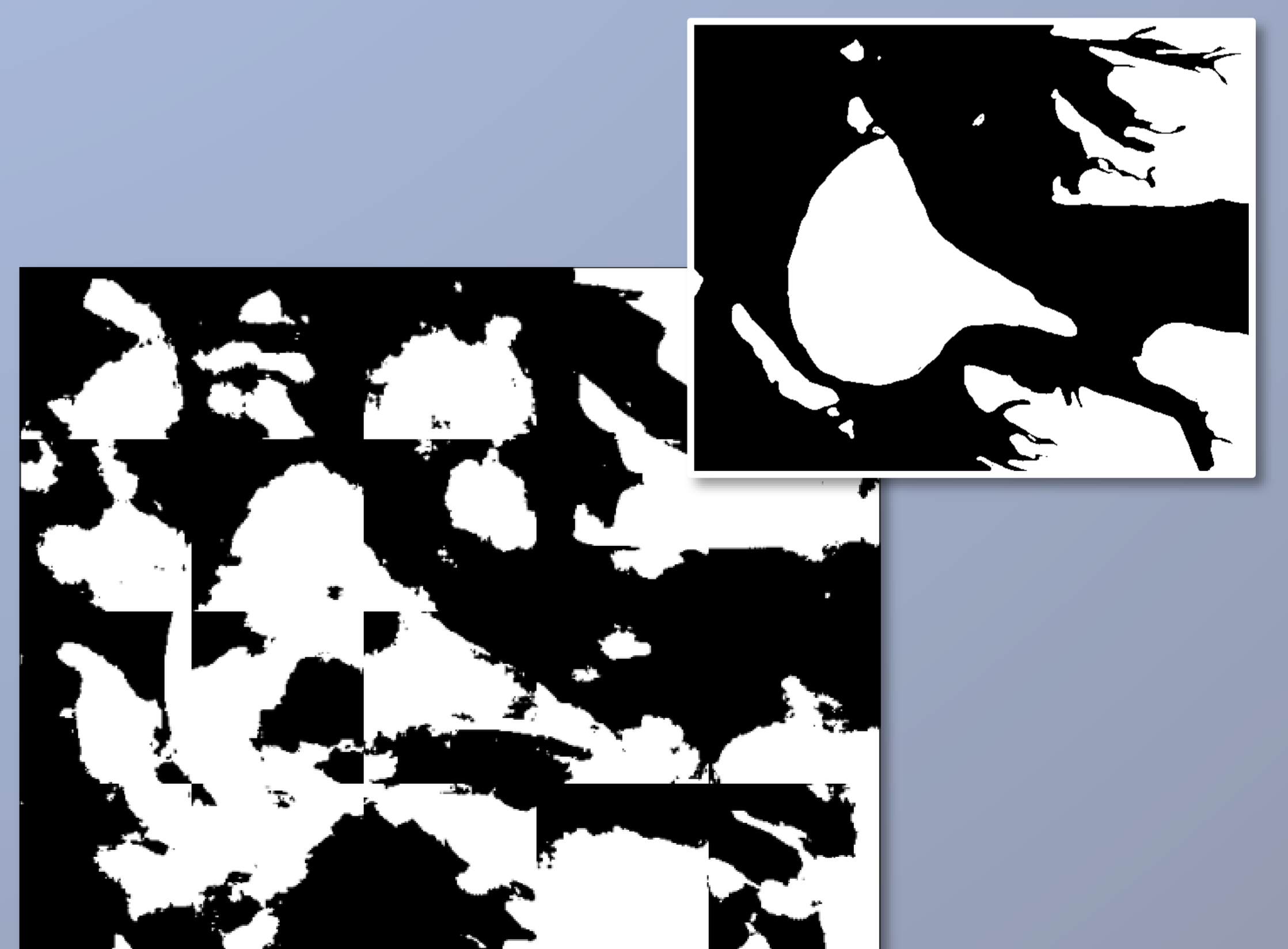


Fig 4: Mosaic of mask predictions. Limitations of the current network are obvious, when these results compared to the manually created mask of Fig. 2 (upper right). Remarkable errors are mostly found in submerged areas, and recurrent shapes point to an over-fitting due to the small amount of data.

References

[1] S. Wiehle and S. Lehner. "Automated Waterline Detection in the Wadden Sea Using High-Resolution TerraSAR-X Images". Journal of Sensors (2015). DOI: 10.1155/2015/450857

[2] S. Peters, "Bestimmung morphodynamischer Veränderungen an der deutschen Nordseeküste mithilfe von Synthetik Apertur Radar Daten". BSc thesis, Univ. Hamburg, FB Erdsystemwissenschaften, 26 pp., 2022