Solar Potential Analysis of Aerial Imagery using Machine Learning and Computer Vision

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Introduction

Since the Paris Agreement in 2015, countries worldwide are striving to achieve ambitious climate protection goals. The transition from fossil to renewable energies, including solar energy, is an important part of achieving these goals. In light of the ongoing worldwide growth of urban spaces, rooftop areas - both in urban and rural contexts - create a large number of currently unused surface areas that have a large potential for providing renewable, solar energy by photovoltaics. Identifying potentials can, especially in fragmented neighbourhoods, be a massive challenge. With our project, we hope to develop an algorithm that can identify single buildings and their solar suitability from satellite imagery without further human intervention, thereby massively speeding up analysis processes.

Currently the most commonly used method to determine the solar potential of an area is based on GIS (Geographic Information Systems), hence the analysis of map-based geographical data. However, it is often dependent on the availability of high-quality surface elevation data, and still requires relatively much effort, divided into multiple sub-steps (Margolis et al., 2017; Martin et al, 2015). Machine Learning, on the other hand, applied on satellite or aerial imagery, could promise a much easier solution: Imagery is often easily available for most regional contexts, and far easier obtainable. With well-trained models, even untrained personnel could one day perform solar potential analyses. Other projects have successfully demonstrated that machine learning algorithms can be used to detect roofs and classify their shape (Alidoost, et. al , 2018). Determining their solar potential however proves to be more complicated as other factors such as solar radiation, the roof´s shape orientation and shading. Lastly, social and economic factors of that region also need to be considered. Due to these complications machine learning has been combined with GIS in a previous study (Assouline et. al., 2017). To figure out how successful a project solely relying on machine learning can be we wanted to develop a simple prototype for solar potential analysis based upon building detection. Thus, our research could provide an estimate of how simplistic solar potential analysis can get.

Materials and Methods

Solar Potential Analysis - An Overview

Machine learning (ML) has already been used to estimate the solar potential of a given area in similar projects. In a 2017 study from Assouline et al., researchers have demonstrated that machine learning in combination with GIS can be used to estimate the solar potential of

1901 communes in Switzerland by relying on so-called support vector machines (SVM). This study also shows that multiple aspects have to be taken into account: the *physical potential*, based on the total energy received as sunlight, the *geographic* or *urban potential*, reflecting the constraints on the locations concerning the installation and use of solar panels, and the *technical potential*, or the actual transformed electrical energy created using certain solar panel technologies (Assouline et al., 2017). On the other hand, this project used geographical data for analysis, and no images were used as source data.

There are also projects that have already successfully combined image analysis with ML to detect buildings and determine roof shapes (e.g., Alidoost & Arefi, 2017). In this second example, datasets containing several top-view images for roof classes were created manually from an aerial image, and used to train two seperate networks: The first network to detect and classify objects as buildings, roads or trees, and the second network to recognize the roof´s shape (e.g., flat, gable etc.). A VGG-F architecture featuring 3x3 convolution- and 2x2 pooling-layers was used for the entire network. In execution, the model was able to distinguish objects with an accuracy of 99,6%. Roof types were identified with 100% and 95,7% recall, and 98,4% and 100% precision based on two separate images, respectively. Thus, machine learning can be a promising tool for roof detection and classification. In a third project (Kumar, 2018) multiple edge detection algorithms were tested to detect buildings on satellite images from India. The project concentrated on adaptive edge detection and contours to segment rooftop boundaries for solar panel installation. After the optimal roof shape was determined solar panels of three different sizes were placed on the polygons and rotated to achieve maximal power efficiency. Notably, the project faced several issues due to the low quality of satellite images in India.

In these three examples both the chances and problems associated with ML-based approaches for photovoltaic potential analysis. In our project we aimed at implementing a combination of the last two approaches, using machine learning to detect roofs and edge detection to determine the rooftop polygon shape to calculate its solar potential. Ideally, our model should be able to predict roofs from given aerial imagery, and feed these predictions into subsequent algorithms for statements about the *physical* and *technical potential* of individual roofs.

Model Description

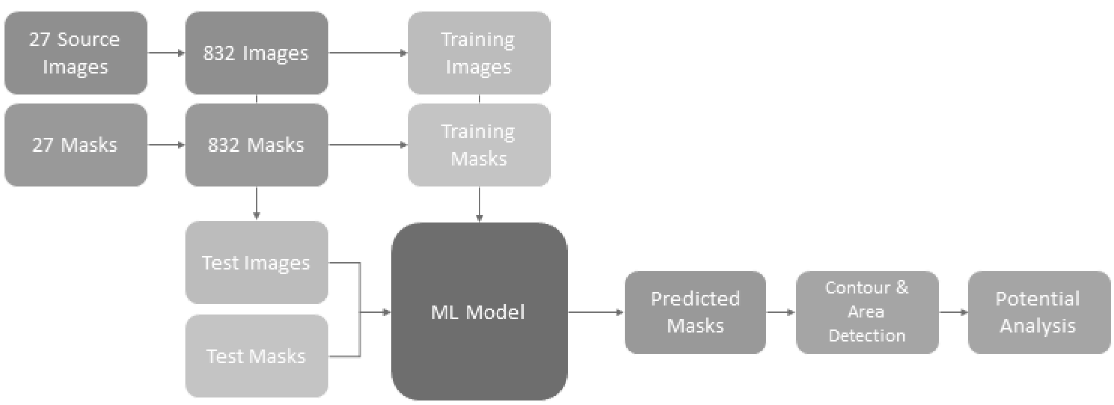
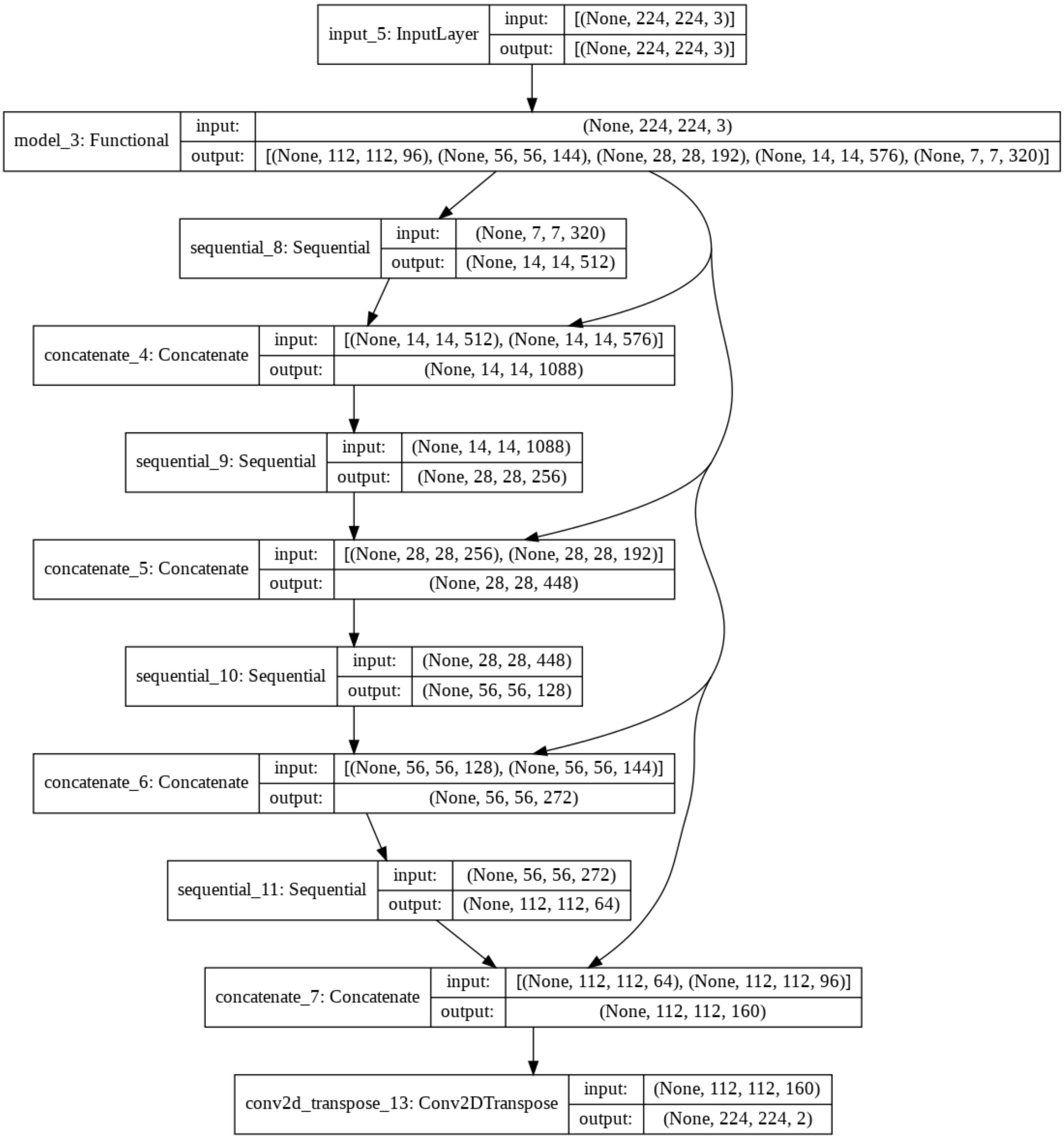


Figure 1: Flowchart showing the model structure



ML architecture was taken from tensorflow core (Image Segmentation: Tensorflow Core)

We created training and test images by hand using the free-to-use image editing software Krita. In total, 26 original images, originally obtained from Google Earth were used for the project, and overlaid with masks for further processing. To expand the original image stock into a format usable for Machine Learning, we processed all 26 original images by cropping their sizes to 500x500 pixels, this allowed us to further expand our dataset as images could be cropped into 4 subimages. These images were then mirrored and flipped and saved as new images, this augmentation allowed a x4 x8 expansion of the original data. In total, the process of image alteration resulted in a stock of 832 images with corresponding masks.

Training was then performed using a pre-existing U-Net model from Tensor flow. The training was run for 20 EPOCHS before the predicted masks and model summaries were extracted. These can be seen in the original code. The predicted masks were found to be rough and lacking uniform edges. This is likely due to our relatively small dataset and that our masks were not always perfectly annotated or inconsistently annotated which led to a lot of false positives within the training data. To clean up the predicted mask we ran them through a pixel filler loop which fills in holes and frayed edges within the predicted mask. Seeing as we expect our roofs to be uniform with straight edges these allowed us to turn the blob-like maks into more geometric shapes.

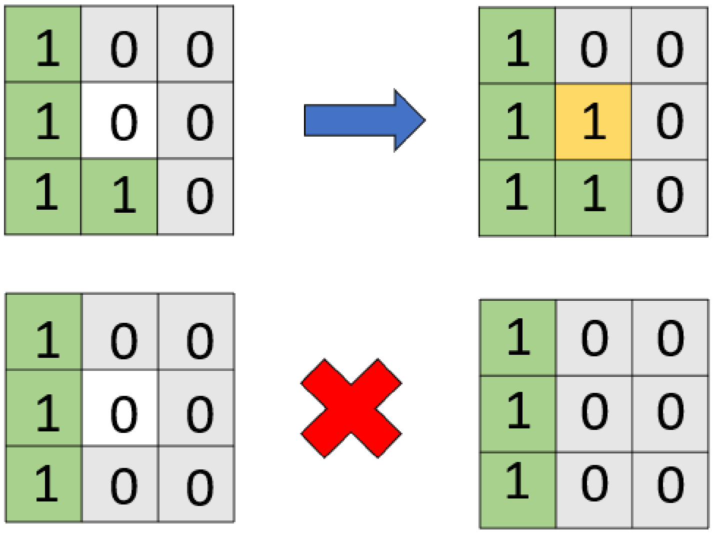


Figure 2: Pixel filling kernel

Here is a visual representation of the kernel that we passed over our predicted masks. When a pixel is boarded by 4 or more true pixels with value one that pixel becomes one. If three or less true pixels border then the pixel remains 0. This means that the overall footprint of the predicted mask should not expand to a great degree as they are confined to straight and angular lines.

We also developed a second part for our algorithm that allows us to calculate roof area and its associated solar potential based. For this, we used built-in contour analysis tools provided in the computer vision library *OpenCV* that identifies the edges of successfully detected buildings, calculates polygon approximations for their shapes, and allows to obtain further insight into the shape and area of shapes found. As all images used were shown and used in the same scale, the area detected within images could be scaled up and translated into statements about their true area (in m2). The resulting building areas were further fed into an additional algorithm that calculates how many solar panels would ideally fit onto the roof and how much power generation capacity can be achieved with the panels. To calculate the estimated annual power generation from a roof, the following equation will be used:

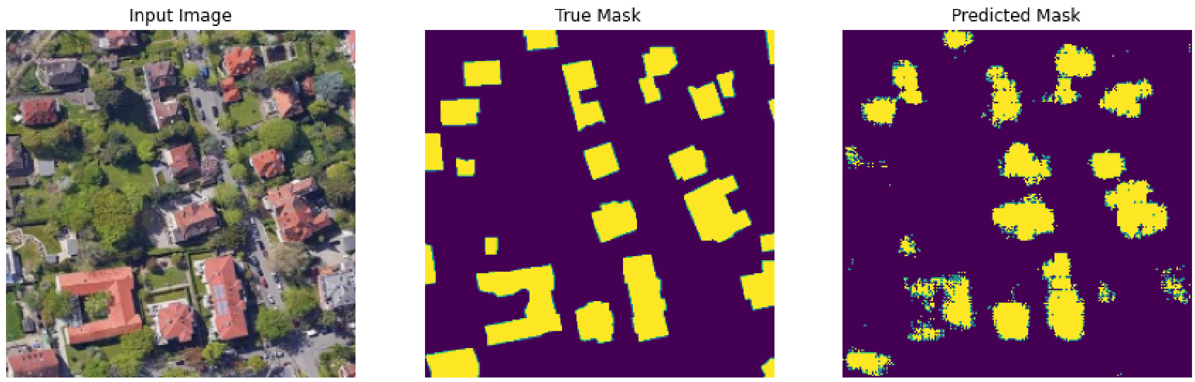
*Annual solar power generation = ((Annual amount of Global Horizontal Irradiance * area of panels) * Electrical loss index) * System capacity*

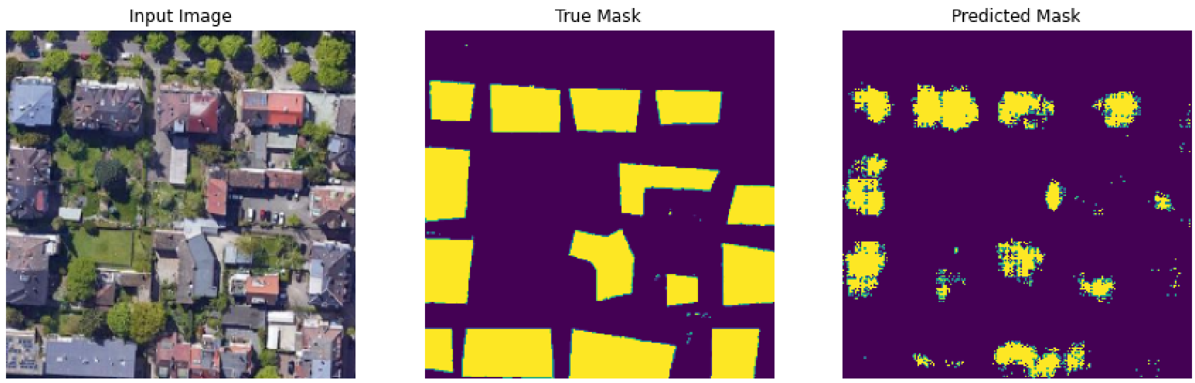
Amount of annual Global Horizontal Irradiance (GHI) in Freiburg is derived from a dataset provided by Solcast, a Sydney based company providing solar related actual and forecast data (Solcast, n.d.). The electrical loss index indicates loss of electricity in the process of DC/AC conversion, degradation of solar panel efficiency by mechanical and physical reasons and other types of energy losses related to solar power generation. In our calculation it is assumed that a system loses 27% of electricity (JPEA, n.d.).

The algorithm may derive the estimated amount of profit from a photovoltaic system. All electricity generated from panels is assumed to be sold to the electricity market via Feed in Tariff (FIT) scheme. Currently electricity from rooftop PV can be sold at the fixed FIT price of 0.0816 €-cts/kWh for 20 years in Germany. Thus, the annual revenue will be calculated by multiplication of annual power generation (kWh) by the FIT price (Fraunhofer Institute, 2021).

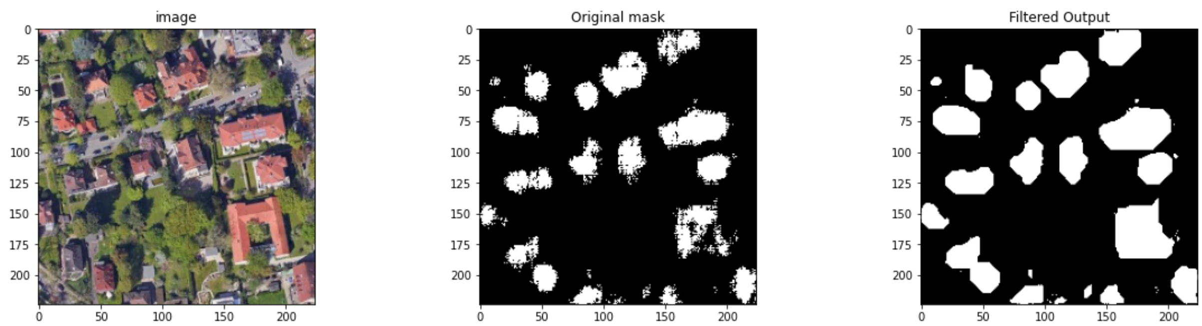
Results

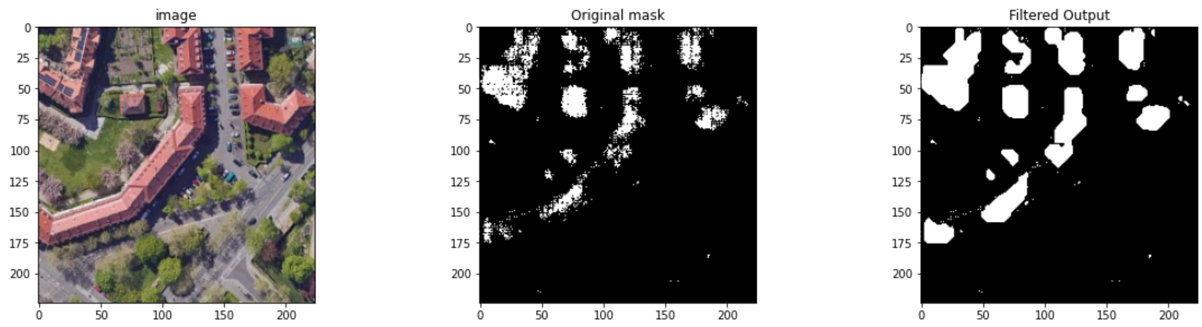
Model Predictions: **accuracy 0.7285**

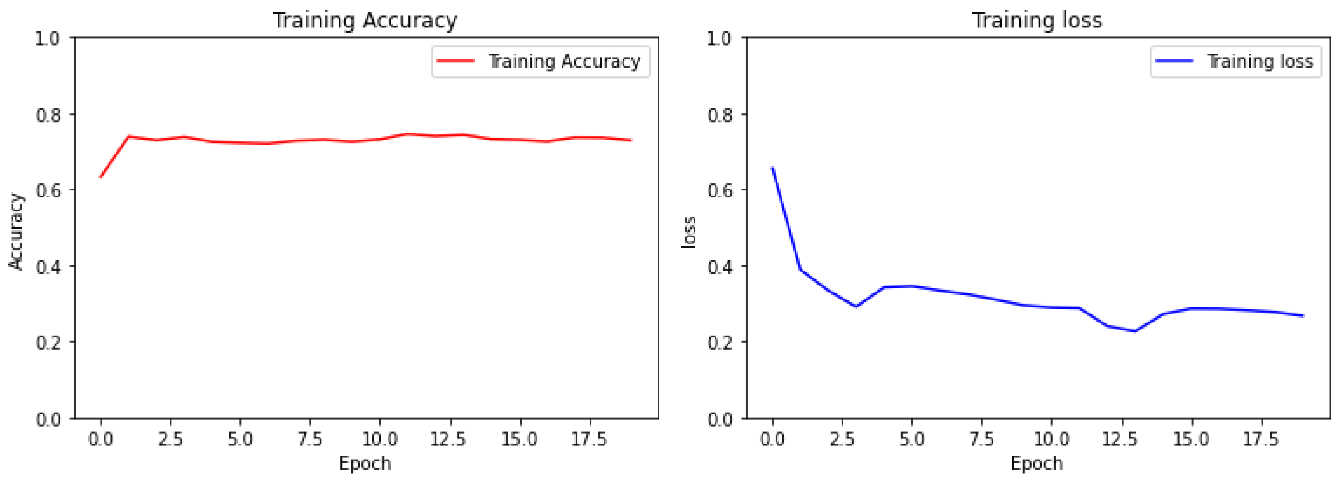




Model Predictions: After running pixel filling







The model could have likely benefited from further training but in the interest of time and memory we set the cut off to 20 repetitions. The training was more costly as we were using higher resolution which showed a better result in early testing.

Discussion

In general, our model was able to correctly predict a majority of roof areas in given aerial images. In around 70% of all cases, parts of an image were correctly identified as roof areas. However, in about a third of all cases rooftops were not completely detected or there was a high degree of false positives. Again this could likely be remedied by including further training data and tweaking the U-Net parameters. While, for a prototype developed without extensive knowledge, this result is more than satisfying, it might not necessarily suffice to apply our model in real-world use. While we adapted our model a few times and tried different configurations, we were unable to obtain predictions above an 80% benchmark. While, for a first prototype, this is still a respective result, more complex models featuring more layers or more complex model architectures might achieve higher results. In addition, combinations with more complex colour channel combinations - as present in some satellite images, or the preparation of model inputs using, e.g., colour filtering, might also lead to better performances. Another potential improvement could be the inclusion of more segmentation channels, such as road and greenspaces as this would help to weed out false positives when training the model. Lastly, the quality of the masks we prepared using Krita can also be viewed critically: Building masks sometimes lacked smaller details, or did not differentiate between individual neighbouring buildings. While hard to estimate, improvements in this regard could also have improved our model.

Apart from that, our project also shows several limitations, without which higher prediction success or applicability for practical use would have been possible. To begin with, our model was developed and trained only with 27 images, a relatively small number. Although we expanded this image stock to more than 800 images to avoid overfitting, and ensure higher prediction successes, a larger set of images might have yielded better results. In addition, all of the images we used were - for the sake of convenience - taken within a single city, thereby only representing only one specific context, and a single set of conditions concerning lighting and colour. Our model will therefore be inherently biased in its predictions. As an example, most roofs visible on test and training images are - as typical for Freiburg - covered in brown or red tiles. Flat roofs with vegetation or concrete cover, as well as other kinds of roof tiles, were therefore less likely to be detected.

Thirdly, our model's functionality still is only on the level of a prototype, and not comparable with the features or scope of more professional and complex models. While our goal was to successfully recognize roof areas, we did not further differentiate the kind or shape of these roof areas, or the orientation or location of individual roofs (compare, e.g., Alidoost, 2018, Assouline et al., 2017). Shadows by neighbouring buildings or tilted roofs, for example, were not taken into account. Therefore, our estimates are likely to lie above actual solar potentials, as our model pays little attention to the *geographical potential* of roofs. In addition, ideally a model like ours would not only take into regard one specific size of solar panels, but several, and allow for a more realistic prediction of potentials. Lastly, we also limited the model to the use of a single image scale. In consequence, our model is not suitable for analysing larger geographical regions at once (see, e.g., Bodis et al, 2019). Therefore, combining our simplified model with the approach of other authors, or developing further features, might lead to more detailed, realistic, and practically useful predictions in the future.

Conclusion

The aim of our project was to figure out how successful a simple machine learning approach can be for solar potential analysis using satellite images. With an obtained accuracy of 70% our study has demonstrated that satellite imagery can be used to estimate the solar potential of a given area. Thus it can be used for the promotion and planning of more renewable energy sources. However, due to significant limitations, such as the small train image set and adjusted solar potential analysis, future research is needed.

Contributions

Each team member contributed images to the used training set. The specific contributions to this report will be indicated here: Introduction (Carla Mallmann & Felix Schachenmayr);

Solar potential analysis - overview (Carla Mallmann, Felix Schachenmayr); Model description (Logan Poehlman, Felix Schachenmayr, Daichi Yoshioka); Results (Logan Poehlman); Discussion (Carla Mallmann, Felix Schachenmayr, Logan Poehlman) and Conclusion (Carla Mallmann, Logan Poehlman).

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