Deep Learning for Detecting Tilt Angle and Orientation of Photovoltaic Panels on Satellite Imagery

Ammar Memari[1(✉)], Van Cuong Dam[1], and Lars Nolle[1,2]

[1] Jade University of Applied Sciences, Friedrich-Paffrath-Straße 101, 26389 Wilhelmshaven, Germany
ammar.memari@jade-hs.de, lars.nolle@dfki.de

[2] German Research Center for Artificial Intellingece, Marie-Curie-Straße 1, 26129 Oldenburg, Germany
https://www.jade-hs.de/ , https://www.dfki.de/

Abstract. The goal of this research is to accomplish two tasks that increase the accuracy of the process of estimating solar power generation in real time for different regions around the world. Specifically, we explain a method for detecting the tilt angle and installation orientation of photovoltaic panels on rooftops using satellite imagery only. The method for detecting tilt angles is based on their dependence on the roof shapes. As for the architectures used in this research, we chose MobileNetV2 and Yolov4 since both require only medium hardware resources, without the need for graphics processing units (GPUs). Since it was difficult to find a suitable data set, we had to create our own, which, although not large, was proven to be sufficient to confirm the capabilities of our method. As for the final results, our approach provides good predictions for the tilt angle and the orientation of photovoltaic panels based on a data set of images from six different locations in Europe collected via Google Maps.

Keywords: Solar energy · Object detection · Object classification · YOLOv4 · MobilenetV2

1 Introduction

In this day and age, renewable energy is constituted as the best solution when it comes to providing energy to mankind for living and manufacturing. The major rationale for this is that producing energy from solar or wind power is an environmentally friendly process. Furthermore, utilizing these power sources is also deemed as an excellent approach owing to their unlimited availability. The intermittency of solar energy is its main obstacle for widespread integration into the mix of energies in current electricity networks. Solar energy is produced only when the sun is shining, and even then, its output can vary depending on cloud cover. This makes it difficult to rely on solar energy as a primary source of power, since there must always be a backup source of energy available to fill in

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the gaps. To overcome this obstacle, efforts have been made for predicting the solar power output for the next few hours or days, so that network operators can adjust the schedule of backup sources of energy accordingly.

Fundamentally, our project supports the prediction of power outputs from photovoltaic panels in specific areas. In terms of the prediction, the installation orientation of the panels and the weather in the area in addition to the installed capacity of the panels are the main factors that could impact on the final results. Regarding local climate predictions, modern forecast methods are capable of predicting the regional weather conditions for the next days quite precisely. Hence, local weather prediction are no problem when it comes to power output prediction. Nevertheless, when it comes to the direction of the solar panels, there are numerous factors that affect the power output. The two most influential parameters are the orientation of the installed panels and the tilt angles on the roofs. Our research solves this problem of predicting the installation orientation as well as the tilt angle from satellite imagery. If satellite images are not available or are outdated, drone images can be used instead, considering the low cost of high-end camera drones today.

Since the last decade, computer vision has improved remarkably. The applications of computer vision could be witnessed in various aspects of real-life, such as in transportation, health-care, manufacturing or even retail. This has been achieved thanks to the advancement of artificial intelligence and machine learning technologies. The most well-known sub-discipline of machine learning is deep learning, which prevalent applications are in natural language processing and computer vision. For this reason, we chose to apply deep learning algorithms as the initial approach to solve our problem.

The paper starts with a discussion of related work in Sect. 2. The next section depicts the methodology used, including building and utilizing the data set. Section 4 presents the results for testing the models developed on random images from different locations in different countries. The last section concludes this paper and points out relevant directions for further work on the topic.

2 Related Work

DeepSolar [13] is researched by Stanford University in 2018 with a view of developing an accurate deep learning framework to automatically localize photovoltaic panels from satellite imagery for the contiguous United States and to estimate their sizes.

Fundamentally, the research aims at tasks different from ours. Nonetheless, the idea of applying Transfer Learning [15] to detect the panels from satellite imagery gave us an initial direction to find the solution for our own tasks.

Position Detection And Direction Prediction for Arbitrary-Oriented Ships by Yang et al. [12] proposed a new detection model based on a multi-task rotational region convolutional neural network with a view to detect positions and to predict directions of arbitrary-oriented ships.

At first sight, the proposed method seems to be able to solve one of our tasks, namely the detection of rooftop directions. Nonetheless, the method could not distinguish the orientation of two roofs with the same angle. In Fig. 1, it can be observed that the two rooftops have the similar angle θ in the rotational bounding box regression [12]. Nevertheless, the two rooftops demonstrate entirely different directions (southeast and southwest). Therefore, the result is incorrect. In addition, it also seems to be possible to improve results by applying prow direction prediction, like in the research. However, it is only feasible with rectangular rooftops that have long and short edges. This does not apply to the majority of rooftops, as there are various types that make the model impossible to work.

Fig. 1. Despite the similar angle θ, the two rooftops have different directions

Maji and Bose [5] proposed a method to detect the orientation angle of a captured image. Namely, a post-processing step captured in any camera (both older and newer camera models) with any tilted angle (between 0° and 359°).

Zhou et al. [14] proposed a kernel mapping CNN which can recognize the rotated images without altering the network's basic structure and requiring extra training samples for the rotated data. Shima et al. [10] proposed a novel orientation detection method for face images that relies on image category classification by deep learning. Rotated images are classified in four classes, namely 0°, 90° clockwise, 90° counter-clockwise, or 180°. Unfortunately, the three methods mentioned above only predict the direction of image frames, not the direction of objects in the images. Nevertheless, they still gave us several thoughts for dealing with the problem of detecting object directions.

3 Methodology

There are four fundamental challenges, which commonly arise when solving problems in the field of computer vision.

1. Object classification
2. Object localization
3. Object detection
4. Object segmentation

Based on the attributes of each task, we try to combine them to come up with a solution for our problem. We rely on the dependence of the panels' arrangements on the roof shape; They are mostly installed parallel to one of the roof sides. From this rationale, we eventually build the solution depicted in Fig. 2.

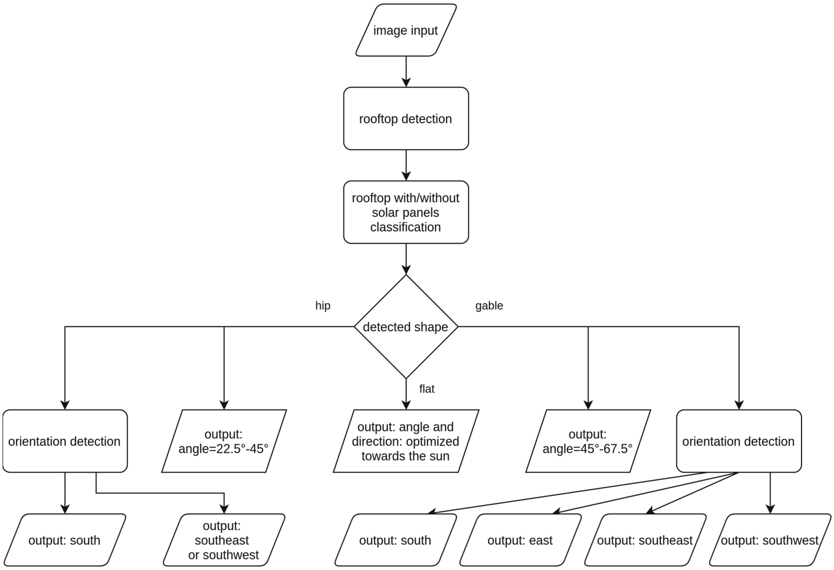


Fig. 2. Schematic of solution

1. Input satellite images are obtained from Google Maps
2. A trained model is applied to detect rooftops in the input images. Afterwards, the rooftop images are cropped out from the original ones.
3. Subsequently, the rooftop images are classified based on whether they are equipped with photovoltaic panels or not. Only the ones with photovoltaic panels proceed to be examined.
4. Then the rooftop shape of each image is classified with the aim to categorize them into the respective tilt angles.
5. Eventually, another trained model is used to detect, in which orientation the photovoltaic panels are installed.

3.1 Rooftop Detection

First and foremost, there are various algorithms for detecting objects in images, which could be applied to locate photovoltaic panels, such as R-CNN (Region-Based Convolutional Neural Networks) or YOLO (You Only Look Once). As far as we are concerned, the R-CNN algorithm is extremely slow. Even though its updated versions Fast R-CNN [3] and Faster R-CNN [9] present an improvement, they still are no match for the YOLO algorithm in terms of computational costs. Out of five YOLO versions [1,6–8], we chose "YOLOv4" [1], which has the best accuracy in comparison to the others.

Secondly, a proper data set containing images and annotations is a prerequisite to be able to apply "YOLOv4" for object detection. Unfortunately, in computer vision, image data sets are always the most challenging ones to acquire. After a lot of effort to find an appropriate data set, we have only found one, which lead to very poor results. That is why we decided to create our own data set instead of looking further for an existing one. Basically, our data set consists of 430 images generated through Google Maps from 6 different cites in 5 countries in Europe: Oldenburg (Germany), Wilhelmshaven (Germany), Liverpool (England), Bordeaux (France), Milan (Italy), and Vigo (Spain). These images are captured from a height of around 10 m above ground level (an example is depicted in Fig. 3). We also used the free open-source tool "LabelImg" [11] to accelerate the labeling of images as seen in Fig. 4. Subsequently, the recommendations from the authors of Yolov4 [1] were followed for training a detection model using our data set.

Fig. 3. Image input

Owing to the restriction of using GPU in standard "Google Collab" accounts, it took for each data set about 2 days to gain the weights files. Actually, it could have been better had we trained for longer, but the test results already satisfy our expectation. Moreover, we have also modified the source code of YOLOv4 in order to gain the required outputs as a collection of roof images, which are cropped out from the image input. Table 1 shows the accuracy achieved for the rooftop detection model.

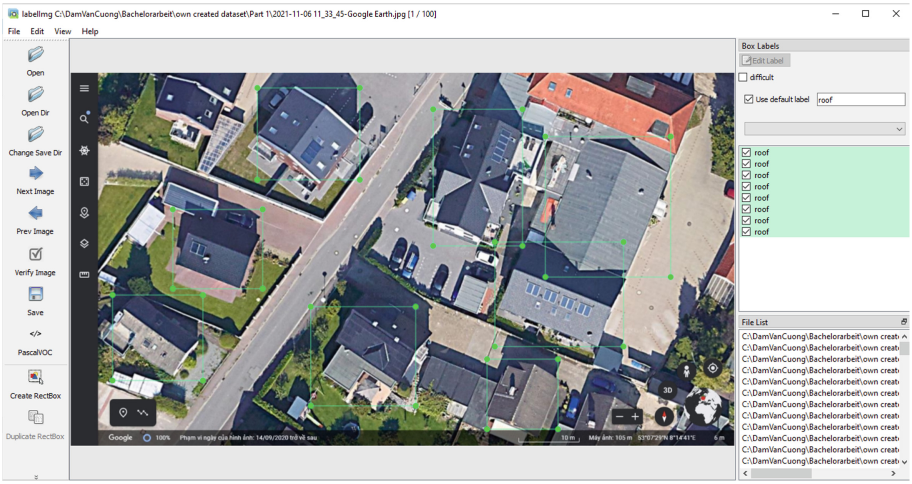


Fig. 4. LabelImg

Table 1. Accuracy metrics of rooftop detection model

	Precision	Recall	F1-score	mAp@0.50
conf_thresh = 0.25	0.61	0.89	0.72	80.71%

3.2 Rooftop Classification

The next step is the classification of roofs, whether they are equipped with photovoltaic panels or not. Based on the old data set for YOLOv4, we have generated a new data set by cropping out all single roof images from the big ones and dividing them into two classes, "roof with photovoltaic panels" and "roof without photovoltaic panels". The new data set contains 340 images of rooftops with or without photo voltaic panels. For the training, 80% of the images in our data set were used for training and the remaining 20% of the images were used for testing. To build a model for this step, we have used "Transfer learning" [15], which facilitates building our model by applying pre-trained models. In our case, we chose "MobileNetV2" [4] because of its lightweight deep neural networks. In addition, we have also used the data augmentation technique to expand the amount of training images. Table 2 shows the accuracy achieved for the rooftop classification task.

Since only the roofs with photovoltaic panels are examined, all the others without such panels were deleted from the output folder.

3.3 Tilt Angle Estimation

The tilt angle estimation of installed photovoltaic panels can be achieved by classifying roof shapes, since the tilt angles of the panels and their roof are

Table 2. Accuracy metrics of rooftop classification model

	Precision	Recall	F1-score	Support
Roof with pv	0.85	0.94	0.89	31
Roof without pv	0.94	0.86	0.90	37
Accuracy			0.90	68
Macro avg	0.90	0.90	0.90	68
Weighted avg	0.90	0.90	0.90	68

usually the same. Hence, the prediction of the tilt angle of the panels boils down to the task of detecting roof shapes. The three most ubiquitous roof shapes are flat, hip and gable (Fig. 5. It is well-known that gable roofs typically have an angle from 22.5 to 45 °C, while hip roofs have an angle between 45 and 67.5 °C. Additionally, the angle of flat roofs is always 0 °C. Thus, if a roof is classified as gable, hip or flat, the tilt angle of the panels on this roof will be $22.5 - 45.5°$, $45 - 67.5°$, or a manually optimized tilt angle in the case of flat roofs.

Fig. 5. Three most common roof shapes [2]

To build a model for classifying rooftop shapes, we have repeated the same process that we have conducted in the previous step. This time, the data set consists of 819 images that are divided equally in three classes "gable", "flat", and "hip". The ratio remains unchanged, with 80% for the training set and 20% for the testing set. Data augmentation technique is still applied during the training process. The resulting model, which was built based on the pre-trained model "MobileNetV2" to predict whether the roof shape is flat, gable or hip, provides quite a good precision (Table 3).

3.4 Orientation Detection

The final step is detecting the orientation of the panels. According to the conventional construction, the panels in the Northern Hemisphere are intentionally installed on the roof side facing south as much as possible. Thus, the directions of the panels on the gable roof are normally south, east, southeast or southwest. Furthermore, in light of the special shape with 4 similar edges, the collectors on hip roofs are installed on either the south or the southwest+southeast orientation. Furthermore, it is understandable that based on the house's latitude and longitude, the collectors on flat roofs are installed straight towards the sun in

Table 3. Accuracy metrics of rooftop shape classification model

	Precision	Recall	F1-score	Support
Flat	0.84	0.91	0.87	57
Gable	0.88	0.75	0.81	51
Hip	0.90	0.95	0.92	55
Accuracy			0.87	163
Macro avg	0.87	0.87	0.87	163
Weighted avg	0.87	0.87	0.87	163

order to optimize the power produced. There are two models, which need to be built for this task.

The first model is used to detect the orientation of gable roofs. As mentioned, the data set needs to be divided into 4 classes "south", "east", "southeast" and "southwest". This data set consists of 3728 images for 4 classes with the percentage of 80% and 20% for the training and the testing set respectively. The unusual feature during the training process of this model is that the data augmentation technique could not be applied to avoid rotating the images, since the orientation of the roofs is not preserved in the rotated images. For this reason, we had to rotate the images and then label them manually. Once again, we used "MobileNetV2" as the pre-trained model in the training process. Table 4 presents the accuracy achieved for the orientation detection for gable roofs.

Table 4. Accuracy metrics of orientation detection model for gable roofs

	Precision	Recall	F1-score	Support
east	0.99	1.00	1.00	169
south	0.99	1.00	1.00	198
southeast	0.89	0.97	0.93	162
southwest	0.98	0.91	0.94	216
accuracy			0.97	745
macro avg	0.97	0.97	0.97	745
weighted avg	0.97	0.97	0.97	745

Another model is built for estimating the orientation of hip roofs. Like the idea mentioned above, there are two classes for the model "south" and "southwest+southeast". Due to the minority of houses built with a hip roof in general, we could only collect a smaller data set with 760 images in comparison with the data set of gable roofs. The images are also divided with 80% for training and 20% for testing. Similar to the first model, the data augmentation technique is not applied and "MobileNetV2" is used as basis for the training. Table 5 shows the accuracy achieved by the orientation detection model for hip roofs.

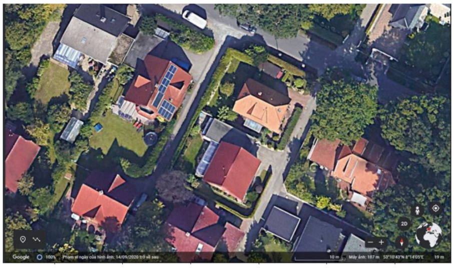
Table 5. Accuracy metrics of orientation detection model for hip roofs

	Precision	Recall	F1-score	Support
east or south	0.99	0.99	0.99	73
southeast or southwest	0.99	0.99	0.99	79
accuracy			0.99	152
macro avg	0.99	0.99	0.99	152
weighted avg	0.99	0.99	0.99	152

4 Results

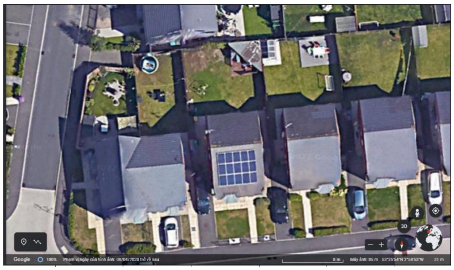
Performances of the individual models are described in the aforementioned tables. Moreover, we are confident that a trained model would also be able to correctly detect and classify objects that were not included in the data set. This is because the features extracted by the model are abstract enough to be applicable for a variety of different situations.

In order to test the validity of this claim, we included a simple "out-of-sample"-test. We had tested the whole pipeline on random images from five different European cities. Sample results are depicted in Figs. 6, 7, and 8.

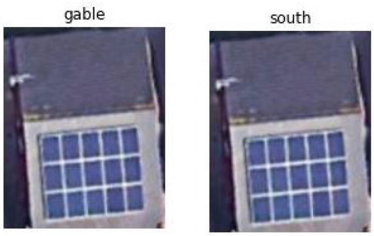


(a) Oldenburg - Input

(b) Oldenburg - Final results are correct



(c) Liverpool - Input

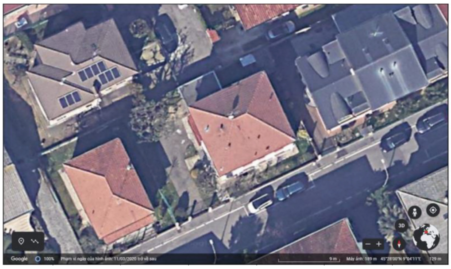


(d) Liverpool - Final results are correct

Fig. 6. Oldenburg - Germany and Liverpool - England

(a) Bordeaux - Input

(b) Bordeaux - Final results are correct



(c) Milan - Input

(d) Milan - Final results are correct

Fig. 7. Bordeaux - France and Milan - Italy

(a) Vigo - Input

(b) Vigo - Final results are correct

Fig. 8. Vigo - Spain

5 Conclusion and Future Work

In this research, we have applied deep learning technologies to predict the tilt angle and orientation of photovoltaic panels installed on rooftops from satellite imagery. Based on the attained results and the weather forecast, the produced energy from photovoltaic panels in a specific region is estimated more precisely, aiding the efforts aiming at integrating this energy source into the power grid, and maintaining the stability of grids that rely on solar power.

The trained model have performed fairly well and produced usable results, even though only relatively few resources and little time were devoted for the training thereof. We are confident, that having a larger and more diverse data set and dedicating more time on more power full computer hardware for the training would improve the overall performance even more.

Merging results from [13] and building upon them, we were able to build a model that can reliably scan a region of the world and provide us with all data necessary for describing its photovoltaic capacity, including the installed power, directions, and tilt angles of the panels. Applying weather forecast to such data provides a high-resolution forecast of expected produced power. For areas without proper resolution satellite images, drone footage can be used for extracting still frames for the training and recognition purposes.

It is acknowledged that nowadays, despite the considerable technological advancement, results of deep learning still cannot overcome human performance, especially when it comes to computer vision tasks, such as object detection or localization. However, it is worth mentioning that even the human eyes could not tell the exact angle of roofs when looking at satellite imagery. Shortcomings of our approach are unfortunately related to such limitations.

In years to come, we would like to apply the same principle used in this work to solve the problem of detecting tilt angle and orientation of objects from images. This remains a problem that has not been solved yet.

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