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Deep learning for photovoltaic panels segmentation

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Due to advanced sensor technology, satellites and unmanned aerial vehicles (UAV) are producing a huge amount of data allowing advancement in all different kinds of earth observation applications. Thanks to this source of information, and driven by climate change concerns, renewable energy assessment became an increasing necessity among researchers and companies. Solar power, going from household rooftops to utility-scale farms, is reshaping the energy markets around the globe. However, the automatic identification of photovoltaic (PV) panels and solar farms' status is still an open question that, if answered properly, will help gauge solar power development and fulfill energy demands. Recently deep learning (DL) methods proved to be suitable to deal with remotely sensed data, hence allowing many opportunities to push further research regarding solar energy assessment. The coordination between the availability of remotely sensed data and the computer vision capabilities of deep learning has enabled researchers to provide possible solutions to the global mapping of solar farms and residential photovoltaic panels. However, the scores obtained by previous studies are questionable when it comes to dealing with the scarcity of photovoltaic systems. In this paper, we closely highlight and investigate the potential of remote sensing-driven DL approaches to cope with solar energy assessment. Given that many works have been recently released addressing such a challenge, reviewing and discussing them, it is highly motivated to keep its sustainable progress in future contributions. Then, we present a quick study highlighting how semantic segmentation models can be biased and yield significantly higher scores when inference is not sufficient. We provide a simulation of a leading semantic segmentation architecture U-Net and achieve performance scores as high as 99.78%. Nevertheless, further improvements should be made to increase the model's capability to achieve real photovoltaic units.

Keywords: *remote sensing; solar energy; photovoltaic systems; deep learning; segmentation architecture U-Net.*

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1. Introduction

The world nowadays is facing a crisis regarding the lack of natural energy resources. In addition to this, global warming is the major threat that triggers survival alarms across the planet. Nevertheless, the majority of countries are still using non-green energy sources such as natural gas and coal, or even green hydro-power, but that also comes at the cost of water waste. Quite naturally, the most prominent energy source is the sun. This source increases energy availability in emerging nations and lowers energy costs. Solar panels are being installed faster than can be accurately registered, particularly in many developing countries where most data are being self-reported or relied upon on voluntary surveys such as the recently closed National Renewable Energy Laboratory's Open PV Project, for further details see [1]. Since this type of data is usually facing risks of being incomplete or outdated, Governments, companies, and International environmental organizations are constantly facing the photovoltaic panels and solar energy farms identification challenges.

Finding the proper way to do so will help increase the number of solar power operations, whether it is for environmental or financial purposes. Remote sensed data has become the pillar for all kinds of land observation tasks [2,3]. Given the availability of such data and thanks to deep learning methods, different kinds of implementations have emerged in domains such as agriculture, urban development and environmental purposes [3–9].

Considerable research has been devoted to solar panels' detection tasks such as [10–15]. The downside of those approaches is the data itself: most images are a small portion of the Earth and the main content of the image represents the solar panels. Furthermore, the number of such instances per image is considerable. Nonetheless, the main purpose of this research area is to identify the decentralized photovoltaics nature. This leads to neural networks being biased as the number of true negative pixels represents the integrity of the image's mask, leaving the model with very little ability to close the gap between the real-world data and the one it has been trained on, even with higher performance scores. Thanks to this phenomenon, and since deep learning methods are regarded as data-driven [16], many studies involving deep learning on remotely sensed data are being constantly published with the perspective of providing the best tool for land observation purposes. However,these papers mainly focus on classification and object detection tasks [17–19] or the DL-based remote sensing analysis in specific environmental fields such as hydrology [20] or atmospheric aerosol [21]. The comprehensive analysis of remote sensing in solar energy using DL has been poorly explored. The traditional NN and DL models have been used in solar energy assessment, and a few works have been published in recent years. Therefore, this review will concentrate on the DL applications during the past five years to advance the solar energy remote sensing process.

The main outline of this paper is arranged as follows. Section 2 will bring forward an overview of remote sensing and how is it different from normal photography. Section 3 will discuss the potential of DL methods and some novel research and achievements made regarding remotely sensed data. Section 4 brings to light the most recent works and methods in the literature that made use of valuable remotely sensed data and deep learning novel approaches for a solar energy assessment. Section 5 discusses the potential research direction and future perspectives. Section 6 explores our new approach to facing the previous problem using more reliable data with the most relevant image segmentation network architecture UNet and brings forward the dataset used, the mask computation and our proposed image segmentation architecture. Section 7 discusses the results achieved and finally Section 8 concludes the paper along with our potential research directions and future perspectives.

2. Remote sensing overview

The term remote sensing, according to [22], is the science and art of obtaining information about an object, area or phenomenon by analyzing data acquired through a device that is not in contact with the object, zone or phenomenon being studied. And, according to NASA, it refers to the scanning of the Earth using different kinds of sensors to collect electromagnetic radiation known as spectral response, reflected from different kinds of objects on the Earth's surface.

2.1. The workflow of satellites

The sun is constantly emitting solar radiation. A part of those electromagnetic radiations is reflected by the Earth's surface while the other part is absorbed by objects on the surface to emit a different kind of spectral response [23]. Satellites being constantly orbiting around the globe, are capturing all kinds of radiations emitted from the ground, i.e., terrestrial and reflected energy. To ensure the continuous scanning of all areas, satellites are also equipped with active sensors that allows emitting artificial radiations in absence of the sun or during cloudy seasons [24]. When the scanning process is done, the satellite provides a matrix representing the spectral response of each area alongside with its geo-coordinates resulting in what remote sensing experts call a scene which is, keeping only the visible information, the equivalent of an image in the photography area. Although such advancement provided a breakthrough in the past decades, high quality satellite data is still expensive and hard to come by. With the motivation of pushing research forward, there came the emergence of unmanned aerial vehicles (UAV) which provided an alternative to using satellite images and thus the introduction of aerial images. However, with more technological advancement in recent years and with the UAVs nowadays being equipped with multispectral sensors, many works such as [25, 26] made areal aerial imagery from satellite data thanks to the conclusion of [27] proving that no difference was found between post-processed satellite imagery and optical aerial images.

2.2. Multiple resolutions

When addressing remote sensing imagery, resolution plays a big role in how data from a sensor can be used. Resolution can vary depending on the satellite's orbit and sensor design. When considering which type of remotely sensed data is useful for a given problem, four types of resolution are considered. Radiometric being the maximum amount of information in each pixel (e.g., 2-bit, 4-bit, 8-bit etc.) has a great impact on remotely sensed imagery understanding as we can see in [28]. Spatial resolution is considered the most used metric when evaluating satellite imagery. It represents how much area on the Earth's surface is represented within each single pixel as verified in [29], an increased spatial resolution always provides better results regardless of the method used to deal with remotely sensed imagery. Another form of resolution is called spectral and it defines the sensor's ability to discriminate finer spectral wavelengths, many sensors are considered multi-spectral, that is, having from 3 to 10 bands. Others called hyperspectral sensors having the capability to capture several hundred and even thousands of bands, this allows for more levels of interpretations in the non-visible area of studies [30]. Last but not least, the temporal resolution providing the information of how much tie does it take for a satellite to fully complete an orbit and return to the same observation area such kind of information allows more expendable research most commonly agricultural applications [31, 32].

3. Remote sensing-driven deep learning

For its simplicity, deep learning may be looked at as a form of automating the process of making prediction analysis. Unlike traditional machine learning algorithms which are linear, deep learning approaches are layered in a hierarchy of escalating complexities and abstractions. Neural networks, being the highest artificial representation of how the human brain works, provided over the years a variety of forms such as back propagation neural networks (BPNN), convolutional neural networks (CNN), recurrent neural networks (RNN), and auto encoders (AE). This chapter will bring forward an overview of each method and its recent contribution to the remote sensing area.

3.1. Back propagation neural networks

BPNN is one the most basic form of neural networks fine-tuning weights using the back propagation method and thus updating the network's weights. Being the simplest form of neural networks, many works made use of it in remote sensing fields. Recent studies such as [33] made use of Modis and Landsat satellite images with the use of BPNN to provide support for wheat fields quality and improve mass production. [34] attempted to estimate and solve soil moisture using the AMSR-E sensor data as inputs to multiple back propagation neural networks. [35] evaluated the status of water quality feeding the network different band combinations to estimate the water quality index (WQI). Over all, BPNN are widely used with remotely sensed data. However, the subsequent implementation is restricted by slow convergence during the training and sensitiveness to the network's initial weights.

3.2. Auto-encoders

Auto-encoders have been rarely applied for remote sensing applications due to the fact that a single autoencoder may not be able to reduce the size of the input features. Thus came the idea of using stacked auto encoders (SAE) with some successful cases adoptions and promising prospects. In the task of hyper-spectral remote sensing, stacked autoencoders proved powerful outperforming traditional methods including principal component analysis (PCA), support vector machine (SVM) classifiers, and also combined PCA-SVM classifiers as demonstrated in [36] work. We can also see improvements in Semi-supervised learning (SSL), with only 0.08% labeled data became more reliable with closer results to supervised learning with expensive remotely sensed data [37].

3.3. Recurrent neural networks

When it comes to time series or sequential data, the classic feedforward networks cannot be used for learning and prediction. For instance, multi-temporal Remote Sensing data allowed recurrent neural networks (RNNs) to be highly robust in predicting end-of-season yearly biomass [38], we can also see further combined methods such as involving difference kinds of networks for detection purposes then implementing the RNNs for bi-temporal modeling as we can see in [39] for urban change detection.

3.4. Convolutional neural networks

When addressing remote sensing data, nothing like CNNs can achieve higher results whether for classification, retrieval or object detection tasks. We can see over the past decade two decades the continuous contribution to provide the most reliable dataset. Bringing forward land use and land cover classification datasets [2, 25, 40–42], each one providing higher challenges and levels of classification that allowing the reliability of CNNs for land monitoring purposes. Another core feature of convolutional neural networks in the remote sensing areas is the emergence of different kinds of networks allowing object detection tasks. With the use of high-resolution satellite data, we can bring into light mapping of Ice-Wedge Polygons [43] showcasing the performance of state-of-the-art Mask R-CNN, Marine pollution assessment such as plastic and litter detection [44], and oil spill [45], buildings and vehicles detection [16, 46, 47].

4. Remote sensing-driven DL or solar energy

Several works made use of remote sensing data to assess solar energy. The manual use of such data is still a trend in the literature. Remote sensed data such as the Corine land cover database provides a good reference to analyze the solar energy potential and calculate yearly production [48]. The use of geographic information systems (GIS) is the most common approach to deal with remotely sensed data. To meet requirements in power consumption and map the potential solar power zone instalments, we can see the use of GIS and remote sensing to evaluate the solar irradiance [49] and identify suitable zones to maximize land use locations for solar energy harvesting [50]. Google project Sunroof, on the other hand, provided a much higher contribution to power consumption predictions, mapping and measuring photovoltaic potential and quantifying the role of political affiliation in rooftop PV adaptation [51]. Deep learning, being able to automate diverse fields of study, is poorly explored in solar energy assessment. However, the recent studies provided promising works using deep learning mainly in the detection of photovoltaic panels. DL provides high fidelity when it comes to providing a database of solar installation locations and size. As opposed to Google's Sunroof project, which does not give any information about the sizes of solar installations and its focus on the US borders only, the ability to use transfer-learning to classify land containing photovoltaic panels then using semi supervised learning to extract the shape and size from Google's static map API non-annotated images proved to be much successful as we can see with the introduction of DeepSolar framework [52]. The Inception-v3's convolutional layers output, which is basically a stack of feature maps, can be combined to produce a class activation maps (CAM) [53] providing information about the segmented area of interest and thus getting the size estimation without having to use expensive annotated remotely sensed data.

While the work provided useful insights about using CNNs, DeepSolar framework provides data of the US residential areas only. China, for instance, being the world's major installer of photovoltaic panels, cannot make use of such a framework nor the image data it was based on to identify its solar panels. Power plants and solar farms are located in areas with complex backgrounds like mountains, deserts and even lakes. A network called SolarNet [54], based on the Expectation-Maximization Attention (EMA) algorithm [55] and inspired by the EMANet [56], was released to improve upon DeepSolar's performance and address China's solar panels installments. SolarNet is an optimized multitask-EMANet which combines pixel-wise segmentation and global classification at the image level. Using only 819 With data augmentation methods and Resnet101 as a backbone the proposed SolarNet achieved higher performances, with the mean intersection over union (IoU) as a criterion, than state-of-the-art detector Unet and normal EMANet, it is also worth mentioning that the scores were also higher when benchmarking their dataset against the one used in training the DeepSolar framework.

Alternatively, [57] provided further improvements made upon DeepSolar framework. First, the authors explored the ability to extend the original dataset by 8.1% google static map API imagery adding more landscape types such as rocks, woods, water etc. This dataset will then be used to train a new framework called DeepSolar GER (for Germany). By Fine-tuning the initial weights from the US version and introducing a tunable threshold to turn CAMs into binary masks, the DeepSolar GER amplified the original model's recall by 8.5%. Moreover, further investigations were made to improve the framework's applicability to imagery with 4 times lower resolution thanks to an OpenNRW-based dataset. DeepSolar GER was fune-tuned a second time and tested on this dataset to achieve 63.96% and 86.69% precision and recall scores illustrating the potential of future research to improve upon such work.

Subsequently, encoder–decoder model U-net with a cross learning approach inspired by [58] is showcased in [59] and used residential areas obtaining a 74% IoU results. Another U-net based research [60] was conducted on urban areas showed an increasing IoU by nearly 2% when using the model with edge detection networks.

Further study proved the usefulness of transfer learning, with a simple implementation of InceptionV3 architecture, when it comes to classifying images containing solar farms installations from low number of training data. Although [61] did not reach state of the art precision when evaluating their model. The combination of free apple maps imagery and the Regulatory Authority for Energy (RAE) to automatically annotate remote sensing data demonstrated to be promising and can be further improved in future works.

Exploring the low number of images approaches, Sentinel-2 free satellite data can also provide better understanding. When experimenting with (e.g., U-net, DeepLabv3+, PSPNet, FPN) alongside different backbones (Efficient-net and ResNet families), the use of only 280, 256×256 pixels images to detect solar farms in Brazil as shown in [12], has led the authors to selected U-net to be used with sliding windows mosaicking algorithm for high tolerance to full scene reconstruction errors when performing the final solar farms' detection task.

It is clear that the PV panel detection approaches vary in all forms and ways. It is indeed proven that deep learning can be useful for detecting solar panels in different ways. Table 1 displays a summary gathering of all mentioned methods and approaches investigated in this paper as well as the results obtained.

5. Future studies

This field of research provides many possible future studies. The use of remotely sensed imagery has proved useful for solar energy assessment. However, the use of such technology, as shown in this paper, lies only in the automatic detection of photovoltaic panels whether it is for solar farms or residential areas. In this section, we will discuss other possibilities and potential of future research.

5.1. Improving solar panels' detection results

From the results in previous mentioned studies, we can clearly deduce that mapping PV panels can be addressed as data-driven. While works such as Deep Solar provided some breakthroughs regarding the way future research can look at object detection it is highly dependent on huge volumes of data. As for the other different deep learning methods, they provide significantly similar results when used with lower sizes of datasets and even shallow networks reached good results (see [42]).

When we look at the remote sensing field in the past two decades, and as mentioned in Section 3, the contribution of many research was concentrated on releasing benchmarking novel dataset. An effort such as [62] and [63] provided a multi-resolution PV panel dataset with ground truth masks, however, the lack of multispectral data can be critical in some case of studies. Thus, in order to achieve better results, providing more meaningful satellite datasets with ground truth labels is mandatory to advance such field of research.

Table 1. Comparative study.

Ref.	Method(s)	Location	Data	Model Description	Outcome/observation(s)
[53]	Deep solar	US	A collection of 472 953 google static maps imagery over 50 different cities and binary labeled on the image-level. The dataset was split as following (77%, 3%, 20%) for Train, Val and testing sets.	The classification procedure was made by state-of-the-art Inception-v3 CNN architecture pretrained on ImageNet. The positive samples were then fed to a semi-supervised method, based on the extraction of class activation maps, to generate clear boundaries of solar panels without any supervision of actual panel outlines and thus estimate the size.	The developed method reached a classification precision of 93% with approximately 90% recall in both residential and non-residential testing areas. As for the size estimation the mean relative error was 3.0% and 2.1% for residential and non-residential areas respectively.
[55]	SolarNet	China	819 training and 119 testing satellite images annotated at the pixel level.	The network is an optimized version of Emanet [52] which is based on the expectation minimization algorithm. Resnet101 was used as the feature extractor feeding information to the EMA module to combine pixel level and image level classification.	The mean intersection over union of SolarNet outperforms both U-net and standard EmaNet on their proper dataset achieving a 94% score. Moreover, the combination of their dataset and DeepSolar's proved once more that SolarNet is the best performing method in this case achieving 93.94% IoU.
[58]	Deep solar	Germany	An 8.1% extension over original DeepSolar's google static map API imagery and an OpenNRW-based low resolution dataset.	The extended dataset was used to fine-tune the original model to further improve the classification results. An additional improvement was made through tunable thresholding to turn class activation maps into binary masks. Another finetuning was made in order to make the model robust to lower resolution imagery.	The provided modification improved the original method's recall by 8.5%. However, it is clear that the network, even after improvements, is still not as good performing when looking at 63.96% and 86.69% precision and recall classification scores.
[60]	CrossNets	US	Publicly available dataset [59] of US residential areas. 1414, 256×256, 0.3 m per pixel image patches were divided into train, val, and test images (920, 231, and 263).	The suggested approach was inspired by swarm intelligence and it is mainly a set of generic U-Nets that updates individually their weights and then learns other generic U-Nets' parameter values at specific epochs.	The average Intersection over union of the proposed CrossNets bested two benchmarks based on cross learning U-nets "IndivNets" reaching a total of 74.268%.
[61]	Multi-task learning	California	526 images, 256×256 pixels, collected by the United States Geological Survey with a 0.3 m spatial resolution were split into 50% for testing data and the other 50% is split into training and validation by 8:2 ratio.	The multi task learning approach was conducted by the combination of an encoder-decoder edge detection network and a U-net structure with Efficientnet-B1 for semantic segmentation to allow the detection of small PV panels and solve segmentation?s blurred edges.	The proposed method was tested on two datasets and compared with different SegNet, LinkNet, U-Net and FPN and reached higher accuracy with finer segmentation edges and an F1-scores of 84.79% and 94.03%, on the California dataset and Shanghai Distributed Photovoltaic Power Station dataset respectively.
[12]	CNN	Greece	Two free apple maps imagery datasets of solar farms. A high-resolution dataset of 220 images and a lower resolution one of 350 patches.	A raw usage of transfer learning using Keras' InceptionV3 architecture with ImageNet's initial weights.	The CNN reached a classification precision of 60% in 15 epochs while it was lower (42%) on the lower resolution dataset.
[62]	U-net	Brazil	280, 256×256 pixels, solar farm images from sentinel2 data.	An implementation of U-net was used with sliding windows mosaicking algorithm to solar panels' detection task.	Different models with different backbones were tested to conclude that U-net with Eff b7 backbone showed the best results with 98% accuracy, 92% IoU and 95% F-score

5.2. Energy production estimation

Multispectral data and hyperspectral data have been used previously in energy production estimation. The automation of such field of study is highly recommended after photovoltaic panel detection. An attempt such as the google project sunroof is small example of such direction, but the limitations are far greater such as the focus on few regions in the US and the sole focus residential blocks. This led many studies [63, 64] to making use of manual methods to address a concerned region. Further improvements can make use of remote sensing and deep learning methods in order to make solar energy estimation global, automatic and publicly available.

5.3. Solar energy optimal sites

When we hear the solar energy assessment topic, the first question that comes to mind is what is the optimal location to install solar farms? The use of geographic information systems proved useful for manually identifying potential sites for PV plants. We can see in many works with GIS [65, 66]. The evaluation of land suitability based on different criteria such as solar irradiation, air temperature, proximity to residential areas etc. Among all research provided in remote sensing-driven deep learning, the identification of land type [2], detecting residential areas [46] and air temperature mapping [15] proved to be very successful for each given problem. We can conclude that merging such techniques into one single framework can be introduced in future research allowing the built of an optimal land recommender system.

6. Our proposed model

6.1. Dataset

Fig. 1. A snapshot highlighting sample georeferenced scenes from the US border.

It was proved in previous works that dealing with a full multi-spectral remotely sensed data is not necessary when most solar panels were detectable using the visible spectrum data (RGB). However, as opposed to mentioned works, the dataset used in our research is composed of remotely sensed scenes representing 1500 meters $\times$ 1500 meters on the Earth which, with a 0.3 ground sampling distance, results in 5000 $\times$ 5000 pixels per image provided by the U.S. Geological Survey [67], Figure 1.

6.2. Masks

The given data was labeled in a JSON file with the georeferenced centroids of each solar panel alongside with the polygon vertices coordinates, i.e., longitude and latitude. With a simple computing algorithm, we created the binary masks containing with solar panel pixels for each image in our dataset, Figure 2.

6.3. U-Net

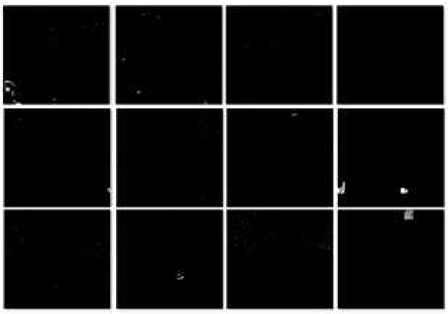

Fig. 2. A preview of the binary masks, we can clearly notice the scarcity of the solar panels in the real-world data.

We tackle the above by reformulating the problem as a binary semantic segmentation task. Inspired by [68] and previous mentioned works, U-Net proved to be the top performing and efficient network. Our architecture is composed of 3 main components; the encoder block that performs two convolution operations followed by a down-sampling using a max pooling layer, a bridge that performs a simple two convolution operations and finally the decoder block transposes the convolution layers, perform another two convolution operations and keep this up-sampling method to produce the final binary mask, Figure 3.

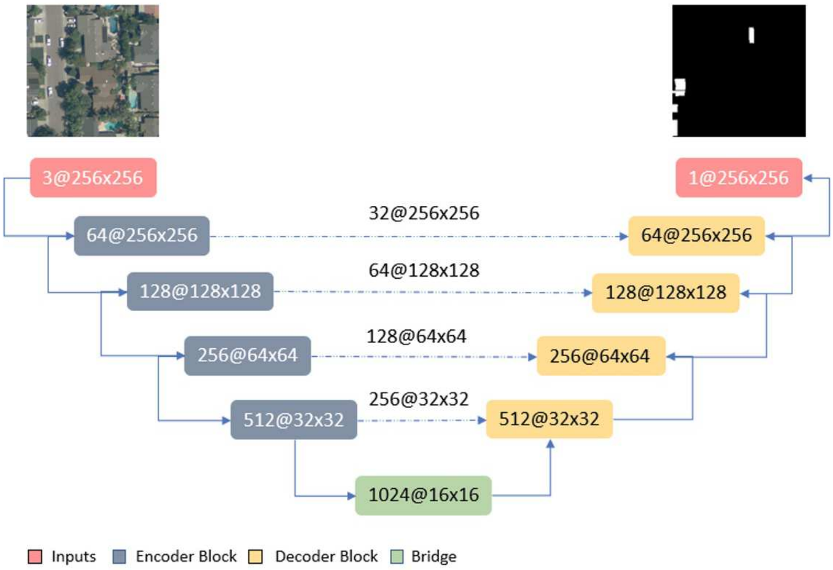

Fig. 3. A schema representing our proposed U-Net architecture.

7. Training results

Due to computation limitations, our U-Net cannot be trained on the full dataset, which led us to use a single remotely sensed image and slice it to 361, 256×256 pixels, image patches. We also left all patches that does not include solar panels to address the problem of their scarcity of the image. We used Adam as an optimizer with a 1e-3 learning rate, and our goal is to minimize the binary cross entropy since we are dealing with binary masks, Table 2.

Table 2. The training process; the model's score by epoch.

Epoch	Mean loss	Mean accuracy
1	708.793	0.0071
2–6	13061.854	0.01
7	91.485	0.0536
8	22.4537	0.1506
9	1.9813	0.5871
10	0.7733	0.7486
11	0.3830	0.9254
12–25	0.02	0.9978

The results mentioned above may seem very promising giving the 99.78% accuracy. However, those results are insignificant when it comes to the model's likelihood for inference. Clearly from the graphs in Figure 4, the training can be described as poor and its behavior must be addressed.

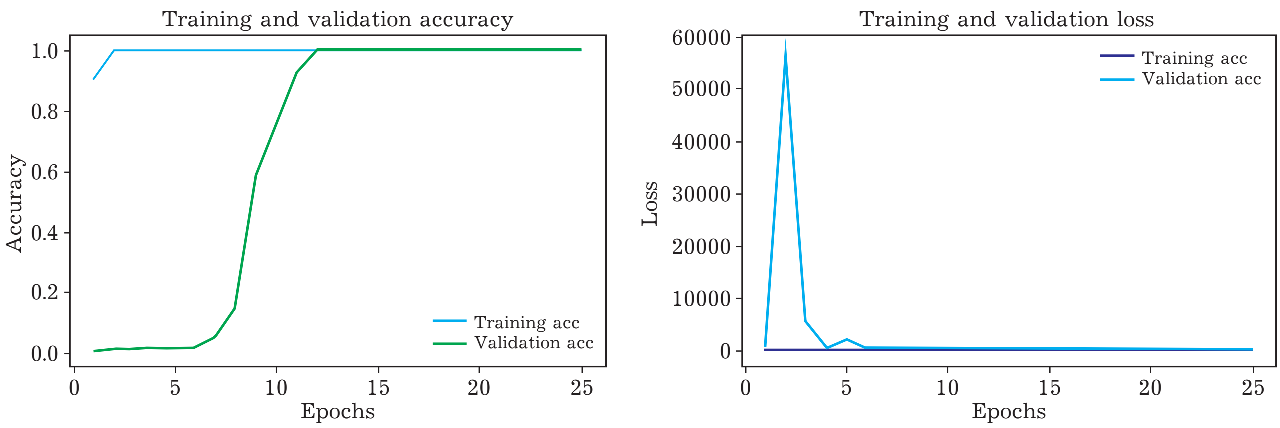

Fig. 4. Accuracy and training loss results.

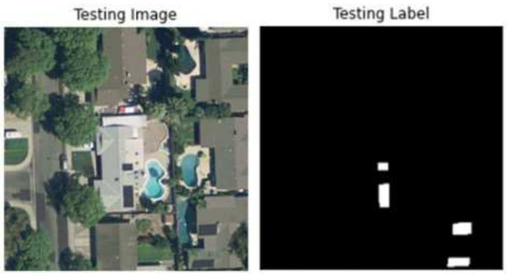

Fig. 5. Accuracy and training loss results.

We can also see for example in Figure 5 below the model's performance on testing data. The model has a tendency to predict all pixels in the mask to be black. And since the majority of the pixels in the slices and the number of true negatives it learned from is considerably high, the photovoltaic pixels became a minor thing to consider.

8. Conclusion

In this work, we shed light on the task of the photovoltaic instance segmentation in high-resolution remotely sensed data. This process has brought forward a primary challenge derived from the data itself, which is keeping a considerable number of true negatives in the training process to boost the model's ability for inference. We can address the given problem by exploring some possibilities in our future work such as:

1. Adding more training images: while it is definitely our goal to train our model on the entire data available. We are currently limited by the computing power since our NVIDIA® Tesla® P4 cannot handle higher tensor operations.
2. Working on the data itself: we can further explore some image compression methods to reduce the high dimensionality of the Inputs.
3. Introducing a customized behavior for the model: inspired by the work presented in [62] with different loss function designs to improve the model's tendency to distinguish between the importance of the PV panels' detection and the irrelevance of the rest of the pixels present in the scenes.

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Глибоке навчання для сегментації фотоелектричних панелей

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Завдяки передовій сенсорній технології супутники та безпілотні літальні апарати (БПЛА) виробляють величезну кількість даних, що дозволяє вдосконалювати всі види програм спостереження Землі. Завдяки цьому джерелу інформації та через занепокоєння зміною клімату оцінка відновлюваної енергії стала все більш необхідною для дослідників і компаній. Сонячна енергія, що переходить від дахів будинків до комунальних ферм, змінює енергетичні ринки по всьому світу. Однак автоматична ідентифікація фотоелектричних (PV) панелей і статусу сонячних електростанцій все ще залишається відкритим питанням, яке, якщо на нього дадуть належну відповідь, допоможе оцінити розвиток сонячної енергії та задовольнити потреби в енергії. Віднедавна методи глибокого навчання (DL) виявилися придатними для роботи з даними дистанційного зондування, що надає багато можливостей для подальших досліджень стосовно оцінки сонячної енергії. Координація між доступністю даних дистанційного зондування та можливостями комп'ютерного зору глибокого навчання дозволила дослідникам знайти можливе рішення для глобального картографування сонячних електростанцій і житлових фотоелектричних панелей. Однак оцінки, отримані під час попередніх досліджень, викликають сумніви, коли йдеться про дефіцит фотоелектричних систем. У цій статті детально висвітлюється та досліджується потенціал підходів DL, керованих дистанційним зондуванням, для оцінки сонячної енергії. З огляду на те, що нещодавно було опубліковано багато робіт, присвячених такій проблемі, їх рецензування та обговорення має високу мотивацію, щоб зберегти стабільний прогрес у майбутніх розробках. Потім подається коротке дослідження, яке підкреслює як моделі семантичної сегментації можуть бути упередженими та давати значно вищі бали у випадку, коли висновок недостатній. Ми забезпечуємо симуляцію провідної архітектури семантичної сегментації U-Net і досягаємо показників продуктивності до 99.78%. Тим не менш, необхідно внести подальші вдосконалення, щоб збільшити здатність моделі створювати справжні фотоелектричні блоки.

Keywords: *дистанційне зондування; сонячна енергія; фотоелектричні системи; глибоке навчання; архітектура сегментації U-Net.*