Universidade de Brasília
Instituto de Ciências Humanas
Departamento de Geografia
Programa de Pós-Graduação em Geografia

UNIVERSIDADE DE BRASÍLIA
PÓS-GRADUAÇÃO EM GEOGRAFIA

Sensoriamento Remoto para o Monitoramento de Plantas Solares Fotovoltaicas no Brasil usando Segmentação Semântica Profunda

Marcus Vinícius Coelho Vieira da Costa
Dissertação de Mestrado

Brasília – DF
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Dissertação apresentada ao Programa de Pós-Graduação em Geografia-Gestão Territorial e Ambiental, Instituto de Ciências Humanas da Universidade de Brasília, como requisito parcial para a obtenção do título de Mestre em Geografia na área de Geoprocessamento.

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Marcus Vinícius Coelho Vieira da Costa

Sumário

1. APRESENTAÇÃO

A energia solar é uma das fontes mais promissoras de energia renováveis, sendo estratégica para o desenvolvimento sustentável em locais com intensa luminosidade solar. Os sistemas de energia solar possibilitam ganhos econômicos e de eficiência impulsionados pelo desenvolvimento tecnológico e de produção. Portanto, os sistemas de energia solar apresentam confiabilidade, baixos custos de operação e manutenção, utiliza fonte de energia gratuita e limpa, e normalmente com a geração mais próxima do consumidor. Mostra-se um tipo de energia de baixo impacto ambiental, potencial para mitigar as emissões de gases de efeito estufa e silencioso.

1.1 ENERGIA SOLAR NO CENÁRIO MUNDIAL

O presidente americano Joe Biden, em um discurso na Cúpula de Líderes sobre o Clima, em 22 de abril de 2021, disse que estamos na década onde se faz urgente agir contra a crise climática mundial. Para tanto, é mais do que urgente investir esforços na instalação e manutenção de tecnologias que preservem a qualidade de vida do planeta.

Em janeiro de 2021, o Secretário Geral da Organização das Nações Unidas (ONU), António Guterres, veio a público fazer um apelo para que os Estados Membros apresentassem contribuições que reduzissem mais de 50% as emissões de gás carbônico na atmosfera até o final da década. Solicitou que os países desenvolvidos fizessem uma mobilização anual de US$ 100 bilhões para países em desenvolvimento, com o intuito de minimizar os impactos climáticos.

Atualmente, China, União Europeia e Estados Unidos da América lideram em capacidade de energia solar fotovoltaica (UFV). De acordo com Hein (2021), a China é o maior consumidor mundial de energia solar, com mais de 130 GW de capacidade instalada, com estimativa de atingir 400 GW até 2030, cerca de 10% da produção de energia primária.

1.2 ENERGIA SOLAR NO CENÁRIO BRASILEIRO

O território brasileiro apresenta alta disponibilidade de incidência solar, com vasta área próxima ao equador e sem variações significativas na duração solar diurna. A região semiárida tem a aptidão mais significativa para a instalação de usinas de energia solar. Entre as duas tecnologias de geração de energia solar, o governo brasileiro priorizou inicialmente a fotovoltaica em vez de energia solar concentrada. A saber, a energia fotovoltaica é aquela gerada a partir de células fotovoltaicas, capazes de transformar a radiação solar diretamente em energia elétrica através do chamado “efeito fotovoltaico”, enquanto a energia solar concentrada é aquela gerada a partir de um sistema de espelhos (ou concentradores) que concentram a radiação solar, e só então transformam este calor em energia elétrica.

O Brasil oferece boas perspectivas para energia de carbono zero líquido devido à sua abundância de energias renováveis: hidrelétrica, bioenergia, eólica e solar. A energia hidrelétrica é o principal gerador de energia elétrica do Brasil. No entanto, a energia térmica ainda é necessária para suprir a demanda doméstica em períodos de seca prolongada. Portanto, o desafio é aumentar a produção de energia renovável para suprir a crescente demanda de energia devido ao crescimento populacional e às novas tecnologias. Um problema detectado é que as perspectivas de expansão hidrelétrica estão na região amazônica, com restrições ambientais substanciais, como extensas áreas de inundação por reservatórios de barragens, emissões de metano e mudanças ecológicas.

Apesar dos impactos causados pela atual Pandemia da COVID-19, o setor brasileiro adicionou, do final de 2019 até o início de 2021, 1381 MW em capacidade instalada, o que representa um crescimento de 30,6% em plantas solares em relação ao que já existia, incluídos aí as placas solares residenciais, incluídas na Geração Distribuída. Até março de 2021, o Brasil já dispunha de 8 GW de potência instalada em seu território (ABSOLAR, 2021).

Veloso *et al.* (2021) consideram que a indústria fotovoltaica, estando bastante ligada às decisões dos formuladores de políticas, acaba por se colocar em um campo de grandes oscilações. No entanto, nada foi tão drástico ou tão cercado de incertezas como as relativas à pandemia global e sua subsequente recessão global.

Entretanto, apesar dos impactos acima descritos, estima-se que até 2024 o Brasil terá cerca de 887.000 sistemas de Energia Solar conectados à rede, o que pode resultar em economia e preservação ambiental. Isto abre perspectivas, segundo estudos projetivos, de que até 2035 seja evitada a emissão de cerca de 75,38 milhões de toneladas de CO_2 na atmosfera (ABSOLAR, 2021)

Koloszuk (2020) aponta um crescimento exponencial, e que em 2040 a fonte solar vai ultrapassar a hidrelétrica aqui no Brasil, sendo a fonte número 1 no país.

> *“A taxa de crescimento da tecnologia solar é mais do que o dobro e chega a quase 11% ao ano, produzindo um enorme crescimento de capacidade instalada de 17GW em 2019 para quase 390GW em 2050. O setor fotovoltaico cresceu em média 86% ao ano nos*

últimos cinco anos, embora partindo de um pequeno volume de instalações (BLOOMBERG, 2021).”

O universo das publicações, aqui tendo como referência a revista Energies, relativas à indústria fotovoltaica mostra que se trata de algo que inegavelmente demanda trabalho desde seus projetos de implantação, regulação, instalação, geração e distribuição, mas que caminha a largos passos no sentido da evolução dos modos de vida humano.

1.3 ANEEL – AGÊNCIA NACIONAL DE ENERGIA ELÉTRICA

No Brasil, a ANEEL é responsável por regulamentar a expansão da capacidade instalada e monitorar o andamento das construções das usinas geradoras. Fiscalizar e monitorar todo o trabalho das indústrias fotovoltaicas no país sempre foi uma tarefa árdua, onerosa, tendo em vista que o monitoramento presencial é algo que dispende tempo e exige um trabalho de campo especializado, com profissionais qualificados e altos custos.

A fiscalização da distribuição tem por base o monitoramento contínuo de indicadores de desempenho das distribuidoras (**Figura 1**). De acordo com o banco de dados da ANEEL, a expectativa de crescimento da energia solar fotovoltaica é considerável. Para 2021, são esperados 32 novos empreendimentos e mais de 140 para 2022. Além disso, os empreendimentos de fontes de energia eólica e solar tendem a ser numerosos, mas com baixa produção de energia, aumentando o número de processos para avaliação e a necessidade de formular sistemas automatizados.

Os dados de sensoriamento remoto (fotografia aérea e imagens de satélite) permitem a inspeção periódica e têm sido amplamente utilizados no setor elétrico para a manutenção eficaz de linhas de transmissão elétricas, monitoramento térmico de usinas nucleares, mudanças ambientais de represas hidrelétricas, e consumo de energia usando imagens de satélite. Na energia solar, muitos estudos usam imagens de sensoriamento remoto, como estimativas de energia solar, seleção do local da usina solar, potencial fotovoltaico em telhados de edifícios e estimativa de área.

Aqui, portanto, se faz necessário o aprendizado da máquina, ou seja, um subtópico da inteligência artificial. A tarefa é a de construir técnicas que levem o computador a aprender com os dados (CHOLLET, 2018). As técnicas de aprendizado de máquina, sabidamente se mostram bastante superiores aos métodos convencionais de trabalho voltados para a geração fotovoltaica, em vista da sua capacidade própria em modelar processos dinâmicos e não lineares (SU *et al.*, 2019)

Na detecção automática, o Deep Learning (DL) surge como um método poderoso, especialmente para problemas de visão computacional usando redes neurais convolucionais (CNN) devido à sua capacidade de processar matrizes multidimensionais, com amplas aplicações de sensoriamento remoto. Várias revisões foram realizadas sobre os diferentes métodos de DL, nos quais detecção de objetos, segmentação semântica e segmentação de instâncias são as abordagens mais comuns. A escolha do método é altamente dependente dos objetivos da tarefa.

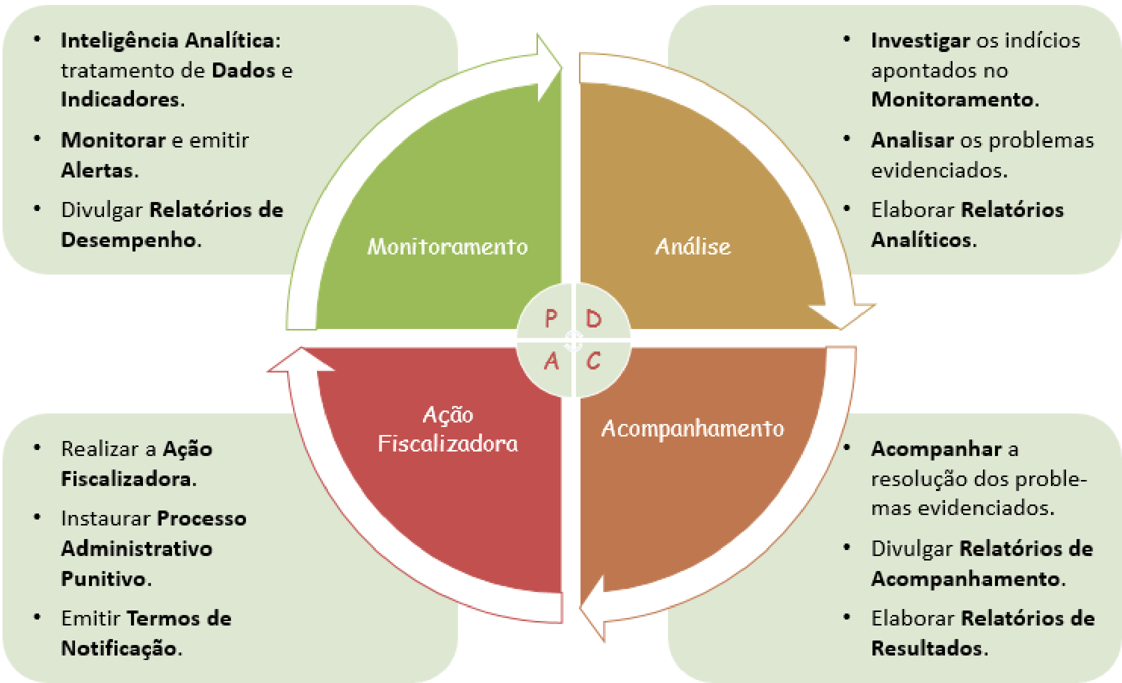

Fig. 1 – Monitoramento, Análise, Ação Fiscalizadora e Acompanhamento das Usinas de geração e distribuição de energia (ANEEL, 2021)

Estudos em detecção de painéis solares fotovoltaicos mostraram resultados promissores utilizando o método DL, apontando níveis de alta precisão. No entanto, a maioria dos estudos considera painéis fotovoltaicos urbanos usando imagens aéreas ou de satélite de alta resolução, enquanto o mapeamento de usinas solares fotovoltaicas ainda é restrito. Essa abordagem é uma alternativa eficaz para a inspeção de construção, exigindo dados periódicos e imagens de satélite gratuitas (TEO *et al.*, 2016; OGAWA & MORI, 2019; KAFFASH & DECONINCK, 2019; THEOCHARIDS *et al.*, 2018; JIANG *et al.*, 2019; SEHN, 2019).

A principal motivação para este estudo é o desenvolvimento de uma metodologia baseada em sensoriamento remoto para o monitoramento automático de novas instalações de usinas solares fotovoltaicas. No Brasil, país de dimensão continental, é notória a inviabilidade de fiscalização in loco, motivo que traz a urgência do desenvolvimento de tecnologias inteligentes e alternativas.

1.4 OBJETIVOS

O objetivo da presente pesquisa é avaliar a utilização de métodos DL, que consiste o estado da arte em visão computacional, para identificar e monitorar usinas solares fotovoltaicas usando banco de dados da ANEEL e imagens do Sentinel-2. A segmentação semântica profunda permite uma inovação no processamento digital de imagens e constitui uma promissora alternativa para auxiliar no gerenciamento e monitoramento das estruturas de energia solar instaladas no território brasileiro. Portanto, o estudo busca uma solução tecnológica para resolver um problema premente da ANEEL, avaliando alternativas de algoritmos computacionais para o avanço do trabalho de fiscalização. Pesquisas semelhantes visando a fiscalização a partir de sensoriamento remoto e DL ainda não existem no país.

1.5 ESTRUTURAÇÃO DA DISSERTAÇÃO

A presente dissertação é estruturada no formato de artigo científico, obedecendo os critérios estabelecidos pelo programa de pós-graduação em Geografia da Universidade de Brasília. No caso da dissertação de mestrado, deve-se ter no mínimo um artigo submetido. Este primeiro capítulo apresenta a contextualização do problema, motivação e objetivo geral do trabalho. O Capítulo 2 contém o corpo do artigo científico no formato de submissão com o título "Remote Sensing for Monitoring Photovoltaic Solar Plants in Brazil Using Deep Semantic Segmentation", publicado na revista *Energies* (ISSN: 1996-1073) da editora MDPI, em 20 de maio de 2021 (DOI: 10.3390/en14102960). A revista possui um fator de impacto de 3.004 e um CiteScore - Scopus de 4,7, compatível com a regra vigente. O Capítulo 3 contém a conclusão geral da dissertação.

Referências Bibliográficas

ABSOLAR. Associação Brasileira de Energia Solar Fotovoltaica. Disp. Em www.deixeasolarcrescer.org.br/em.numeros/, acessado em 24.07.2021

BLOOMBERG, LP. Disp. em https://www.bloomberg.com.br/blog/as-energias-eolica-e-solar-serao-metade-da-capacidade-instalada-de-1tw-que-a-america-latina-tera-ate-2050-e-atenderao-a-maior-parte-da-demanda-adicional/#, Acesso em 24.07.2021

CHOLLET, F. Deep Learning with Python. Shelter Island, Nova York, EUA: Manning Publications, 2018.

JIANG, Y. et al. Research on predicting the short-term output of photovoltaic (pv) based on extreme learning machine model and improved similar day. 2019 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), Chengdu, China, p. 3691–3695, 2019.

KAFFASH, M.; DECONINCK, G. Ensemble machine learning forecaster for day ahead pv system generation. 2019 IEEE 7th International Conference on Smart Energy Grid Engineering (SEGE), Oshawa, ON, Canada, p. 92–96, 2019.

Koloszuk, R. Mercado fotovoltaico. Revista Canal Solar. No.1. Dez 2020,

OGAWA, S.; MORI, H. Application of evolutionary deep neural netwok to photovoltaic generation forecasting. 2019 IEEE International Symposium on Circuits and Systems (ISCAS), Sapporo, Japan, p. 1–4, 2019.

Rein, Henrique. Aquecimento global e suas consequências para o Mercado. **Rev. Canal Solar,** Junho, n.4, 2021

SEHN, S. Relatório de estágio longo: Predição de geração fotovoltaica com aprendizado de máquina. UFSC, Florianopolis, 2019.

SU, D.; BATZELIS, E.; PAL, B. Machine learning algorithms in forecasting of photovoltaic power generation. 2019 International Conference on Smart Energy Systems and Technologies (SEST), Porto, Portugal, p. 1–6, 2019.

TEO, T. T. et al. Forecasting of photovoltaic power using regularized ensemble extreme learning machine. 2016 IEEE Region 10 Conference (TENCON), Singapore, p. 455–458, 2016.

THEOCHARIDES, S. et al. Machine learning algorithms for photovoltaic system power output prediction. 2018 IEEE International Energy Conference (ENERGYCON), Limassol, Cyprus, p. 1–6, 2018.

2. REMOTE SENSING FOR MONITORING PHOTOVOLTAIC SOLAR PLANTS IN BRAZIL USING DEEP SEMANTIC SEGMENTATION

Abstract: Brazil is a tropical country with continental dimensions and abundant solar resources that are still underutilized. However, solar energy is one of the most promising renewable sources in the country. The proper inspection of Photovoltaic (PV) solar plants is a problem of great interest for the Brazilian territory's energy management agency, and advances in computer vision and deep learning allows automatic, periodic, and low-cost monitoring. The present research aims to identify PV solar plants in Brazil using semantic segmentation and a mosaicking approach for large image classification. We compared four architectures (U-net, DeepLabv3+, Pyramid Scene Parsing Network, and Feature Pyramid Network) with four backbones (Efficient-net-b0, Efficient-net-b7, ResNet-50, and ResNet-101). For mosaicking, we evaluated a sliding window with overlapping pixels using different stride values (8, 16, 32, 64, 128, and 256). We found that: (1) the models presented similar results, showing that the most relevant approach is to acquire high-quality labels rather than models in many scenarios; (2) U-net presented slightly better metrics, and the best configuration was U-net with the Efficient-net-b7 encoder (98% overall accuracy, 91% IoU, and 95% F-score); (3) mosaicking progressively increases results (precision-recall, and receiver operating characteristic area under the curve) when decreasing the stride value, at the cost of a higher computational cost. The high trends of solar energy growth in Brazil require rapid mappings, and the proposed study provides a promising approach.

Keywords: solar panel; deep learning; semantic segmentation

2.1 INTRODUCTION

Solar energy is one of the most promising renewable energy sources, being crucial for sustainable development in places with intense sunlight. Several studies have shown that solar energy systems allow for economic and efficiency gains, driven by technological and productive development that enables cost reduction to overcome technical barriers [1,2]. According to Sampaio and Gonçalez [3], the main advantages of solar energy systems are reliability, low costs of operation and servicing, low maintenance, free energy source, clean energy, high availability, generation closer to the consumer, low environmental impact, potential to mitigate greenhouse gas emissions, and noiseless. In contrast, the main disadvantages are high initial cost, large installation area, high dependence on technology development, climatic conditions (solar irradiation). The benefits of solar technology provided an exponential increase in installed solar energy capacity between 1992 and 2020 [4,5]. This detected growth of solar energy was not foreseen in previous scenarios of the Intergovernmental Panel on Climate Change’s fifth assessment report [6]. Creutzig et al. [7] considered that the cause of underestimating the potential of solar energy was rapid technological learning and political support only for specific technologies. In 2019, China leads the Photovoltaic (PV) solar energy capacity, followed by the European Union and the United States of America, where together they hold more than 64% of the world's total capacity.

Brazil offers good prospects for net-zero carbon energy due to its abundance of renewable energies: hydropower, bioenergy, wind, and solar [8]. Hydroelectric power is the primary generator of electric energy in Brazil. However, thermal energy is still needed to supply domestic demand in periods of prolonged drought [9–12]. Therefore, the challenge is to increase renewable energy production to supply the growing energy demand due to population growth and new technologies. One problem is that hydroelectric expansion prospects are in the Amazon region, with substantial environmental restrictions, such as extensive areas of flooding by dam reservoirs, methane emissions and ecological changes [13–16]. Besides, climate change scenarios in Brazil for the 2030s and 2080s demonstrate a decrease in rainfall and an increase in temperature, resulting in a reduction in hydroelectric production and an increase in solar (slightly) and wind (significantly) energy potential [17]. Thus, national progress needs to intensify other energy sources such as combining wind and solar sources [18].

The Brazilian territory has a high solar incidence availability, with a vast area close to the equator and without significant variations in the day's solar duration [19]. The semi-arid region has the most significant aptitude for installing solar power plants [20–25]. Between the two solar energy generation technologies, the Brazilian government has initially prioritized PV instead of concentrated solar power [26]. In 1995, the Hydroelectric Company of San Francisco developed the first PV system connected to Brazil's grid in Recife [27]. The crisis in the Brazilian electric sector in the 2013-2015 period favored the decentralization and diversification of the electric matrix sources. So, since 2014, Brazil's solar energy has had a substantial expansion with the first projects for PV Plants being contracted through public auctions. In the second half of 2015, solar energy production and distributed generation marked an inflection of growth driven by regulations and adoption of incentive changes [28]. Despite the various barriers to the development of solar energy (technological, economic, sociocultural, managerial, environmental and political) [29–34], the current strong growth in PV energy brings optimistic perspectives for the electricity sector. Barbosa et al. [35] demonstrate, by modeling, that PV solar energy in Brazil will reach more than 36% of total electricity in 2050. This rapid expansion is mainly due to technology development, reducing investment costs, increasing the PV Panels capacity, and other enterprise cost reduction [36]. Furthermore, energy security policies and the eco-label design for improving air quality, by reducing greenhouse gas emissions also contribute to solar energy growth [37].

Moreover, in developing countries like Brazil, the PV solar plants are vital for ensuring energy security. Thus, inspecting solar plant constructions is very important to carry out effective public policies. In Brazil, the Brazilian Electricity Regulatory Agency (ANEEL) is responsible for regulating the installed capacity expansion and monitoring the powerplant construction progress [38]. However, the inspection is manual, which will increase complexity over time, requiring laborious work with skilled professionals and high costs for fieldworks and technical analysis. According to the ANEEL database, the growth expectancy for PV solar plant energy is considerable. For 2021, it is expected 32 new ventures and more than 140 for 2022. Besides, sustainable energy sources (e.g., wind, solar) tend to have many ventures with low energy production, increasing the number of processes to evaluate, urgently requiring automatic processes.

Remote sensing data (aerial photography and satellite imagery) enables inspection periodically, and has been widely used in the electrical sector for effective maintenance of electrical lines [39–41], thermal monitoring from nuclear power plants [42–45], environmental changes from hydroelectric dams [46–49], and energy consumption using nighttime light satellite imagery [50–52], among others. In solar energy, many studies use remote sensing images, such as solar energy estimates [53–56], solar power plant site selection [57–62], PV potential on building rooftops [63–66], and area estimation [67,68]. In automatic detection, Deep Learning (DL) emerges as a powerful method, especially for computer vision problems using convolutional neural networks (CNN) due to its ability to process multi-dimensional arrays [69], with wide remote sensing applications [70–75]. Several reviews were carried out on the different DL methods, in which object detection, semantic segmentation, and instance segmentation are the most common approaches [76–78]. The method’s choice is highly dependent on the task objectives. When the main goal is to make a pixel-wise classification (as the case with PV solar plants), semantic segmentation is a great alternative [79,80].

Previous studies in PV solar panel detection have shown promising results using the DL method, presenting very high accuracy. However, most studies consider urban PV panels using aerial or high-resolution satellite images [81–83], while PV solar plant mapping is still restricted [84]. This approach is an effective alternative to construction inspection, requiring periodic data and free satellite imagery. Besides, previous studies on PV panel detection have not yet shown reasonable solutions for classifying large regions, and the usage of mosaicking with sliding windows is a promising solution [85–87].

The primary motivation for this study is the development of a methodology based on remote sensing for the automatic monitoring of new installations of PV solar plants. In Brazil, the high growth of solar energy throughout the territory, with a continental dimension, prevents on-site inspection due to the financial and time cost, requiring the development of technological alternatives. Therefore, the research aims to evaluate the use of DL methods, representing the state of the art of computer vision, to identify and monitor PV solar power plants from ANEEL's database using Sentinel-2 images. This methodology represents an innovation for the management and monitoring of installed solar energy structures on the Brazilian territory, and similar research does not yet exist in the country.

2.2 MATERIALS AND METHODS

The present research had the following methodological steps (Figure 1): (2.1) data preparation; (2.2) DL models; (2.3) DL accuracy analysis; (2.4) mosaicking; and (2.5) mosaicking accuracy analysis.

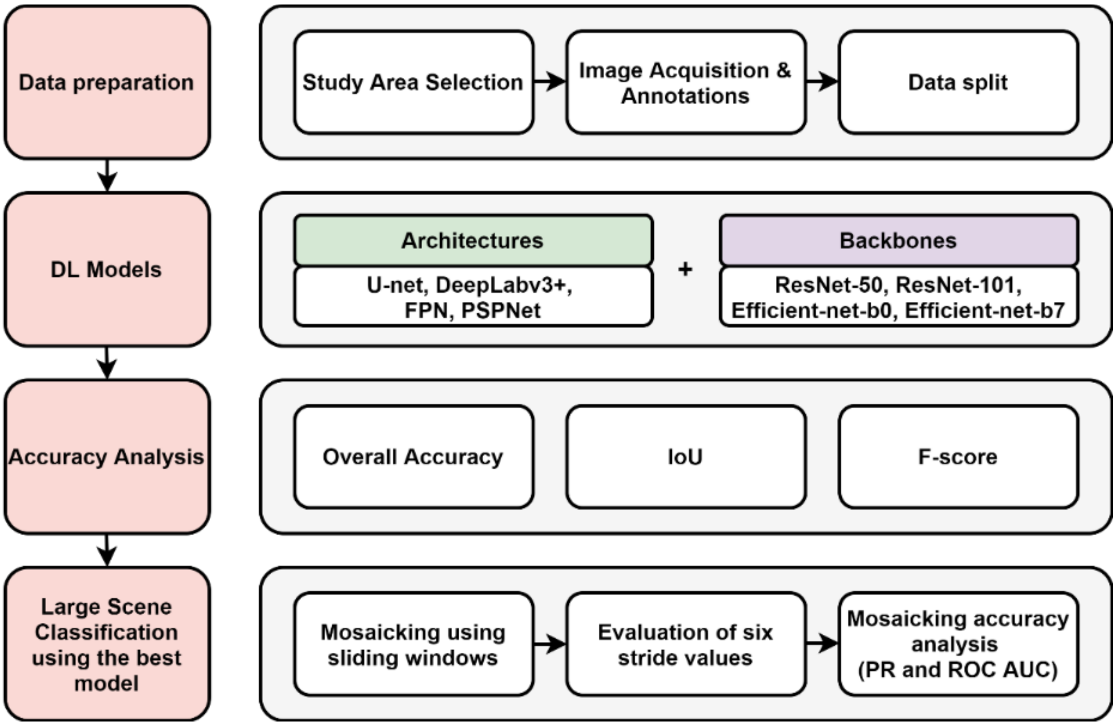

Figure 1. Methodological flowchart.

2.2.1. Data Preparation

2.2.1.1. Study Area

Brazil has a large and diverse territory, presenting different solar energy incidence [21]. Nevertheless, many areas are extremely suitable for the installation of PV panels. For this reason, we selected 24 areas to conduct this experiment (Figure 2). There are still few PV plants installed in the Brazilian territory and currently no open datasets considering Sentinel-2 data [88]. However, the development of methodologies and expansion of databases is a fundamental strategy for monitoring large-scale PV with a high growth trend.

We obtained Sentinel-2 cloudless images with four channels (Red, Green, Blue, and near infra-red) for each region containing PV solar power plants. For each image, a specialist manually annotated ground truth (GT) masks using the ArcGIS software considering two classes: background and PV solar plant. The background class presents a wide variety of spectral behaviours, including different soil and vegetation compositions present in a large-scale country as Brazil. The research considered the difference in the light incidence and the construction of panels in each region for DL model training.

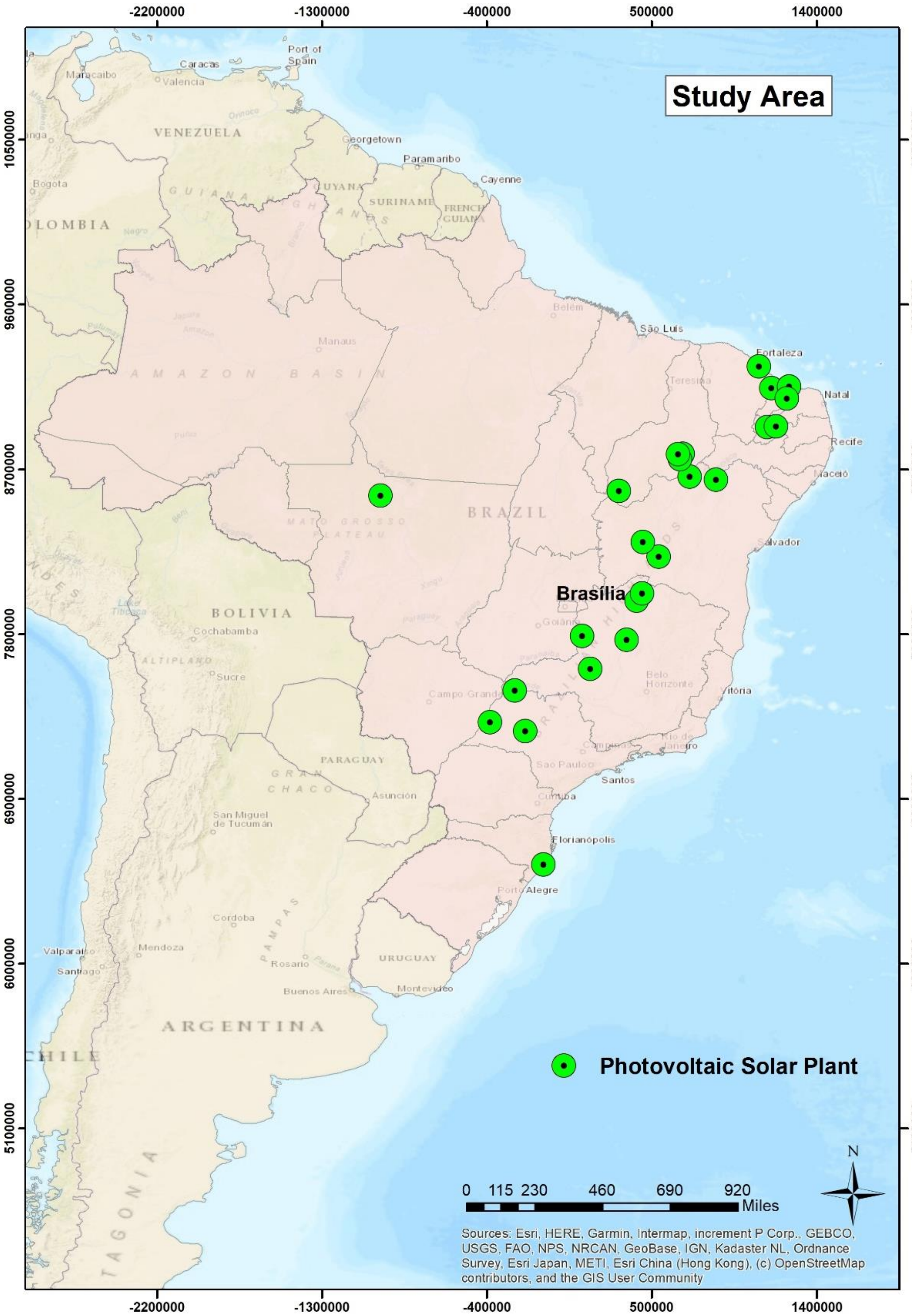

Figure 2. Study Area.

2.2.1.2. Image Acquisition and Annotations

We obtained Sentinel-2 cloudless images with four channels (Red, Green, Blue, and near infra-red) for each region containing PV solar power plants. For each image, a specialist manually annotated ground truth (GT) masks considering two classes: background and PV solar plant. The background class presents a wide variety of spectral behaviors, including the different soil and vegetation compositions present in a large-scale country such as Brazil. The research considered the difference in the light incidence and the construction of panels in each region for DL model training.

2.2.1.3. Data Split

After preparing each tile with their respective annotations, we separated the dataset into training, validation, and testing sets. For each area of interest that may contain more than one PV solar plant, we cropped at least seven 256x256-pixel tiles. Table 1 lists the distribution of areas and images for training, validation, and testing.

Table 1. Data split in training, validation, and test sets.

Set	number of areas	number of images
Train	15	210 (75%)
Validation	5	40 (14.28%)
Test	4	30 (10.71%)

2.2.2. DL Models

2.2.2.1. Architectures and Backbones

Semantic segmentation allows for a pixel-wise classification, being highly suitable for many remote sensing applications [74]. Most semantic segmentation networks include an encoder/decoder structure. The encoder aims to extract features, whereas the decoder restores the image's original dimensions. In the last few years, many architectures were proposed to increase performance in this task (e.g., U-net [89], SegNet [90], Feature Pyramid Network (FPN) [91], DeepLab [92,93], Pyramid Scene Parsing Network (PSPNet) [94], and backbones (e.g., ResNet [95], ResNeXt [96], Efficient-net [97]). This present study evaluated four commonly used architectures (U-net, DeepLabv3+, FPN, and PSPNet) and four backbones (ResNet-50 (R-50), ResNet-101 (R-101), Efficient-net-b0 (Eff-b0), and Efficient-net-b7 (Eff-b7)). We used models from the Semantic Segmentation repository [98], which provides different architectures and backbones in Pytorch.

2.2.2.2. Model Configurations

In addition to choosing the appropriate models, it is crucial to make fine adjustments for the task at hand. The first problem is the reduced number of available samples. Therefore, in addition to obtaining at least seven frames from each location, we applied two augmentations in the training process: random horizontal flip and random vertical flip (both with a probability of 0.5). The second problem is class distribution (there are much more background pixels than solar panel pixels). Thus, we used a loss function that minimizes this effect, the Dice Loss:

$$Dice\ Loss = \frac{2x(pred \cap GT)}{|pred| + |GT|}\ , \tag{1}$$

In which pred is the DL prediction, and GT is the ground truth mask. Besides, we used transfer learning with Imagenet [99] pre-trained weights for faster convergence, and to avoid overfitting, we applied callbacks, saving the model with the lowest Dice Loss in the validation set. Regarding hyperparameters, we used: (a) 300 epochs; (b) Adam optimizer; (c) 5x10-3 learning rate (lr); and (d) batch size of 5.

2.2.3. DL Accuracy Analysis

Accuracy analysis is a fundamental step for DL model evaluation. Since semantic segmentation models provide a pixel-wise mask, the metrics compare the predicted mask and the GT mask through confusion matrix metrics. The confusion matrix (Table 2) has four quadrants in binary tasks: True Negatives (TN), True Positives (TP), False Positives (FP), and False Negatives (FN).

Table 2. Confusion matrix.

		Prediction	
		0	**1**
Ground truth	0	TN	FP
	1	FN	TP

The model outputs probabilities, whereas the GT are integers. Thus, a necessary fit for threshold metrics is establishing a cutoff point. A stricter threshold tends to reduce the commission errors, while a more permissive threshold tends to reduce omission errors. Thus, we applied a commonly intermediate threshold of 0.5 for three metrics (overall accuracy, F-score, and IoU):

$$Overall\ Accuracy = \frac{TP + TN}{TP + TN + FP + FN}\ , \tag{1}$$

$$IoU = \frac{TP}{TP + FP + FN}\ , \tag{2}$$

$$F - score = \frac{TP}{TP + \frac{1}{2}(FP + FN)}\ , \tag{3}$$

2.2.4. Mosaicking

The 256x256 pixel tiles used in training may not represent an entire scene, requiring a postprocessing stage. Mosaicking using a sliding window algorithm is a very promising solution. However, combining frames side by side to reconstruct a scene may also induce errors in the single frame edges. A way to minimize this effect is to apply a sliding window with overlapping pixels, where the final pixel will be the average from the overlapped pixels. Thus, we compared six different stride values for the mosaicking strategy: 8, 16, 32, 64, 128, and 256 (adjacent frames). Figure 3 shows four images with consecutive frames using different stride values. The smaller the stride value, the more overlapping pixels (which tends to reduce errors in the frame edges).

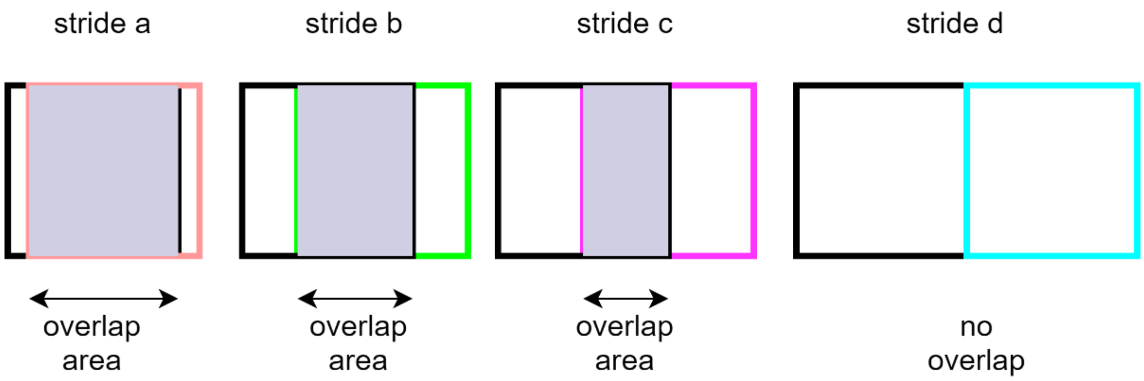

Figure 3. Four examples of different stride values of two consecutive frames in ascending order, where the stride value a<b<c<d.

2.2.5. Mosaicking Accuracy Analysis

To evaluate the mosaicking, we analyzed the ranking metrics Receiver Operating Characteristic Area Under the Curve (ROC AUC) and Precision-Recall (PR) AUC, considering six stride values: 8, 16, 32, 64, 128, and 256. The ROC curve considers the true positive rate ($TP/(TP+FN)$) and false positive rate ($FP/(TN+FP)$) and the PR curve considers the precision ($TP/(TP+FP)$) and recall ($TP/TP+FN$). From the points generated, it is possible to calculate the area under these curves.

2.3. RESULTS

2.3.1. DL Metrics Results

Overall, the different architectures and backbones presented good results (Table 3). The U-net presented the best metrics results regarding the different architectures, followed by DeepLabv3+, FPN, and PSPNet. Despite the higher complexity of the DeepLabv3+ architecture, the U-net presented better results since the targets do not present a high variance in scaling, one of the most significant benefits of this model. Moreover, even though PSPNet provided the worst results, the difference is not extremely large, and the training period is considerably lower (less than half the time to train the Eff-b7 using the U-net architecture, and nearly one-fifth of the period for training on the DeepLabv3+ architecture). When analyzing the different backbones, apart from Eff-b0 with the PSPNet architecture, the results did not change much. Moreover, metrics-wise, the accuracy score shows high values among all models (<3% variation), possibly because there are many more pixels corresponding to the background class than the panels class. The IoU and F-score provide much meaningful results. The Eff-b7 using the U-net architecture had the best IoU and F-score results and an intermediate computational cost.

Figure 4 shows three examples from the test set, and three examples from the validation set with their corresponding original images (RGB channels), GT, and prediction. Despite some errors in the edges of the objects, these results suggest a correct identification of the target, with few errors.

Table 3. Semantic segmentation evaluation (accuracy, IoU, F-score, and epoch period) using three architectures (U-net, DeepLabv3+, and PSPNet), and four backbones (Efficient-net-b7 (Eff-b7), Efficient-net-b0 (Eff-b0), ResNet-101 (R-101), and ResNet-50 (R-50)).

Architecture	Backbone	Accuracy (%)	IoU (%)	F-score (%)	Epoch period (s)
U-net	Eff-b7	98.08	91.17	95.38	12
	Eff-b0	98.05	90.97	95.27	5
	R-101	97.96	90.58	95.06	5
	R-50	97.98	90.70	95.12	4
DeepLabv3+	Eff-b7	97.83	89.98	94.73	26
	Eff-b0	97.77	89.82	94.64	5
	R-101	97.46	88.47	93.88	7
	R-50	97.02	86.63	92.84	6
PSPNet	Eff-b7	97.35	88.03	93.64	5
	Eff-b0	96.73	85.43	92.14	3
	R-101	97.06	86.98	93.04	3
	R-50	97.23	87.60	93.39	3
FPN	Eff-b7	97.38	87.99	93.61	12
	Eff-b0	97.45	88.21	93.73	5
	R-101	97.58	89.21	94.30	6
	R-50	97.25	87.74	93.47	5

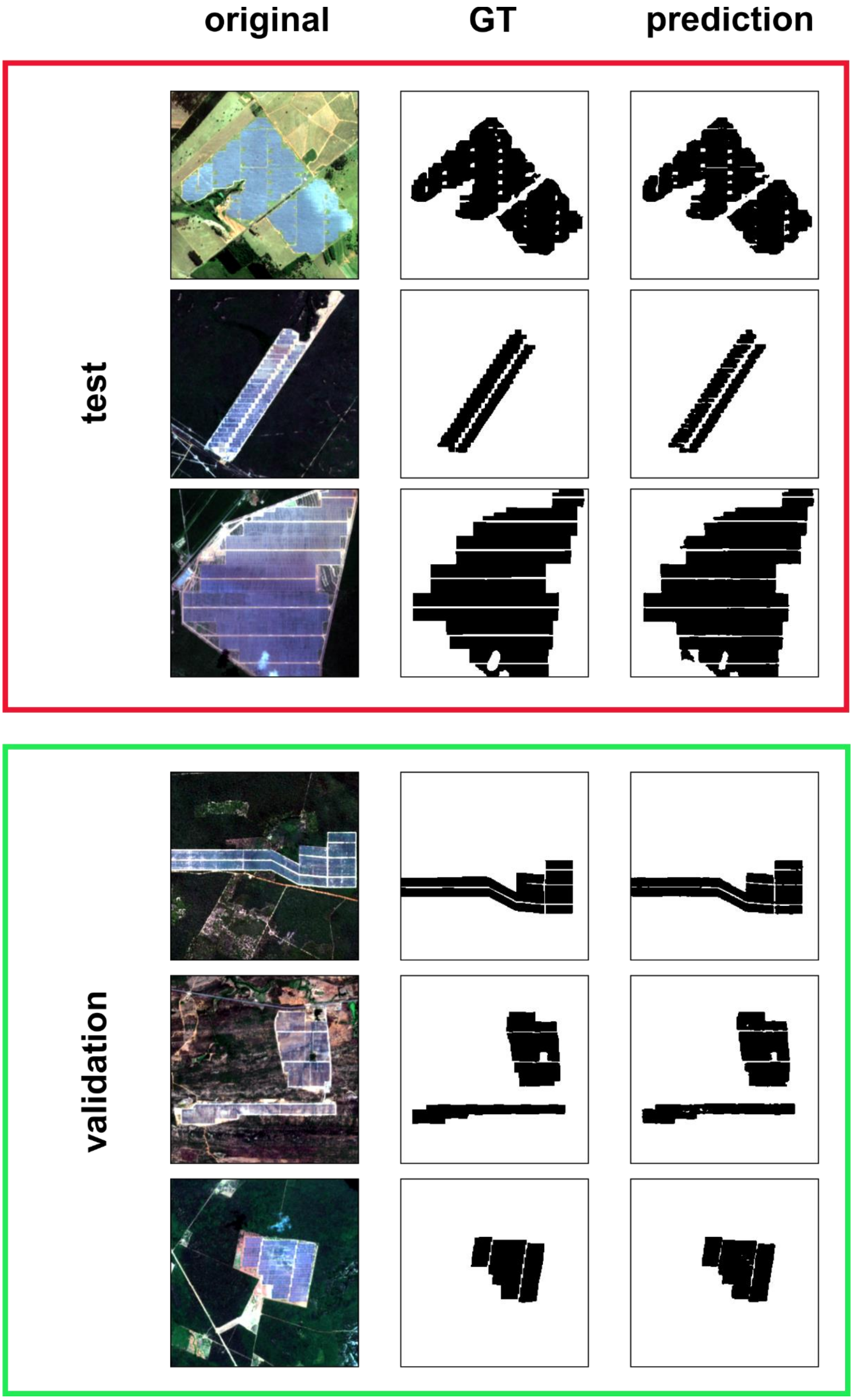

Figure 4. Three examples from the test set and three examples from the validation set with their corresponding original image, ground truth (GT), and prediction.

2.3.2. Mosaicking Results

Table 4 shows the ROC AUC scores using the 1536x768 area, using six different stride values (8, 16, 32, 64, 128, and 256). The analysis only considered the best model (U-net with Eff-b7 backbone). When the stride value decreases, results progressively improve in both metrics. Nevertheless, decreasing the stride value increases the computational cost needed, being a significant limitation, especially for practical applications.

Figure 5 shows the original image, its corresponding GT; and the prediction using U-net with Eff-b7 backbone and 8-pixel stride value on a 1532x768-pixel image. This mosaicking strategy enables the classification of areas with large dimensions, outputting images with no discontinuity.

Table 4. ROC AUC, PR AUC, and processing time for 8, 16,32, 64, 128, and 256 stride values.

Stride	ROC AUC	PR AUC	Processing time (s)
8	99.42	97.85	2829
16	99.25	97.56	734
32	98.89	96.99	193
64	98.66	96.42	63
128	98.36	95.39	15
256	98.16	94.49	4

2.4. DISCUSSION

The better result of our study was the U-net with the Eff-b7 backbone, although the other methods also reach high and good enough values. However, an unexpected result is that U-net outperformed DeepLabv3+ with a slight margin. This result is probably because the input images do not present multi-scale objects, one of the main contributions of the DeepLabv3+ method. Therefore, these results show that simpler structures may be well suited in some scenarios, highlighting the importance of testing different architectures.

Other solar panel detection studies using DL methods have demonstrated high accuracy in different locations. However, studies carried out on PV solar plants are still much lower than residential PV solar panels. Considering the large-scale solar plants, Hou et al. [84] proposed a study in China with one thousand images achieving 95% IoU from the U-net model. They used a much more significant amount of data, and the results were not far from ours (92% IoU).

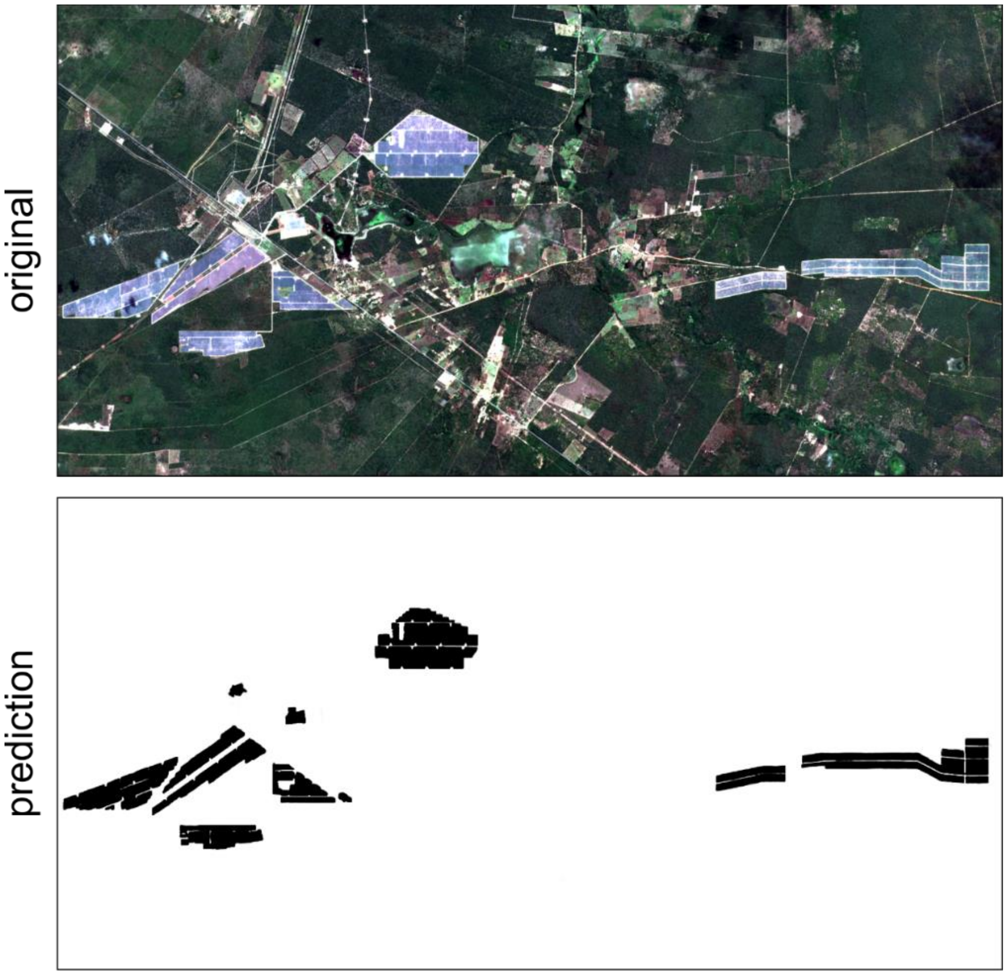

Figure 5. Mosaic representation on a 1536x768-pixel image with the original image, the corresponding ground truth (GT), and prediction using the U-net with Efficient-net-b7 backbone.

Generally, accuracy results are lower in residential PV solar panels because of their smaller dimension and more susceptibility to noise interference. Yuan et al. [100] applied a simple ConvNet for large-scale solar panel mapping from aerial images and evaluated their model in Boston and San Francisco cities using completeness (0.84 and 0.87) and correctness (0.81 and 0.85) metrics. Yu et al. [101] proposed DeepSolar with a substantial amount of training data using high-resolution satellite images, obtaining 93.1% recall and 88.5% precision, results very similar to our F-score (95%). Zhuang et al. [83] applied the U-net in satellite images for residential panels, achieving 74% IoU. Recently, Jie et al. [82] combined a U-net model with edge detection networks. The authors showed that the edge detection increased performance on two city panel datasets in nearly 2% IoU. This effect might be even less in large solar plants since it is easier to detect borders, as shown in our study. Even though these studies trained with smaller PV solar panels, the results show an excellent ability to segment panels even with simpler models.

Thus, the results of our and previous studies suggest that the mapping PV solar panels should be addressed in a data-driven rather than model-driven perspective, i.e., the DL models do not present a significant difference, and the most important is to obtain a reliable source of generating good annotations. Moreover, the present study showed significant results using data augmentation even with a low amount of data.

The mosaicking procedure enables the classification of areas with indefinite and large sizes. We have shown that using a smaller stride value increases performance but also the computational cost. The stride value for a practical application should take into consideration both factors. Regarding the mosaicking technique on semantic segmentation models, de Albuquerque et al. [86] performed a comparative analysis using different stride values, presenting progressively better ROC AUC scores for lower stride values, a result also verified in our research.

This research presents many possibilities for future studies. A first proposition would be to estimate energy production using the mapping of the photovoltaic solar panel from DL and the level of solar incidence in the specific region. Another relevant test would be evaluating radar images due to cloud cover and atmospheric interference in optical images. Even though synthetic aperture radar (SAR) images are noisy, they can be useful in some scenarios. Besides, studies comparing the frame sizes according to the proposal by Bem et al. [102] can be valuable in understanding the model's differences in various tasks (for example, binary and multiclass) and object scales.

2.5. CONCLUSIONS

The survey and monitoring of PV solar power plants are extremely important for energy management and planning. The high growth of solar energy in Brazil, a country with continental dimensions, generates an increase in inspection processes for ANEEL that is only possible through technological innovation. Thus, this paper presented a comparison between DL models for the classification of PV solar plants using Sentinel-2 images with four spectral bands (RGB and near infra-red), comparing four architectures (U-net, DeepLabv3+, FPN, and PSPNet) with four backbones (ResNet-50, ResNet-101, Eff-b0, and Eff-b7), totaling 16 combinations. Besides, we used augmentation and transfer learning. The PV panel spectral and shape characteristics facilitate the accurate detection of the panels. Results were satisfactory using the different backbones and architectures, but U-net with Eff-b7 backbone presented the best results with 98% accuracy, 92% IoU, and 95% F-score. We estimate that the most critical factor when mapping PV solar panels are a reliable source of data and their possible applications. For the classification of large regions, the image mosaicking procedure significantly improves when using more overlapping pixels, minimizing edge errors. The results are also expressive when analyzing the ROC AUC score and PR AUC score, in which the results progressively increase when decreasing the stride value. However, the computational cost may be a significant challenge for practical applications since the processing time significantly increases with the stride value reduction. This methodology has many applications and satisfies the conditions for automatically classifying PV solar plants using free Sentinel-2 imagery, allowing for a significant advance in monitoring the implanted infrastructure.

References

1. Kabir, E.; Kumar, P.; Kumar, S.; Adelodun, A.A.; Kim, K.H. Solar energy: Potential and future prospects. *Renew. Sustain. Energy Rev.* **2018**, *82*, 894–900, doi:10.1016/j.rser.2017.09.094.
2. Subtil Lacerda, J.; Van Den Bergh, J.C.J.M. Diversity in solar photovoltaic energy: Implications for innovation and policy. *Renew. Sustain. Energy Rev.* **2016**, *54*, 331–340, doi:10.1016/j.rser.2015.10.032.
3. Sampaio, P.G.V.; González, M.O.A. Photovoltaic solar energy: Conceptual framework. *Renew. Sustain. Energy Rev.* **2017**, *74*, 590–601, doi:10.1016/j.rser.2017.02.081.
4. Jäger-Waldau, A. Snapshot of photovoltaics-February 2020. *Energies* **2020**, *13*, doi:10.3390/en13040930.
5. Rabaia, M.K.H.; Abdelkareem, M.A.; Sayed, E.T.; Elsaid, K.; Chae, K.J.; Wilberforce, T.; Olabi, A.G. Environmental impacts of solar energy systems: A review. *Sci. Total Environ.* **2021**, *754*, 141989, doi:10.1016/j.scitotenv.2020.141989.
6. IPCC. Painel Intergovernamental sobre Mudanças Climáticas *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., Kriemann, B., Savolainen, J., Schlömer, S., Stechow, C. von, Zwickel, T., Minx, J.C., Eds.; Cambridge University Press: Cambridge, 2014; ISBN 9781107654815.
7. Creutzig, F.; Agoston, P.; Goldschmidt, J.C.; Luderer, G.; Nemet, G.; Pietzcker, R.C. The underestimated potential of solar energy to mitigate climate change. *Nat. Energy* **2017**, *2*, doi:10.1038/nenergy.2017.140.
8. Gils, H.C.; Simon, S.; Soria, R. 100% Renewable energy supply for Brazil-The role of sector coupling and regional development. *Energies* **2017**, *10*, doi:10.3390/en10111859.
9. Mendes, L.F.R.; Sthel, M.S. Analysis of the hydrological cycle and its impacts on the sustainability of the electric matrix in the state of Rio de Janeiro/Brazil. *Energy Strateg. Rev.* **2018**, *22*, 119–126, doi:10.1016/j.esr.2018.08.015.
10. Mendes, L.F.R.; Sthel, M.S. Thermoelectric Power Plant for Compensation of Hydrological Cycle Change: Environmental Impacts in Brazil. *Case Stud. Environ.* **2017**, *1*, 1–7, doi:10.1525/cse.2017.000471.
11. Melo, L.B.; Estanislau, F.B.G.L. e.; Costa, A.L.; Fortini, Â. Impacts of the hydrological potential change on the energy matrix of the Brazilian State of Minas Gerais: A case study. *Renew. Sustain. Energy Rev.* **2019**, *110*, 415–422, doi:10.1016/j.rser.2019.05.018.
12. Reichert, B.; Souza, A.M. Interrelationship simulations among Brazilian electric matrix sources. *Electr. Power Syst. Res.* **2021**, *193*, 107019, doi:10.1016/j.epsr.2020.107019.

13. Athayde, S.; Mathews, M.; Bohlman, S.; Brasil, W.; Doria, C.R.; Dutka-Gianelli, J.; Fearnside, P.M.; Loiselle, B.; Marques, E.E.; Melis, T.S.; et al. Mapping research on hydropower and sustainability in the Brazilian Amazon: advances, gaps in knowledge and future directions. *Curr. Opin. Environ. Sustain.* **2019**, *37*, 50–69, doi:10.1016/j.cosust.2019.06.004.
14. Manyari, W.V.; de Carvalho, O.A. Environmental considerations in energy planning for the Amazon region: Downstream effects of dams. *Energy Policy* **2007**, *35*, 6526–6534, doi:10.1016/j.enpol.2007.07.031.
15. Latrubesse, E.M.; Arima, E.Y.; Dunne, T.; Park, E.; Baker, V.R.; D'Horta, F.M.; Wight, C.; Wittmann, F.; Zuanon, J.; Baker, P.A.; et al. Damming the rivers of the Amazon basin. *Nature* **2017**, *546*, 363–369, doi:10.1038/nature22333.
16. de Faria, F.A.M.; Jaramillo, P. The future of power generation in Brazil: An analysis of alternatives to Amazonian hydropower development. *Energy Sustain. Dev.* **2017**, *41*, 24–35, doi:10.1016/j.esd.2017.08.001.
17. de Jong, P.; Barreto, T.B.; Tanajura, C.A.S.; Kouloukoui, D.; Oliveira-Esquerre, K.P.; Kiperstok, A.; Torres, E.A. Estimating the impact of climate change on wind and solar energy in Brazil using a South American regional climate model. *Renew. Energy* **2019**, *141*, 390–401, doi:10.1016/j.renene.2019.03.086.
18. Ferraz de Andrade Santos, J.A.; de Jong, P.; Alves da Costa, C.; Torres, E.A. Combining wind and solar energy sources: Potential for hybrid power generation in Brazil. *Util. Policy* **2020**, *67*, doi:10.1016/j.jup.2020.101084.
19. Ferreira, A.; Kunh, S.S.; Fagnani, K.C.; De Souza, T.A.; Tonezer, C.; Dos Santos, G.R.; Coimbra-Araújo, C.H. Economic overview of the use and production of photovoltaic solar energy in brazil. *Renew. Sustain. Energy Rev.* **2018**, *81*, 181–191, doi:10.1016/j.rser.2017.06.102.
20. Martins, F.R.; Abreu, S.L.; Pereira, E.B. Scenarios for solar thermal energy applications in Brazil. *Energy Policy* **2012**, *48*, 640–649, doi:10.1016/j.enpol.2012.05.082.
21. Martins, F.R.; Rüther, R.; Pereira, E.B.; Abreu, S.L. Solar energy scenarios in Brazil. Part two: Photovoltaics applications. *Energy Policy* **2008**, *36*, 2865–2877, doi:10.1016/j.enpol.2008.04.001.
22. Martins, F.R.; Pereira, E.B.; Silva, S.A.B.; Abreu, S.L.; Colle, S. Solar energy scenarios in Brazil, Part one: Resource assessment. *Energy Policy* **2008**, *36*, 2853–2864, doi:10.1016/j.enpol.2008.02.014.
23. Lima, F.J.L. de; Martins, F.R.; Costa, R.S.; Gonçalves, A.R.; dos Santos, A.P.P.; Pereira, E.B. The seasonal variability and trends for the surface solar irradiation in northeastern region of Brazil. *Sustain. Energy Technol. Assessments* **2019**, *35*, 335–346, doi:10.1016/j.seta.2019.08.006.
24. Azevêdo, V.W.B.; Candeias, L.B.; Tiba, C. Location study of solar thermal power plant in the state of Pernambuco using geoprocessing technologies and Multiple-Criteria analysis. *Energies* **2017**, *10*, doi:10.3390/en10071042.
25. Medeiros, S.E.L.; Nilo, P.F.; Silva, L.P.; Santos, C.A.C.; Carvalho, M.; Abrahão, R. Influence of climatic variability on the electricity generation potential by renewable sources in the Brazilian semi-arid region. *J. Arid Environ.* **2021**, *184*, doi:10.1016/j.jaridenv.2020.104331.
26. Vieira de Souza, L.E.; Gilmanova Cavalcante, A.M. Concentrated Solar Power deployment in emerging economies: The cases of China and Brazil. *Renew. Sustain. Energy Rev.* **2017**, *72*, 1094–1103, doi:10.1016/j.rser.2016.10.027.
27. de Faria, H.; Trigoso, F.B.M.; Cavalcanti, J.A.M. Review of distributed generation with photovoltaic grid connected systems in Brazil: Challenges and prospects. *Renew. Sustain. Energy Rev.* **2017**, *75*, 469–475, doi:10.1016/j.rser.2016.10.076.
28. Amaral, A.B.A.; Mendonca, A.L.Z.L.G.; Resende, A.A.M.; Rego, E.E. Solar energy and distributed generation: 2015, a year of inflection in Brazil? *IEEE Lat. Am. Trans.* **2016**, *14*, 3731–3737, doi:10.1109/TLA.2016.7786357.
29. Elgamal, G.N.G.; Demajorovic, J. Barriers and perspectives for electric power generation out of photovoltaic solar panels in the brazilian energy matrix. *Rev. Gest. Ambient. e Sustentabilidade* **2020**, *9*, 1–26, doi:10.5585/GEAS.V9I1.17157.
30. Garlet, T.B.; Ribeiro, J.L.D.; de Souza Savian, F.; Mairesse Siluk, J.C. Paths and barriers to the diffusion of distributed generation of photovoltaic energy in southern Brazil. *Renew. Sustain. Energy Rev.* **2019**, *111*, 157–169, doi:10.1016/j.rser.2019.05.013.
31. Vilaça Gomes, P.; Knak Neto, N.; Carvalho, L.; Sumaili, J.; Saraiva, J.T.; Dias, B.H.; Miranda, V.; Souza, S.M. Technical-economic analysis for the integration of PV systems in Brazil considering policy and regulatory issues. *Energy Policy* **2018**, *115*, 199–206, doi:10.1016/j.enpol.2018.01.014.
32. Hoffmann, A.S.; Carvalho, G.H. de; Cardoso, R.A.F. Environmental licensing challenges for the

implementation of photovoltaic solar energy projects in Brazil. *Energy Policy* **2019**, *132*, 1143–1154, doi:10.1016/j.enpol.2019.07.002.
33. Queiroz, J.V.; Borges, K.K.; Queiroz, F.C.B.P.; Lima, N.C.; Da Silva, C.L.; Morais, L. de S. Barriers to expand solar photovoltaic energy in Brazil. *Indep. J. Manag. Prod.* **2020**, *11*, 2733–2754, doi:10.14807/ijmp.v11i7.1098.
34. Denes_Santos, D.; da Cunha, S.K. Transformative innovation policy for solar energy: particularities of a developing country. *Clean Technol. Environ. Policy* **2020**, *22*, 43–57, doi:10.1007/s10098-019-01764-3.
35. Barbosa, J.; Dias, L.P.; Simoes, S.G.; Seixas, J. When is the sun going to shine for the Brazilian energy sector? A story of how modelling affects solar electricity. *Renew. Energy* **2020**, *162*, 1684–1702, doi:10.1016/j.renene.2020.09.091.
36. Viana, A.G.; Ramos, D.S. Outcomes from the first large-scale solar PV auction in Brazil. *Renew. Sustain. Energy Rev.* **2018**, *91*, 219–228, doi:10.1016/j.rser.2018.04.003.
37. Echegaray, F. Understanding stakeholders' views and support for solar energy in Brazil. *J. Clean. Prod.* **2014**, *63*, 125–133, doi:10.1016/j.jclepro.2013.02.017.
38. Orlandi, A.G.; Farias, R.A.N.; de Carvalho Junior, O.A.; Guimarães, R.F.; Gomes, R.A.T. Controle gerencial na administração pública e transformação digital: sensoriamento remoto. *Cad. Gestão Pública e Cid.* **2021**, *26*, 1–24, doi:10.12660/cgpc.v26n83.80456.
39. Deng, C.; Wang, S.; Huang, Z.; Tan, Z.; Liu, J. Unmanned aerial vehicles for power line inspection: A cooperative way in platforms and communications. *J. Commun.* **2014**, *9*, 687–692, doi:10.12720/jcm.9.9.687-692.
40. Matikainen, L.; Lehtomäki, M.; Ahokas, E.; Hyyppä, J.; Karjalainen, M.; Jaakkola, A.; Kukko, A.; Heinonen, T. Remote sensing methods for power line corridor surveys. *ISPRS J. Photogramm. Remote Sens.* **2016**, *119*, 10–31, doi:10.1016/j.isprsjprs.2016.04.011.
41. Ahmad, J.; Malik, A.S.; Xia, L.; Ashikin, N. Vegetation encroachment monitoring for transmission lines right-of-ways: A survey. *Electr. Power Syst. Res.* **2013**, *95*, 339–352, doi:10.1016/j.epsr.2012.07.015.
42. Bonansea, M.; Ferrero, S.; Ferral, A.; Ledesma, M.; German, A.; Carreño, J.; Rodriguez, C.; Pinotti, L. Assessing water surface temperature from Landsat imagery and its relationship with a nuclear power plant. *Hydrol. Sci. J.* **2021**, *66*, 50–58, doi:10.1080/02626667.2020.1845342.
43. Ma, P.; Dai, X.; Guo, Z.; Wei, C.; Ma, W. Detection of thermal pollution from power plants on China's eastern coast using remote sensing data. *Stoch. Environ. Res. Risk Assess.* **2017**, *31*, 1957–1975, doi:10.1007/s00477-016-1293-8.
44. Ahn, Y.H.; Shanmugam, P.; Lee, J.H.; Kang, Y.Q. Application of satellite infrared data for mapping of thermal plume contamination in coastal ecosystem of Korea. *Mar. Environ. Res.* **2006**, *61*, 186–201, doi:10.1016/j.marenvres.2005.09.001.
45. Chen, C.; Shi, P.; Mao, Q. Application of remote sensing techniques for monitoring the thermal pollution of cooling-water discharge from nuclear power plant. *J. Environ. Sci. Heal. - Part A Toxic/Hazardous Subst. Environ. Eng.* **2003**, *38*, 1659–1668, doi:10.1081/ESE-120021487.
46. Bauni, V.; Schivo, F.; Capmourteres, V.; Homberg, M. Ecosystem loss assessment following hydroelectric dam flooding: The case of Yacyretá, Argentina. *Remote Sens. Appl. Soc. Environ.* **2015**, *1*, 50–60, doi:10.1016/j.rsase.2015.06.003.
47. Chen, G.; Powers, R.P.; de Carvalho, L.M.T.; Mora, B. Spatiotemporal patterns of tropical deforestation and forest degradation in response to the operation of the Tucuruí hydroelectricdam in the Amazon basin. *Appl. Geogr.* **2015**, *63*, 1–8, doi:10.1016/j.apgeog.2015.06.001.
48. Jiang, X.; Lu, D.; Moran, E.; Calvi, M.F.; Dutra, L.V.; Li, G. Examining impacts of the Belo Monte hydroelectric dam construction on land-cover changes using multitemporal Landsat imagery. *Appl. Geogr.* **2018**, *97*, 35–47, doi:10.1016/j.apgeog.2018.05.019.
49. Feng, L.; Hu, C.; Chen, X.; Zhao, X. Dramatic inundation changes of China's two largest freshwater lakes linked to the Three Gorges Dam. *Environ. Sci. Technol.* **2013**, *47*, 9628–9634, doi:10.1021/es4009618.
50. Beyer, R.C.M.; Franco-Bedoya, S.; Galdo, V. Examining the economic impact of COVID-19 in India through daily electricity consumption and nighttime light intensity. *World Dev.* **2021**, *140*, 105287, doi:10.1016/j.worlddev.2020.105287.
51. Dugoua, E.; Kennedy, R.; Urpelainen, J. Satellite data for the social sciences: Measuring rural electrification with night-time lights. *Int. J. Remote Sens.* **2018**, *39*, 2690–2701, doi:10.1080/01431161.2017.1420936.

52. Min, B.; Gaba, K.M. Tracking electrification in Vietnam using nighttime lights. *Remote Sens.* **2014**, *6*, 9511–9529, doi:10.3390/rs6109511.
53. Hammer, A.; Heinemann, D.; Hoyer, C.; Kuhlemann, R.; Lorenz, E.; Müller, R.; Beyer, H.G. Solar energy assessment using remote sensing technologies. *Remote Sens. Environ.* **2003**, *86*, 423–432, doi:10.1016/S0034-4257(03)00083-X.
54. Yang, D.; Kleissl, J.; Gueymard, C.A.; Pedro, H.T.C.; Coimbra, C.F.M. History and trends in solar irradiance and PV power forecasting: A preliminary assessment and review using text mining. *Sol. Energy* **2018**, *168*, 60–101, doi:10.1016/j.solener.2017.11.023.
55. Masoom, A.; Kosmopoulos, P.; Bansal, A.; Kazadzis, S. Solar energy estimations in india using remote sensing technologies and validation with sun photometers in urban areas. *Remote Sens.* **2020**, *12*, 1–25, doi:10.3390/rs12020254.
56. Kausika, B.; van Sark, W. Calibration and Validation of ArcGIS Solar Radiation Tool for Photovoltaic Potential Determination in the Netherlands. *Energies* **2021**, *14*, 1865, doi:10.3390/en14071865.
57. Al Garni, H.Z.; Awasthi, A. *Solar PV Power Plants Site Selection: A Review*; Elsevier Inc., 2018; Vol. 1; ISBN 9780128132173.
58. Gherboudj, I.; Ghedira, H. Assessment of solar energy potential over the United Arab Emirates using remote sensing and weather forecast data. *Renew. Sustain. Energy Rev.* **2016**, *55*, 1210–1224, doi:10.1016/j.rser.2015.03.099.
59. Mahtta, R.; Joshi, P.K.; Jindal, A.K. Solar power potential mapping in India using remote sensing inputs and environmental parameters. *Renew. Energy* **2014**, *71*, 255–262, doi:10.1016/j.renene.2014.05.037.
60. Polo, J.; Bernardos, A.; Navarro, A.A.; Fernandez-Peruchena, C.M.; Ramírez, L.; Guisado, M. V.; Martínez, S. Solar resources and power potential mapping in Vietnam using satellite-derived and GIS-based information. *Energy Convers. Manag.* **2015**, *98*, 348–358, doi:10.1016/j.enconman.2015.04.016.
61. Wang, S.; Zhang, L.; Fu, D.; Lu, X.; Wu, T.; Tong, Q. Selecting photovoltaic generation sites in Tibet using remote sensing and geographic analysis. *Sol. Energy* **2016**, *133*, 85–93, doi:10.1016/j.solener.2016.03.069.
62. Spyridonidou, S.; Sismani, G.; Loukogeorgaki, E.; Vagiona, D.G.; Ulanovsky, H.; Madar, D. Sustainable Spatial Energy Planning of Large-Scale Wind and PV Farms in Israel: A Collaborative and Participatory Planning Approach. *Energies* **2021**, *14*, 551, doi:10.3390/en14030551.
63. Sánchez-Aparicio, M.; Del Pozo, S.; Martín-Jiménez, J.A.; González-González, E.; Andrés-Anaya, P.; Lagüela, S. Influence of lidar point cloud density in the geometric characterization of rooftops for solar photovoltaic studies in cities. *Remote Sens.* **2020**, *12*, 1–21, doi:10.3390/rs12223726.
64. Tiwari, A.; Meir, I.A.; Karnieli, A. Object-based image procedures for assessing the solar energy photovoltaic potential of heterogeneous rooftops using airborne LiDAR and orthophoto. *Remote Sens.* **2020**, *12*, doi:10.3390/rs12020223.
65. Prieto, I.; Izkara, J.L.; Usobiaga, E. The application of LiDAR data for the solar potential analysis based on urban 3D model. *Remote Sens.* **2019**, *11*, doi:10.3390/rs11202348.
66. Li, Y.; Liu, C. Estimating solar energy potentials on pitched roofs. *Energy Build.* **2017**, *139*, 101–107, doi:10.1016/j.enbuild.2016.12.070.
67. Karoui, M.S.; Benhalouche, F.Z.; Deville, Y.; Djerriri, K.; Briottet, X.; Houet, T.; Le Bris, A.; Weber, C. Partial linear NMF-based unmixing methods for detection and area estimation of photovoltaic panels in urban hyperspectral remote sensing data. *Remote Sens.* **2019**, *11*, doi:10.3390/rs11182164.
68. Malof, J.M.; Bradbury, K.; Collins, L.M.; Newell, R.G. Automatic detection of solar photovoltaic arrays in high resolution aerial imagery. *Appl. Energy* **2016**, *183*, 229–240, doi:10.1016/j.apenergy.2016.08.191.
69. Lecun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* **2015**, *521*, 436–444, doi:10.1038/nature14539.
70. Ball, J.E.; Anderson, D.T.; Chan, C.S. Special Section Guest Editorial: Feature and Deep Learning in Remote Sensing Applications. *J. Appl. Remote Sens.* **2018**, *11*, 1, doi:10.1117/1.jrs.11.042601.
71. Maxwell, A.E.; Warner, T.A.; Fang, F. Implementation of machine-learning classification in remote sensing: An applied review. *Int. J. Remote Sens.* **2018**, *39*, 2784–2817, doi:10.1080/01431161.2018.1433343.
72. Yuan, Q.; Shen, H.; Li, T.; Li, Z.; Li, S.; Jiang, Y.; Xu, H.; Tan, W.; Yang, Q.; Wang, J.; et al. Deep learning in environmental remote sensing: Achievements and challenges. *Remote Sens. Environ.* **2020**, *241*, 111716, doi:10.1016/j.rse.2020.111716.
73. Zhang, L.; Zhang, L.; Du, B. Deep Learning for Remote Sensing Data: A Technical Tutorial on the

State of the Art. *IEEE Geosci. Remote Sens. Mag.* **2016**, *4*, 22–40, doi:10.1109/MGRS.2016.2540798.
74. Ma, L.; Liu, Y.; Zhang, X.; Ye, Y.; Yin, G.; Johnson, B.A. Deep learning in remote sensing applications: A meta-analysis and review. *ISPRS J. Photogramm. Remote Sens.* **2019**, *152*, 166–177, doi:10.1016/j.isprsjprs.2019.04.015.
75. Zhu, X.X.; Tuia, D.; Mou, L.; Xia, G.; Zhang, L.; Xu, F.; Fraundorfer, F. Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources. *IEEE Geosci. Remote Sens. Mag.* **2017**, *5*, 8–36, doi:10.1109/MGRS.2017.2762307.
76. Garcia-Garcia, A.; Orts-Escolano, S.; Oprea, S.; Villena-Martinez, V.; Martinez-Gonzalez, P.; Garcia-Rodriguez, J. A survey on deep learning techniques for image and video semantic segmentation. *Appl. Soft Comput.* **2018**, *70*, 41–65, doi:10.1016/j.asoc.2018.05.018.
77. Guo, Y.; Liu, Y.; Oerlemans, A.; Lao, S.; Wu, S.; Lew, M.S. Deep learning for visual understanding: A review. *Neurocomputing* **2016**, *187*, 27–48, doi:10.1016/j.neucom.2015.09.116.
78. Liu, L.; Ouyang, W.; Wang, X.; Fieguth, P.; Chen, J.; Liu, X.; Pietikäinen, M. Deep learning for generic object detection: A survey. *Int. J. Comput. Vis.* **2020**, *128*, 261–318.
79. Yu, H.; Yang, Z.; Tan, L.; Wang, Y.; Sun, W.; Sun, M.; Tang, Y. Methods and datasets on semantic segmentation: A review. *Neurocomputing* **2018**, *304*, 82–103, doi:10.1016/j.neucom.2018.03.037.
80. Lateef, F.; Ruichek, Y. Survey on semantic segmentation using deep learning techniques. *Neurocomputing* **2019**, *338*, 321–348, doi:10.1016/j.neucom.2019.02.003.
81. Bradbury, K.; Saboo, R.; Johnson, T.L.; Malof, J.M.; Devarajan, A.; Zhang, W.; Collins, L.M.; Newell, R.G. Distributed solar photovoltaic array location and extent dataset for remote sensing object identification. *Sci. Data* **2016**, *3*, 1–9, doi:10.1038/sdata.2016.106.
82. Jie, Y.; Ji, X.; Yue, A.; Chen, J.; Deng, Y.; Chen, J.; Zhang, Y. Combined Multi-Layer Feature Fusion and Edge Detection Method for Distributed Photovoltaic Power Station Identification. *Energies* **2020**, *13*, 6742, doi:10.3390/en13246742.
83. Zhuang, L.; Zhang, Z.; Wang, L. The automatic segmentation of residential solar panels based on satellite images: A cross learning driven U-Net method. *Appl. Soft Comput. J.* **2020**, *92*, 106283, doi:10.1016/j.asoc.2020.106283.
84. Hou, X.; Wang, B.; Hu, W.; Yin, L.; Wu, H. SolarNet: A Deep Learning Framework to Map Solar Power Plants In China From Satellite Imagery. *arXiv* **2019**.
85. Audebert, N.; Boulch, A.; Randrianarivo, H.; Le, B.; Ferecatu, M.; Lefèvre, S.; Marlet, R.; Audebert, N.; Boulch, A.; Randrianarivo, H.; et al. Deep learning for urban remote sensing To cite this version : HAL Id : hal-01672854 Deep Learning for Urban Remote Sensing. **2018**.
86. de Albuquerque, A.O.; de Carvalho Júnior, O.A.A.; Carvalho, O.L.F. de; de Bem, P.P.; Ferreira, P.H.G.; de Moura, R. dos S.; Silva, C.R.; Trancoso Gomes, R.A.; Fontes Guimarães, R. Deep Semantic Segmentation of Center Pivot Irrigation Systems from Remotely Sensed Data. *Remote Sens.* **2020**, *12*, 2159, doi:10.3390/rs12132159.
87. Carvalho, O.L.F. de; de Carvalho Júnior, O.A.A.; Albuquerque, A.O. de; Bem, P.P. de; Silva, C.R.; Ferreira, P.H.G.; Moura, R. dos S. de; Gomes, R.A.T.; Guimarães, R.F.; Borges, D.L.D.L. Instance Segmentation for Large, Multi-Channel Remote Sensing Imagery Using Mask-RCNN and a Mosaicking Approach. *Remote Sens.* **2021**, *13*, 39, doi:10.3390/rs13010039.
88. Drusch, M.; Del Bello, U.; Carlier, S.; Colin, O.; Fernandez, V.; Gascon, F.; Hoersch, B.; Isola, C.; Laberinti, P.; Martimort, P.; et al. Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services. *Remote Sens. Environ.* **2012**, *120*, 25–36, doi:10.1016/j.rse.2011.11.026.
89. Ronneberger, O.; Fischer, P.; Brox, T. U-Net: Convolutional Networks for Biomedical Image Segmentation. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*; Navab, N., Hornegger, J., Wells, W., Frangi, A., Eds.; Springer: Cham, 2015; Vol. 9351, pp. 234–241 ISBN 9783319245737.
90. Badrinarayanan, V.; Kendall, A.; Cipolla, R. SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. *IEEE Trans. Pattern Anal. Mach. Intell.* **2017**, *39*, 2481–2495, doi:10.1109/TPAMI.2016.2644615.
91. Lin, T.-Y.; Dollar, P.; Girshick, R.; He, K.; Hariharan, B.; Belongie, S. Feature Pyramid Networks for Object Detection. In Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); IEEE: Honolulu, HI, USA, 2017; pp. 936–944.
92. Chen, L.-C.; Papandreou, G.; Kokkinos, I.; Murphy, K.; Yuille, A.L. DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs. *IEEE Trans. Pattern Anal. Mach. Intell.* **2018**, *40*, 834–848, doi:10.1109/TPAMI.2017.2699184.
93. Chen, L.-C.; Zhu, Y.; Papandreou, G.; Schroff, F.; Adam, H. Encoder-Decoder with Atrous Separable

Convolution for Semantic Image Segmentation. *Pertanika J. Trop. Agric. Sci.* **2018**, *34*, 137–143.
94. Zhao, H.; Shi, J.; Qi, X.; Wang, X.; Jia, J. Pyramid Scene Parsing Network. In Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); IEEE: Honolulu, HI, USA, 2017; pp. 6230–6239.
95. He, K.; Zhang, X.; Ren, S.; Sun, J. Deep Residual Learning for Image Recognition. In Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); IEEE: Las Vegas, NV, USA, 2016; Vol. 45, pp. 770–778.
96. Xie, S.; Girshick, R.; Dollar, P.; Tu, Z.; He, K. Aggregated Residual Transformations for Deep Neural Networks. In Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); IEEE: Honolulu, HI, USA, 2017; pp. 5987–5995.
97. Tan, M.; Le, Q. V. EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. *arXiv* **2019**.
98. Yakubovskiy, P. Segmentation Models Pytorch. *GitHub Repos.* 2020.
99. Deng, J.; Dong, W.; Socher, R.; Li, L.-J.; Kai Li; Li Fei-Fei ImageNet: A large-scale hierarchical image database. In Proceedings of the 2009 IEEE Conference on Computer Vision and Pattern Recognition; IEEE: Miami, FL, USA, 2009; pp. 248–255.
100. Yuan, J.; Yang, H.H.L.; Omitaomu, O.A.; Bhaduri, B.L. Large-scale solar panel mapping from aerial images using deep convolutional networks. *Proc. - 2016 IEEE Int. Conf. Big Data, Big Data 2016* **2016**, 2703–2708, doi:10.1109/BigData.2016.7840915.
101. Yu, J.; Wang, Z.; Majumdar, A.; Rajagopal, R. DeepSolar: A Machine Learning Framework to Efficiently Construct a Solar Deployment Database in the United States. *Joule* **2018**, *2*, 2605–2617, doi:10.1016/j.joule.2018.11.021.
102. de Bem, P.P.; de Carvalho Júnior, O.A.A.; de Carvalho, O.L.F.; Gomes, R.A.T.; Fontes Guimarães, R.; Guimarães, R.F. Performance Analysis of Deep Convolutional Autoencoders with Different Patch Sizes for Change Detection from Burnt Areas. *Remote Sens.* **2020**, *12*, 2576, doi:10.3390/RS12162576.

3. CONCLUSÃO

O levantamento e monitoramento de usinas solares fotovoltaica são extremamente importantes para o planejamento e gerenciamento de energia. O alto crescimento da energia solar no Brasil, um país com dimensões continentais, gera um aumento nos processos de fiscalização da ANEEL que só é possível por meio da inovação tecnológica. O presente trabalho trouxe uma comparação entre modelos DL para a classificação de usinas solares fotovoltaicas usando imagens Sentinel-2 com quatro bandas espectrais (RGB e infravermelho próximo), comparando quatro arquiteturas (U-net, DeepLabv3 +, FPN e PSPNet) com quatro backbones (ResNet-50, ResNet-101, Eff-b0 e Eff-b7), totalizando 16 combinações. O trabalho, também ressalta o modo como realizou a transferência de aprendizado e aumento de dados, mostrando que as características espectrais e de formato da placa fotovoltaica facilitam a detecção precisa dos painéis. Os resultados foram satisfatórios usando os diferentes backbones e arquiteturas, mas a U-net com backbone Eff-b7 apresentou os melhores resultados com 98% de precisão, 92% IoU e 95% F-score. Para a classificação de grandes regiões, o procedimento de mosaico de imagens melhora significativamente ao usar mais pixels de sobreposição, minimizando erros de borda.

Os resultados também se mostraram expressivos quando se analisou o escore ROC AUC e o escore PR AUC, mostrando que os resultados aumentam progressivamente com a diminuição do valor da sobreposição. No entanto, o custo computacional pode ser um desafio significativo para aplicações práticas, uma vez que o tempo de processamento aumenta significativamente com a redução do valor da sobreposição.

Esta metodologia possui diversas aplicações e atende às condições de classificação automática de usinas solares fotovoltaicas utilizando imagens Sentinel-2 gratuitas, permitindo um avanço significativo no monitoramento da infraestrutura implantada. Ademais, há a possibilidade de treinamentos utilizando imagens RADAR, que diminuiria consideravelmente a revisita nas usinas, pois em épocas de grande incidência de nuvens, o monitoramento fica prejudicado utilizando somente imagens espectrais. Por fim, do ponto de vista científico, de produção tecnológica e de benefício para a comunidade usuária da Energia Fotovoltaica, o presente trabalho trouxe sua contribuição na justa medida do *zeitgeist* atual.