A Review of Solar Panel Detection in Aerial Images Using U-net-based Convolutional Neural Network

Ruchira Tabassum and Puja Das

***Abstract*—** To diminish the hazardous carbon emission from the electricity generation of fossil-fuel-based power plants, Photovoltaic (PV) solar panels have been proven to be an effective solution among renewable energy resources. As a groundwork for the estimation and expansion of a solar power system, determining the power capacity and the location of the existing solar panels has become a necessity. Among many schemes to accomplish the mentioned purpose, Deep learning methods have their significance with better accuracy. This work incorporates the review of the implementation of the Convolutional Neural Network with U-Net as a solar panel detection model that is able to perceive the locations of the PV arrays properly having been trained with aerial and satellite images. The resultant image segmentation through the U-Net algorithm enlightens the proficiency and smoothness of the model even when the detection procedure could be complex enough for other mathematical models.

***Keywords*—** Aerial and satellite images, CNN model, solar panel detection, U-Net architecture.

I. Introduction

Renewable energy resources have already started replacing the application of conventional hydrocarbon deposits that causes an intense cost and impairment to the environment. In this transposition, solar energy has become a trusted resource causing solar panels to be installed by consumers effortlessly. For the easy extension of Photovoltaic solar panel usage, data accumulation of the installed capacity should also be straightforward. To avoid any manual involvement and facilitate the procedure, remote sensing is one of the best methods where aerial/satellite image data is utilized for solar panel detection.

On the object detection ground, a multitude of machine learning tools and image processing algorithms have been implemented with different levels of success rates. One detection methodology using an image processing technique included characteristic feature vector extraction of different portions of images for the segmentation purpose [1]. The process was promising based on pixel classification that belongs to the target object but demanded a large amount of time and analysis. Another technique included a machine vision algorithm using UAV (Unmanned Aerial Vehicle) images where a morphological operation was carried out to detect the coordinates of the solar panels in real-time [2]. Though the success rate was high in the process, there existed the possibility of misidentification in the complex aerial images.

For faster performance and higher accuracy, Artificial Neural Network (ANN) can be preferred over any other conventional ML model. Based on the object detection scheme ANN can be applicable in the solar panel detection sphere by adopting two crucial steps, feature extraction and classification [3]. Among the typical Neural Network architectures a few typically implemented frameworks are Multilayer Perceptron (MLP), Hopfield Neural Network, Extreme Learning Machine (ELM), and Convolutional Neural Network (CNN). Compared to the performance of a single-stage ANN classifier, a cascaded network has been proven to be more productive and computationally efficient to handle complexity with minimal expansion of time and cost [4]. This multistage operation enlightened the possibility of deep learning mechanisms that constitute neural networks with multiple layers for advanced computation. At this point, convolutional neural networks (CNN) have started taking the lead, and their application is visible on an enormous scale. Specifically, the reasons for the significant functionality of CNN are the ability of self-feature extraction and to outperform many other deep architectures [5].

As an application of CNN in PV solar panel detection,

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it has been obtained in [6] that how low-quality satellite images can be used efficiently for solar panel detection with high-rate accuracy of almost 87% and low-rate incorrect classification using CNN. The model consists of initial convolution layers of neurons that get connected to the subregions of the input images. These layers are followed by a non-linear activation function and pooling layer respectively where the pooling layer does the downsampling by reducing connections and parameters. The output layers were fully connected that performed the classification task. The aim of the mechanism was to anticipate power capacity and energy generation using three-channel (RGB) satellite images and make better use of low-quality data. On the other hand, manual labeling of the target objects in the input data set of complex images for training the proposed convolutional network (ConvNet) has been implemented in [7] to facilitate large-scale solar panel mapping. So that high accuracy comparable to manual mapping can be achieved. The manual labeling aids to extract features by the network efficiently. The feature extraction took place in multistage, low-level features such as edges or corners at early stages and high-level information such as whether a roof or a road at the last stages. The output was pixel-level segmentation that not only helped to identify the location of very small objects but also the spatial extent. So, one assumption can be stated that the availability and pre-processing of the input data are crucial.

In this paper, a CNN-based U-Net structure will be discussed that is distinct from the conventional CNNs by the means of connection of the valid portions of each convolution layer instead of having a full connection [8]. Along with this, a few more applications of the U-net-based models will be mentioned as well, and a comparison of the performances will be explored. After that, a few sample results will be visualized executing the aforementioned structure where the training data is built up on the aerial images of two sites in California; Oxnard and Stockton where the raw and the manually segmented images are masked by detecting the location of the solar panels using the Geojson files of the images that contain the geographical data. For more precise operation, cropped versions of the input images are implemented. In addition, optimization has been executed using a significant approach that is Hogwild; Stochastic Gradient Decent (SGD) which allowed to mitigate the sparsity of the optimization process [9].

II. RELATED PV PANEL DETECTION ALGORITHMS

To accumulate the data on installed solar panels, many algorithms have been adopted based on object detection schemes. Each model has its significance and shortcoming in respect of data availability, quantity, and feature selection. Usually, the complex background, low resolution, or lacking feature extraction while data preprocessing become responsible for less accuracy. Among many ways of data acquisition, one customary arrangement consists of remotely sensed image data acquired by aerial devices or satellites. Diaz et al. executed two detection methods in [10] by exploiting prior processed thermal images that incorporated a classical machine learning approach consisting of edge detection, segmentation, and segment classification using a Support Vector Machine (SVM) algorithm. Here, thermal images are acquired by exploiting the far-infrared wavelength which is beyond the human eye's spectral range, and by depending on the object's temperature [11]. The second approach was based on a deep learning framework named mask R-CNN that was well applicable to image segmentation purposes. To overcome the challenges such as irregular distribution, edge distortion, saturated regions, etc. due to the use of thermal images, an additional step was adopted that included contouring and extrapolation of the contours for the PV panel-like regions.

There persist an enormous number of deep learning techniques to identify solar panels with high accuracy. In [12], an automated PV installation detection scheme based on CNN had been implemented that used both the high-resolution satellite images and low-resolution Regulatory Authority for Energy (RAE) data and a comparison in outcomes was established. The structure of a CNN contains the sparse connection between the layers that define the connectivity of neurons of one plane to the neurons of a portion of another plane. Thus CNN is different from conventional multilayer neural networks. The identification accuracy with high-resolution data obtained from the aforementioned model was 60% which can be improved further using larger data sets. Progressively, the implementation of two CNN approaches was observed in [13] named VGG [14] and SegNet [15] architecture where the algorithms were compared at the end. In these methods, semantic segmentation was meant to be adopted where SegNet showed better performance in predicting PV panel shape and size than the VGG model in terms of pixel-wise object detection. In this case, high-resolution aerial imagery was used potentially which is publicly accessed in [16].

Finer performances can be noticeable in more CNN models using higher-resolution aerial imagery such as Malof et al. [17] demonstrated the improved output from a CNN model [18] by comparing it to the performance of a machine learning approach named Random Forest (RF) classifier [19]. RF classifier consists of a supervised statistical classification approach that was initially exploited to detect the locations of the PV panels in the large aerial data set [20] and then CNN was executed based on the outcome of the RF model to obtain improved results. In the case of detecting solar panel-like small objects, CNN expresses some difficulties as the operation includes a series of downsampling and loss of recovery of the small object's existence through the process. So, Yuan et al. adopted a novel CNN algorithm named ConvNet [21] in [7] where the methodology had been able to recognize PV panel location as well as spatial extent in images of complex backgrounds. As the training data was manually labeled, the efficiency was comparable to manual mapping and it can be improved further by incorporating road maps to avoid the overlapping of PV panels with buffer areas near roads in the images.

Apart from the CNN-based object detection models, machine learning approaches also contribute to the detection purpose with similar significance. In [22], an Random Forest (RF) classifier [19] had been employed resulting in pixel-wise detection that was improved further with a few post-processing steps. The principal contribution of the proposed approach was the determination of the precise shape and size of the detected PV panels and that was accomplished by the object-level mechanism after having the pixel-based mapping using the RF classifier. The used input imagery was acquired from a huge collection of high-resolution aerial images [20]. Among many other classifiers, Support Vector Machine (SVM) is one of the straightforward methods that deal well with complex features. In [23], SVM had been implemented for distinguishing the solar sites where the data was prescreened and feature extracted in initial steps. The preprocessing saves operational costs and time and helps to evaluate the output efficiently. Another computer vision-based algorithm has been analyzed in [24] that mainly dealt with the statistical analysis of the characteristics of the detected outcome. It showed the homogeneous and heterogeneous texture and color features of the resultant PV panels.

All the above-mentioned algorithms have been summarized and presented in Table 1. This paper includes a brief introduction to a novel CNN structure called U-Net that accomplishes semantic segmentation by mitigating the limitations of the aforementioned methodologies. An implementation of the mentioned U-Net architecture [8] has been done in [25] for solar panel detection having the F1 score of approximately 97.15% where the F1 score defines the average pixel values of the overlap of ground truth and prediction. The algorithm had been able to differentiate the detected PV panels for distinct land types and associated different building patterns with different roof colors. Moreover, the mentioned approach also considered changes in the resolution of input data in the case of low-resolution images to avoid misclassification.

Table 1. Summary of the Solar Panel Detection Algorithms

Method	Description	Weakness
Diaz et al. [10]	One classical ML method and one DL method were used using UAV thermal imagery	Loss of edges, edge distortion, and loss of panel geometry
Ioannou et al. [12]	Based on CNN (InceptionV3 model) that automatically detects PV panels using high-resolution satellite imagery	Better performance for high-resolution images than using low-resolution images
Camilo et al. [13]	Two CNN models (VGG and SegNet) have been implemented and compared	Estimating uncertainty in prediction can be a future scope for the SegNet model [15]
Malof et al. [17]	CNN model [18] performance for the Identification of solar panels was compared with a machine learning process; the Random forest (RF) classifier [19]	The precise shape or size of the PV panels could not be evaluated
Yuan et al. [7]	A novel CNN-based algorithm for solar panel detection in large-scale images using manually labeled training data	Performance would be improved if the road map was provided to avoid the overlapping of PV panels with buffer areas around the roads
Malof et al. [22]	RF classifier-based model [19] that determines the shape and size of the solar panels precisely	The characteristics of the detected PV panels could not be evaluated
Malof et al. [23]	SVM classifier-based model that determines the PV panel locations from preprocessed aerial imagery	Model performance was not evaluated for different landscapes
Li et al. [24]	Computer vision-based algorithm for detection and statistical analysis of obtaining characteristics of the detected PV panels	Uncertainty analysis was not included

III. U-NET-BASED CNN STRUCTURES FOR SOLAR PANEL DETECTION

U-net architecture is one of the most accepted supervised CNN models that requires a small set of training data for object detection and segmentation. In Figure 1, the basic structure of the symmetric U-shaped network has been presented that consists of a fully convolutional network (FCN) architecture [26]. It contains two phases of operation named encoding and decoding [8]. The encoding portion is also called the contracting path that downsamples meaning the max-pooling operation by merging similar features, whereas the decoding includes expansion or upsampling for restoring the high-resolution features into the original image format. One significant property of this framework is that the layers are not fully connected and it rather focuses on the valid part of each convolution by resulting in unpadded output. The missing pixels of the edges are retrieved by extrapolation compared with the input data.

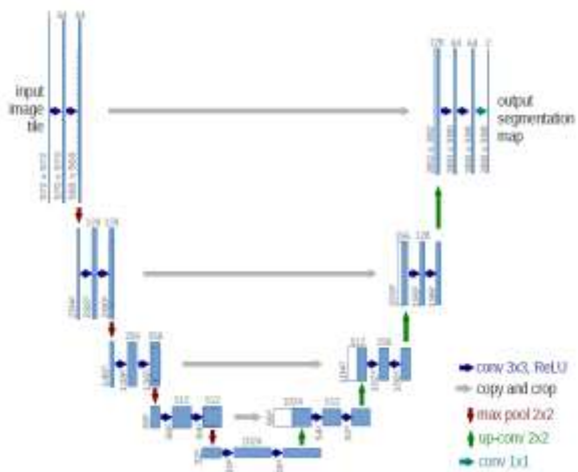


Figure 1 U-net architecture, blue boxes denote the multi-channel feature maps and white boxes denote the copied feature maps [8]

In Figure 1, The construction constitutes four basic convolutional blocks on each side having downsampled output from the left path fed as input to the right upsampling path. Initially, two consecutive 3x3 convolution takes place on the input data which is followed by non-linearity handling with ReLU function and repeated 2x2 max-pooling operation as downsampling resulting in doubled feature channels. On the other hand, a reverse mechanism accomplishes the process in the decoding stage. The intermediate result primarily goes through up-convolution by a 2x2 window where the features are halved and then a rail of 3x3 convolution is done again with the latter ReLU operation. In this assembly, 23 convolutions are done in total having a number of maps as a final result associated with the desired classes with 64 feature vectors for each map.

Like in [25], this novel structure had also been implemented in [27] to identify solar panel location and size with an accuracy of approximately 94%. To get improved accuracy, the training data got passed through semantic segmentation and data augmentation and also network parameters were varied to develop performance. In [28], a combination of the U-net model and EfficientNet-B7 classifier for the encoding framework had been introduced that improved the accuracy of detection to 96%. In the proposed model, the two-branch U-net structure was designed for semantic segmentation to annotate the PV panels in training images, whereas the EfficientNet-B7 classifier identified the existence of the panels in sample data. By deploying the methodology demonstrated in [8], another approach was obtained in [29] where a combination of a classifier ResNet34 and U-net structure was adopted. In the first step, the classifier determined the presence of solar panels and in the next step, the segmentation was accomplished by the U-net framework. In the end, pixel-wise probability distribution was analyzed of the detected PV panel regions.

Table 2. Performance Comparison of the U-net Architecture

Ref.	Classifier Architecture	Accuracy Measurement	Future Scope
[25]	CNN with U-net	F1 score ~ 91.75%	Faster convergence
[27]	CNN with U-net	F1 score ~ 80%	Variation in training data.
[28]	U-net with EfficientNet-B7 classifier	F1 score ~ 92%	Training data from various locations.
[29]	U-net with ResNet34 classifier	F1 score ~ 95%	Determination of suitable classifier.
[30]	U-net with EfficientNet-B7 classifier	F1 score ~ 95%	Use of synthetic aperture radar (SAR) images for training.
[32]	U-net with cross-learning	IoU score ~ 72.8%	Variation in training data.
[34]	U-net with Mobilenet	DSC score ~ 90%	Improvement in the model structure.

To evaluate the efficacy of the U-net architecture, a comparison to several superior algorithms such as DeepLabv3+, Feature Pyramid Network (FPN), and Pyramid Scene Parsing Network (PSPNet) has been established in [30]. In this case, the U-net structure with the EfficientNet-B7 classifier has been proven to be a better performer again. The above-mentioned models are available in the repository that is framed in PyTorch [31]. Another application of U-net can be recognized in [32] for segmenting small-scale Residential Solar Panels (RSP). The generic U-net has been formulated based on cross-learning that contributes to the optimization process of the U-net and makes it perform better. In the further extended version, a threshold was confined to avoid the overfitting caused by the cross-learning process. Along with adequate performance, it is also necessary to minimize operational time consumption and cost as well. To satisfy the mentioned criteria an ensemble of two CNN models named U-net and Mobilenet [33] had been followed in [34]. This kind of combinational arrangement not only increases the accuracy of the results but also minimizes the number of network parameters and saves computational time.

IV. Model Implementation

In this section, to visualize the outcome of a U-net-based deep learning model for PV solar panel detection and segmentation, some results of the model execution [35] will be carried out.

A. Training Data Generation Using Aerial Images

To achieve efficient performance from a CNN model, training of the model should be accomplished sensibly with an intact data set. For this reason, data should be obtained from an authentic source. In this implementation, to detect the solar panels, aerial images had been collected of two regions named Oxnard and Stockton in California as ground data [36]. Not necessarily all the captured images had solar panels. The images were obtained along with the metadata files that consist of the geographical positions of the solar panels.

Using the location coordinates of the solar panel, a masking scheme was generated that visualized the target by suppressing other pixels in the original image as zeros. The masked output is shown in Figure 2. Using the available images from Oxnard and Stockton, a training set was constructed with the original and masked versions of the images. For better learning of the model, other cropped versions of the images were acquired which were implemented for training the CNN model.

B. Resulting Output from the CNN with U-Net Architecture

As an initial step, a CNN model was chosen from the Python library by loading the package named 'torchvision' which contains necessary computational models, data sets, and upgraded image transformation techniques [37]. One of the significant features of using this package is, the pre-trained weights are already provided while training the chosen model. Undoubtedly, these pre-trained models lessen the computational time and complexity.

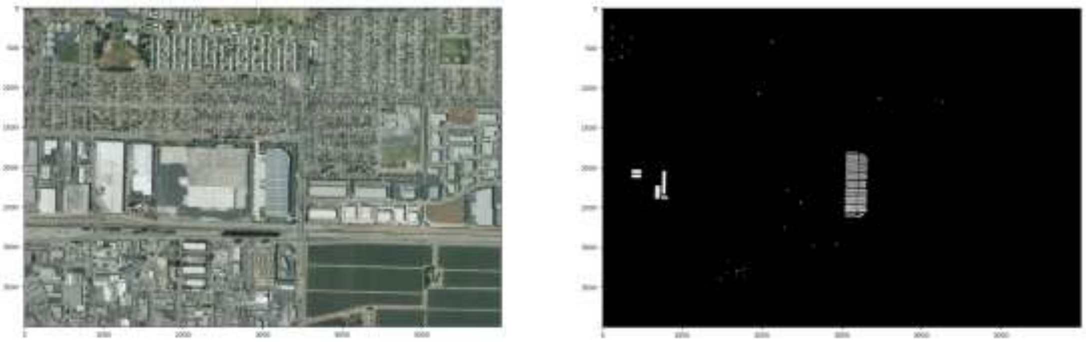
In this work, a CNN model had been chosen that was implemented by following U-Net architecture. As a generalized definition, the U-Net structure adopts such a strategy that requires a few images as a training data set because of the ability to grab and localize potential contexts [8]. Along with features of this novel architecture data, augmentation in a specialized manner was also necessary, so that it might require less processing time.

As an unavoidable part of the deep learning network, optimization should be wisely chosen as well. An outstanding approach had been implemented by following the SGD algorithm. This approach incorporates the mechanism to deal with the sparsity and sequential nature of the basic optimization procedure along with linear speedups [6]. Having a trained model, a test data set can be implemented to get the segmented output as a result. For example, Figure 3 shows the true positive that came up from this model. Besides the successful segmentation, false positive results were also visible but at a low rate.

V. Future Direction

Apart from the generic structure of the U-net-based CNN architecture, modified models can also be in use with improved performance. For instance, in [38], Guo et al. proposed an algorithm for cloud detection named attention U-net that was formulated upon the methodology described in [39]. The process incorporated a few modifications in the original U-net such as skipping some connections between the encoding and the decoding stage that aids to avoid unnecessary information and features. In a very recent work [40], a modified U-net model has been introduced for object detection that included batch normalization layers, faster convergence, and a tool named "RMSprop" to upgrade the parameters promptly as the major upgrades. Likewise in [41], an inception module has been integrated with the U-net which permitted the extraction of features without any resolution loss.

Though the mentioned schemes had been implemented for other applications than the specific PV panel detection, implementing them for this purpose would be noticeable and the improvement should be analyzed. In addition, more upgraded techniques are to be appended in this case such as an enhanced U-net model (E-UNET) [42], a residual U-net [43], a recursive attention U-net [44], and many more.



(a) Original Image Containing Solar Panel (b) Masked Image Detecting Solar Panel

Figure 2. Labeling Solar Panel for Model Training [35]

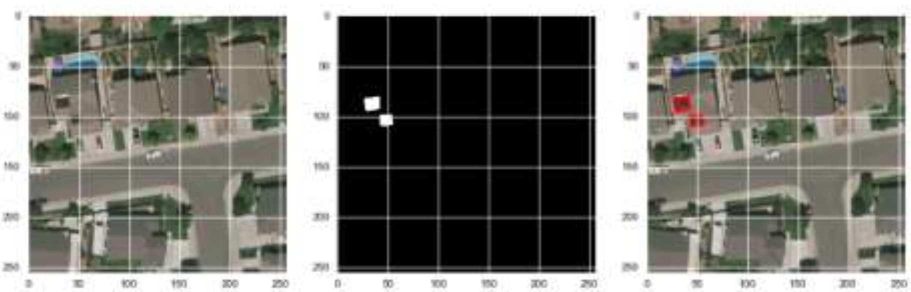


Figure 3. True Positive Results Obtained from the Model [35]

VI. CONCLUSION

Using deep neural networks in semantic segmentation applications always results in high accuracy. The U-net-based CNN model has become another example of that statement. Applying this method to calculate the installed capacity and location of the PV solar panels has become a liberal aid to the minimization of carbon emissions and adoption of renewable energy resources for power generation. To develop the model for better outcomes, more developed technologies can be combined such as U-Net++, FPN, DeepLabV3+, PSPNet, and so on.

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