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PHOTOVOLTAIC INSTALLATIONS CHANGE DETECTION FROM REMOTE SENSING IMAGES USING DEEP LEARNING

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ABSTRACT

The development and monitoring of Photovoltaic (PV) installations is of great interests for the Chinese energy management agency in recent years. The traditional land change detection of PV installations has issues pertaining to low efficiency and high missed detection rates. Therefore, this paper explores an efficient and high accurate detection method of PV installations land use changes from remote sensing images in order to help relevant stakeholders to better manage and monitor urban energy and environment. In this paper, Full Convolutional Network (FCN) and classical segmentation convolutional network (U-Net) based deep learning algorithms are used to build change detection models. To evaluate the model performance, we have built the change detection dataset from Northeast Petroleum University - Photovoltaic Remote Sensing Dataset (NEPU-PRSD) of PV installations in Western China. The experimental results show that both models can achieve good accuracy in change detection regarding PV installations.

Index Terms— Remote sensing, change detection, U-Net, full convolutional network, deep learning, convolutional neural network

1. INTRODUCTION

A transition from traditional energy industry into a green and low-carbon solutions plays an essential role in achieving sustainable development. In 75th session of the United Nations General Assembly, China acknowledged that its carbon emissions will peak in 2030 and announced ambitious target: to be carbon neutral by 2060 [1]. China's high carbon emission industries are concentrated in the energy industry. The energy transformation and monitoring of the power industry is particularly important to the carbon neutral target, as for the heavy industry electric power accounts for more than 30% of the total emissions [2]. In recent years, applications of Photovoltaic (PV) technologies have emerged as a potential alternative low-carbon technology [3]. However, the transition to this new low-carbon energy can cause a change of the land use [4]. Therefore, monitoring the land change resulting from installation of PV systems is important for providing information to policy makers to balance the environmental, social and economic impacts. Moreover, accurate monitoring and detection of PV installations geographic locations and areas of the change in the region can provide useful information for policy makers as a reference for the next energy deployment and estimation decision.

Using remote sensing, satellites can obtain global remote sensing images without geographical restrictions, which provides convenience for monitoring of this renewable energy. With the recent emergence of high-resolution satellites, monitoring PV installations from optical satellite remote sensing images becomes possible.

The deep learning based algorithms are able to address the challenges for change detection from satellite images in large scale application scenarios [5]. Recently, a number of research studies have focused on the detection of the solar PV panels and PV systems from satellite imagery [6]–[8]. One recent research study used Long Short-Term Memory (LSTM) networks to monitor the change of a PV field using Sentinel-2 images [9]. Very little research focuses on the change detection of large-scale PV installations from high-resolution remote sensing datasets and there is also lack of the well-labelled dataset.

To monitor the changes of PV installations in a large scale from high-resolution remote sensing images, we have built a dataset named Northeast Petroleum University - Photovoltaic Remote Sensing Dataset (NEPU-PRSD) by using the high resolution optical remote sensing images from Google Earth Imagery. In this paper, Full Convolutional Network (FCN) [10]–[12] and U-Net convolutional network [13]–[15] algorithms have been selected to determine the geographical location and area of land changes caused by PV installations. We used the NEPU-PRSD dataset to evaluate and compare the performance of these two models.

2. DATASET AND STUDY AREA

2.1. Dataset

The experimental data is the remote sensing satellite image data obtained from Google Earth. Google Earth is virtual Earth software developed by Google. It provides satellite photos, aerial photography and GIS on a three-dimensional model of the earth and also provides remote sensing images with multiple resolutions. This paper uses its remote sensing image with a resolution of 0.25m. We have constructed our NEPU-PRSD dataset using the 0.25m resolution remote sensing satellite image data obtained from Google Earth. It includes the land areas for PV installations in three provinces in China - Qinghai, Gansu and Ningxia. Our dataset includes 4000 samples, and the samples are 1024 *1024 pixels each. The time of the first and last images are of the same scene taken on December 31, 2014 and December 31, 2020 respectively.

2.2 Study area

In this work, the model was built using the images from all three provinces mentioned in Section 2.1. The evaluation area is Jinchang City which located in Northwest China and central Gansu Province, at longitude 101º04'-102º43' (East) and latitude 37º47'-39º00' (North), covering a total area of 9,593 km^2. Jinchang City is altitudinally high in the South and low in the north, with crisscross mountains and rivers. The main peak is 4,442 meters above sea level with rugged and steep terrain. In recent years, with the increasing attention to new energy, several large-scale PV installations have been established in this area.

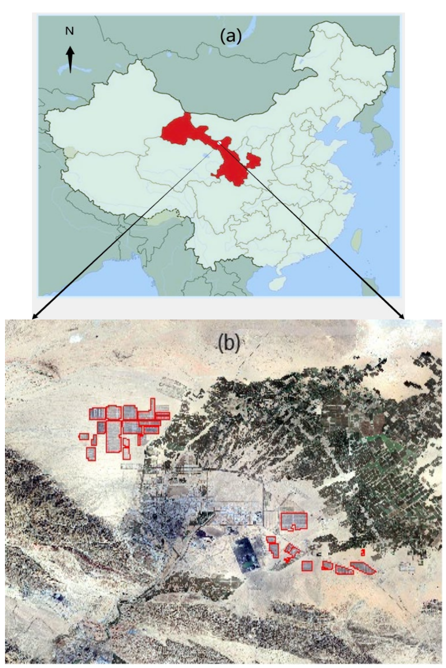

Figure 1 The study area (a) The red area is Gansu Province, China (b) An example of a land area for PV installations in Jinchang City, Gansu Province.

3. METHODOLOGY

FCN is widely used in remote sensing image semantic segmentation, but there are still some problems of poor segmentation accuracy. U-Net is an improved model of FCN. In recent years, it has been applied in all directions of semantic segmentation, such as semantic segmentation of satellite remote sensing images.

As shown in Figure 2, the overall network structure is divided into two parts: convolution part and deconvolution part. The convolution part borrows some classic CNN [16] networks (such as AlexNet [17], VGG [18], GoogLeNet [19]) and replaces the last fully connected layer with a convolution layer to extract features and form a heatmap. The deconvolution part samples the small-size heatmap to obtain the original size of the semantic segmentation image. FCN has no limitation on the size of input images.

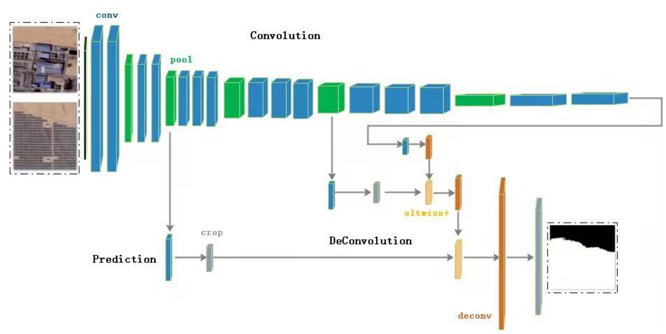

Figure. 2 Structure diagram of remote sensing image change detection model based on FCN

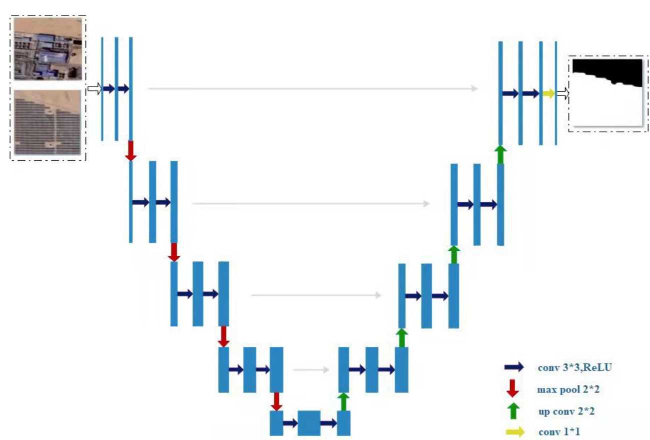

Figure. 3 Structure diagram of remote sensing image change detection model based on U-Net

As shown in Figure 3, the U-Net network consists of an encoder (left) and a decoder (right). We have adopted a 5-layer network structure. All convolution operations are applied to 3×3 convolution kernel, stride and padding value of 1. The activation function used is Rectified Linear Unit (ReLU) [20]. In the encoder, depth is increased by a convolution operation and 2x2 max polling operation is applied with a stride is 2. For the decoder, 2x2 up sampling is applied to enlarge the size of the feature map. The U-Net model uses the jump connection structure to connect to all shallow features, and the pixel positioning is more accurate. The size of the input and output images are the same.

4. EXPERIMENTATION

4.1. Data pre-processing

In this paper, the NEPU-PRSD dataset that we have constructed includes some cloud-affected images. Therefore, in the data pre-processing stage we have applied the wavelet analysis [21] method to remove the low-frequency cloud components by wavelet decomposition. In the labelled sample images, a pixel value of 255 represented the changed class, and the pixel value of 0 represented the unchanged class. 2000 samples are used for training, 800 samples for verification and 800 samples for testing.

4.2. Implementation Environment

The experimental environment of this paper is based on an Ubuntu operating system. Python is used as the main programming language and pytorch library is used for deep learning model implementation. The training time of FCN and U-Net model is 8 hours and 6 hours respectively, and the test time is 3 minutes and 2.5 minutes respectively.

4.3. Model evaluation

As shown in Table 1, the ground truth images are used for the creation of a confusion matrix. TP (True Positives), FN (False Negatives), FP (False Positives) and TN (True Negatives) are defined in the Table 1 below. For example, TP is the number of pixels in the areas has actually changed, while FN is the number of pixels in the areas that has actually changed but is not detected.

Table 1 Change detection confusion matrix

	Prediction Changed	**Prediction Unchanged**
Real Changed	TP	FN
Real Unchanged	FP	TN

Three model performance metrics are used in evaluating the proposed two models including: precision, recall and F1 score. The definition of the three metrics is as follows:

$$\text{Precision} = TP / (TP+FP) \quad (1)$$

$$\text{Recall} = TP / (TP+FN) \quad (2)$$

$$F1 = 2*(\text{Precision}*\text{Recall}) / (\text{Precision} + \text{Recall}) \quad (3)$$

4.4. Experimental Results

Table 2 shows the precision, recall and F1 score of FCN and U-Net model training respectively. The results show that the U-Net model is better than FCN model and the F1 score of U-Net achieved 0.862. Figure 4 shows the prediction of experimental results on images.

Table 2 Precision, Recall and F1 score

Model	Precision (%)	Recall (%)	F1 score
FCN	86.2	83.0	0.846
U-Net	87.8	85.0	0.862

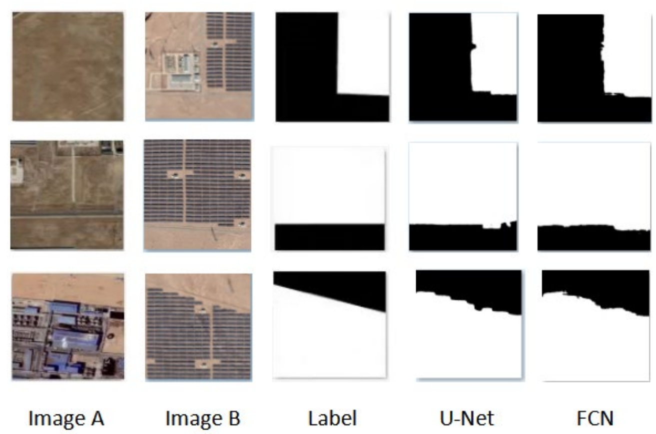

Figure.4 Image A is the front phase, image B is the rear phase, label is the labelled ground truth, and the last two columns are detection results from using the U-Net and FCN models respectively. (The white colour indicates the change area and black colour indicates the unchanged area.)

5. CONCLUSION

The experimental results show that the change detection model framework based on FCN and U-Net can be used as effective models to detect the change of the land areas for PV installations in parts of Western China. It can therefore further provide effective technical support for the deployment and management of this new sustainable low-carbon energy source. The research shows the U-Net model has less loss of boundary information and achieves higher accuracy compared with FCN model. For future work, we plan to carry out multi-phase change detection and further enrich our dataset by subdividing the change types of photovoltaic land to obtain higher change detection accuracy and photovoltaic change type information including bare ground to PV installations, from roads to PV installations, and residential areas to PV installations.

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