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Photovoltaic Output Potential Assessment via Transformer-based Solar Forecasting and Rooftop Segmentation Methods

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ABSTRACT

Given the escalating carbon emission crisis, there is an urgent need for large-scale adoption of renewable energy generation to replace traditional fossil fuel-based energy generation for a smooth energy transition. In this regard, distributed photovoltaic power generation plays a crucial role. Predicting the GHI in advance to predict the power of photovoltaic power generation has become one of the methods to solve the grid-connected stability in recent years, which enables the grid staff to dispatch and plan in advance through the forecast results, reduce fluctuations, and maintain grid stability. In this study, we present a deep learning-based method to assess photovoltaic output potential by solar irradiance forecasting and rooftop segmentation. First, we utilize a multivariate input Transformer model that incorporates various data to predict GHI; Second, using remote sensing images to train Swin-Transformer to identify the potential area of rooftop photovoltaic panel; Finally, the potential assessment was achieved by calculating the array output through the GHI and area data we generated in the first two parts. Our evaluation methodology and results provide technical support for the transition of energy structure.

Keywords: solar forecasting, photovoltaic potential, segmentation, deep learning, renewable energy

NONMENCLATURE

Abbreviations	
GHI	Global Horizontal Irradiance
DNI	Direct Normal Irradiance
POA	Plane of Array Irradiance
LSTM	Long Short-Term Memory
Symbols	
m	Meter
m^2	Square meter

1. INTRODUCTION

As global energy demands continue to rise and environmental concerns escalate, the development and utilization of clean energy sources have become imperative. Photovoltaic power generation, as a renewable and clean energy source, offers advantages such as pollution-free and sustainable energy production, making it a crucial role in the energy transition [1]. GHI is a pivotal indicator of photovoltaic potential, and its accurate prediction is vital for effective planning and management of photovoltaic systems. Rooftop photovoltaics, as a cornerstone of distributed photovoltaic systems, have the capability to fully utilize rooftop spaces in established urban or community settings. By installing photovoltaic panels on rooftops, solar power generation is enabled, maximizing the utilization of resources. In this study, we employed a variant of the traditional Transformer model [2] to achieve multi-variable input single-variable output prediction of GHI in the Christchurch area. Additionally, we utilized the Swin-Transformer model for semantic segmentation of remote sensing imagery in the Christchurch region, identifying rooftop areas. By combining these approaches, we finished an assessment of the photovoltaic power generation potential in the Christchurch area. The framework of our study is illustrated in Figure 1.

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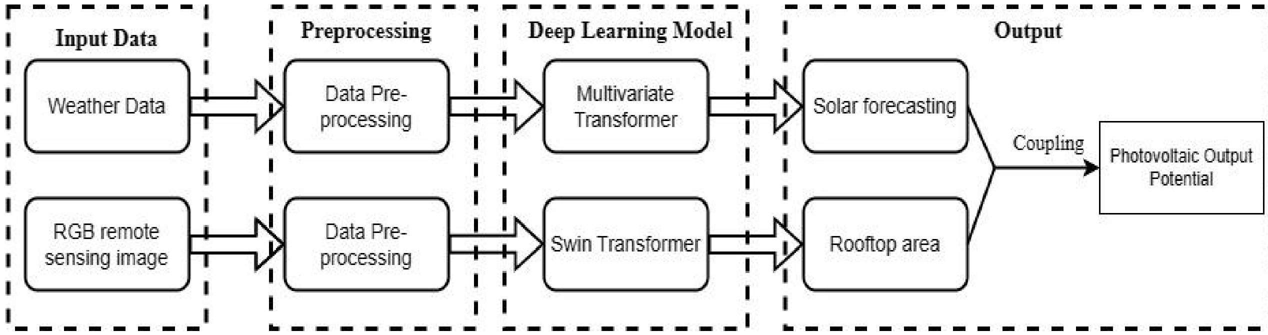

Figure 1.The framework of our deep learning-based photovoltaic output potential assessment method

2. RELATED WORK:

Regarding the forecasting of the GHI, recent research has utilized deep learning-based neural network models [3,4] and advanced time-series models such as LSTM model [5], and Hybrid-LSTM model [6-7], which have demonstrated promising results and facilitated the application of more efficient and innovative models.

As for the assessment of the photovoltaic potential, Some scholars offer a target segmentation method based on Image Grayscale Threshold using remote sensing images to recognize the rooftop area and realize the regional rooftop photovoltaic potential [8]. Researchers have propose a high-resolution remote sensing image building extraction method based on the DeepLabv3+ semantic segmentation model, and a set of assessment methods and steps for the development potential of building roof photovoltaics [9].

3. METHODOLOGY

3.1 forecasting

In comparison of CNN and LSTM models, the Transformer model offers several advantages, such as parallel processing and global information capture ability. Traditional transformer model consist of Encoder and Decoder stacks, innovatively utilizing self-attention mechanisms, enabling it consider the weights of all input variables and the correlations between input variables[10].

As a task for the unsupervised training of our model we consider the auto-regressive task of de-noising the input: specifically, we set part of the input to 0 and ask the model to predict the masked values. We simply use different patterns of masking to achieve different objectives, while the rest of the model and setup remain the same. Using a mask which conceals the last part of target variable to perform forecasting. In this study, We employed a multivariate input Transformer model in our study, where GHI, DNI, air temperature, relative humidity, wind speed, and solar zenith angle were used as inputs for training. By masking out the GHI values and having the model predict the masked regions, we finally achieved GHI prediction.

3.2 segmentation

In order to attain more accurate results for roof area segmentation, we employed the Swin-Transformer as the backbone network, as opposed to the traditional convolutional models used in previous experiments, for the purpose of extracting features from different scales of the input image. The advantage of using the Swin-Transformer model, in contrast to traditional CNN-based image segmentation models, lies in its capability to confine self-attention computations within non-overlapping local windows, while also allowing these windows to maintain connection and movement across the image. This hierarchical structure facilitates modeling at varying scales, exhibiting higher flexibility, and entails linear computational complexity with respect to image size, thereby enhancing the overall system's generalization capacity and efficiency. After fusing image features from different scales, we proceeded to train the Swin-Transformer model to conduct semantic segmentation at the pixel level. During training, each pixel is classified into one of two categories: building and others.

3.3 potential assessment

By considering the photovoltaic array's rated capacity and the coefficient indicating the efficiency change with cell temperature, we can obtain the output of the photovoltaic system. First, through the identified rooftop area, we can assume the photovoltaic array capacity. After setting the capacity of the photovoltaic array. We calculate the time-series local solar position list and surface tilt and azimuth angles for the tracker through the latitude and longitude of the assessment location. Second, in conjunction with the predicted solar irradiance data, we can compute the photovoltaic module temperature variation curve. This process ultimately leads to the calculation of the predicted output values of the photovoltaic array. In this study, we set the panel angle to 43 degrees, facing towards the north direction.

4. EXPERIMENTS

We utilized a three-year dataset from Christchurch, spanning from January 1, 2016, to December 31, 2018, at 60-minute intervals. The input variables consisted of environmental temperature, relative humidity, wind speed, DNI, GHI, and solar zenith angle. Aiming to predict a single variable, the GHI.

In this study, we utilized remote sensing images from within Christchurch. These images were segmented into 512x512 resolution patches and fed into the Swin-Transformer model for training. The objective was to identify and differentiate between building rooftops and other elements within a 1.4km x 1.4km area in Christchurch.

5. RESULTS

In the forecasting task, we use Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to evaluate the model. MAE is the average of the absolute differences between predicted values and actual observations. It measures the average deviation between model predictions and actual observations. The formula is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Here, n is the number of samples, y_i represents the actual observation of the i th sample, and $\hat{y}_i$ represents the model's predicted value.

RMSE is the square root of the average of the squared differences between predicted values and actual observations. Compared to MAE, RMSE is more sensitive to larger errors as it squares the errors before averaging. The formula is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

Similarly, n is the number of samples, y_i represents the actual observation of the i th sample, and $\hat{y}_i$ represents the model's predicted value.

The result is shown as Figure 2. Comparing to LSTM model, Multivariate Transformer have a better performance, Compared to LSTM, MAE has decreased by 2.86 and RMSE has decreased by 15.74, indicating the achievement of higher prediction accuracy.

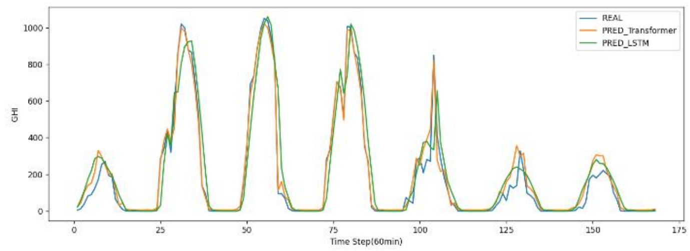

Figure 2. Prediction for one week.

	MAE	$RMSE$
Transformer	17.22	29.25
LSTM	20.08	44.99

Table 1. Results of Solar Forecasting

As for the segmentation task, The recognition results are illustrated in Figure 3. The total rooftop area can be calculated by counting the number of recognized pixels. Each pixel represents an area of 0.07m × 0.07m = 0.0049m². With a total count of 100,697,959 recognized pixels, the total area can be calculated as 0.0049 × 100697959 = 493,240m².

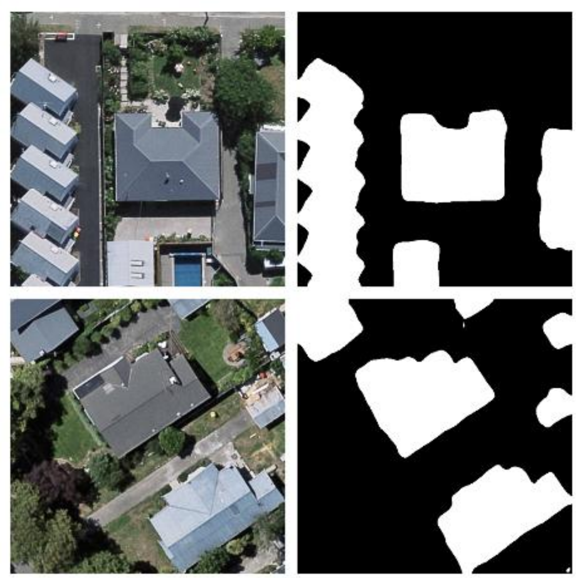

Figure 3. Comparison between segmentation results and the original image.

In the potential assessment task, we assume every 10 square meters of photovoltaic panels can achieve a power output of 1 kW. All the rooftop area have been installed photovoltaic panels. The total output power is

49324kW. Every 1kW array have a temperature coefficient of -0.4%/°C. Figure 3. Shows the photovoltaic potential of the selected area in 2018. Calculated POA and Production results are illustrated in Figure 4. The power output results are shown in Figure 5.

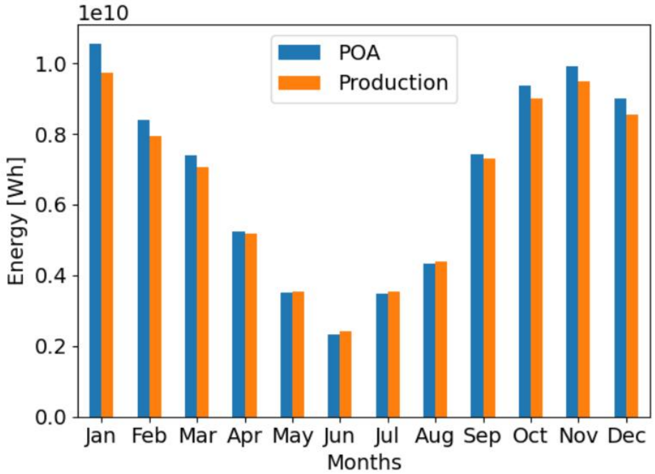

Figure 4. POA and production results calculated based on the predicted outcomes for each month.

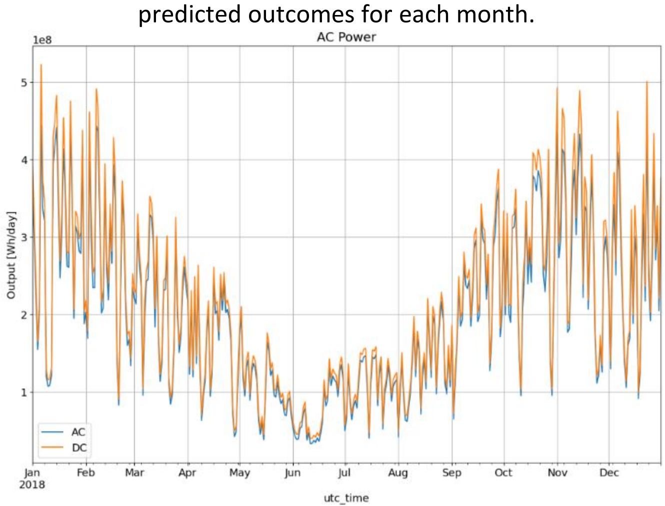

Figure 5. Predicted photovoltaic generation potential for Christchurch in 2018.

6. CONCLUSIONS

In this study, we initially employed a multivariate-input Transformer model to predict the GHI values for Christchurch in the year 2018. Subsequently, we utilized the Swin-Transformer model for semantic segmentation of Christchurch's urban remote sensing images, enabling the identification of roof areas suitable for photovoltaic panel installation. By combining these predictions, we calculated the photovoltaic generation potential for Christchurch. We believe that this study will offer robust support to the solar energy industry, providing technical guidance for the transition from conventional fossil fuels to renewable energy sources, and facilitating the process of energy transformation. In the future, we will design and develop more precise prediction and segmentation models to achieve more accurate assessment of photovoltaic generation potential.

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