Probabilistic Quantification of Solar Power Generation Loss Based on Images Capture by Surveillance Cameras

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Abstract

As the photovoltaic (PV) power has a very low carbon footprint, the use of solar panels is becoming widespread. However, the soiling of solar panels caused by severe weather will reduce up to 50% power generations. This challenge is considered by an existing method for quantifying the solar power loss. Whereas this method utilized a classification method, which is not sufficient for quantification resolution. To solve this, this project makes contribution on modifying the classification problem to a regression problem based on the convolution neural network (CNN), which will increase the resolution of the quantification result.

Keywords—Photovoltaic (PV) power, Solar panel, Convolution neural network (CNN), Regression problem.

1. Introduction

The rapid increase of solar panel installation demand in recent years is assisting to reduce global carbon emissions and the energy cost [1]. Meanwhile, the soiling problem, which diminishes energy strategy improvement, is Widely concerned. In that case, S. Mehta et al. [2] proposed a solution based on Convolution Neural Network (CNN). They utilized CNN to predict the power loss, soiling localization, and soiling type, to present instructions of maintenance. However, the CNN is considered as a classification model, which means the prediction of power loss is an interval (like prediction is 87.5%~100%). Therefore, the resolution of predictions is not enough.

Based on the problem, this project tends to use regression model instead of classification model. The advantage of regression model is that the outputs of CNN are close to certain values, not an interval, which is able to predict the true value more accurately.

In this report, we firstly analysis image data at section 2. Then, we reconstruct the ImpactNet-A model in [2] at section 3. After that, we train the model based on the given data, and show the result of classification error, mean square error (MSE) and L1 loss at section 4. Finally, we give the conclusion that the classification model has poor performance of high-resolution prediction at section 5.

2. Image Data Analysis

The image data is from Solar Panel Soiling Image dataset. It includes 45754 images of solar panels with power loss labels. There are 2 solar panels, and one of the panels is experimental object, which suffered from soiling, while another one is reference object, which is clean.

Images are sampled from experimental object, and power loss is computed by the power difference of experimental object and reference object, in percentage scale, with basis of reference object power. The environmental factors are time of the day and irradiance level. All the numerical values are included in the file name of each image.

Our object is treating images and environmental factors as features, and power loss as output to build a regression model. We extract data as following format:

(a). Image: 45754×3×192×192 (Number of pictures, Channels, Height, Width).

(b). Power loss: 45754 floats.

(c). Environmental factors: 45754 × 4 (Number of Environmental factors, (Hour, Minute, Second, Irradiance level)).

A single image data is shown by Figure 1.

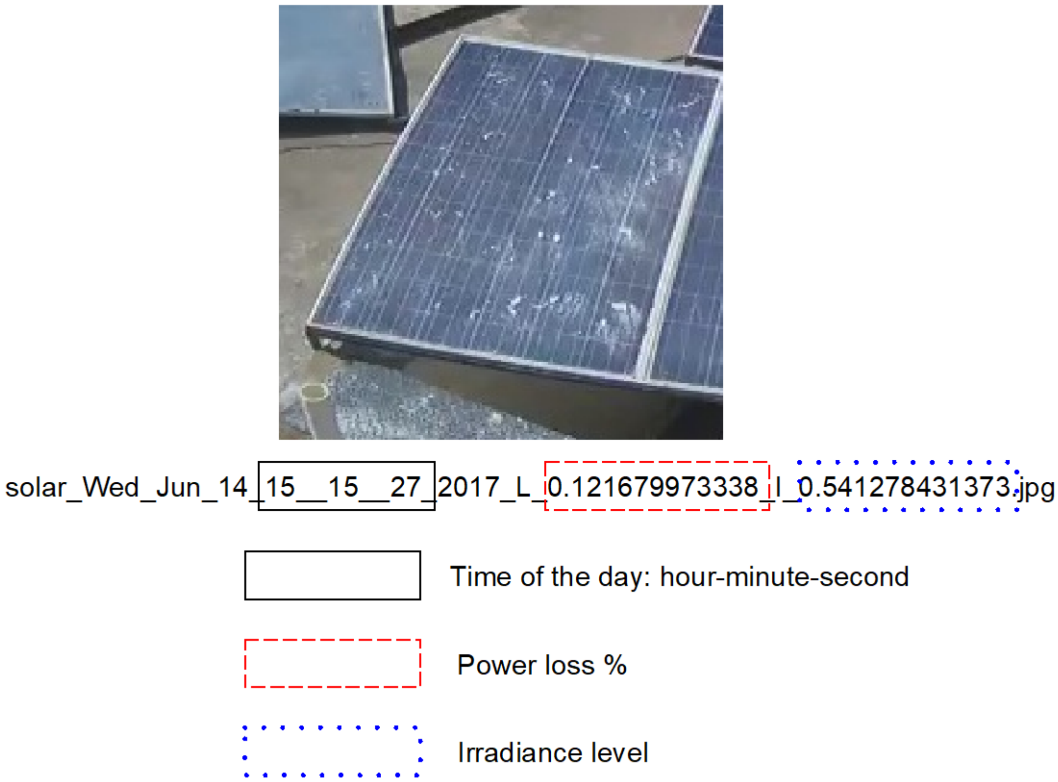


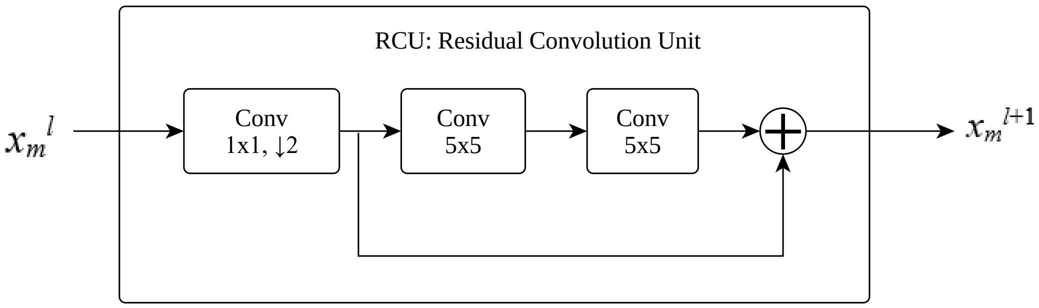
Figure 1. Image data indication.

3. Reconstruction of ImpactNet-A

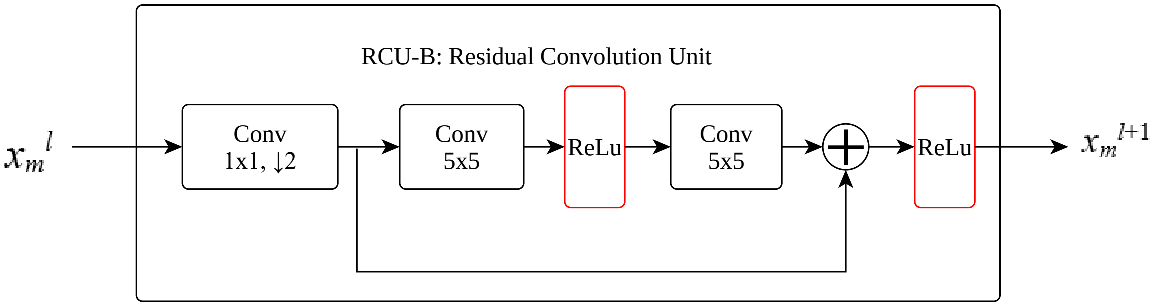
In this section, we will show the illustration of ImpactNet-A, and differences between implemented and original CNN.

In original paper network, ImpactNet-A consists 2 parts: image part and environmental factors part. At image part, the input is a 3-channel image, and the structure includes 1 Convolution layer, 5 Residual Convolution Units (RCU), shown by Figure 2 (a), 1 Average Pool layer and 1 Fully Connected (FC) layer. At environmental factors part, the input is environmental factors vector, and the structure includes 2 FC layers. At the end of the ImpactNet-A, the outputs of image part and environmental factors part concatenated, then connect through 2 FC layers. The output of the ImpactNet-A is an 8-dimensional One-Hot vector, indicates 8 ranges power loss from 0% to 100%. The illustration is shown by Figure 3 (a).

In the project implementation, we make some modifications. First, we add two activate functions, ReLu, in the RCU based on [3], shown by Figure 2 (b). Second, we add activate functions, ReLu, after all FC layers. The reason we add activate functions is that, the convolution and FC layers are linear transformations, and our dataset is apparently non-linear separable, so we need ReLu to perform nonlinear transformation. Finally, our structure is shown by Figure 3 (b).



(a) Original paper RCU



(b) Modified RCU

Figure 2. Residual Convolution Unit (RCU) structure.

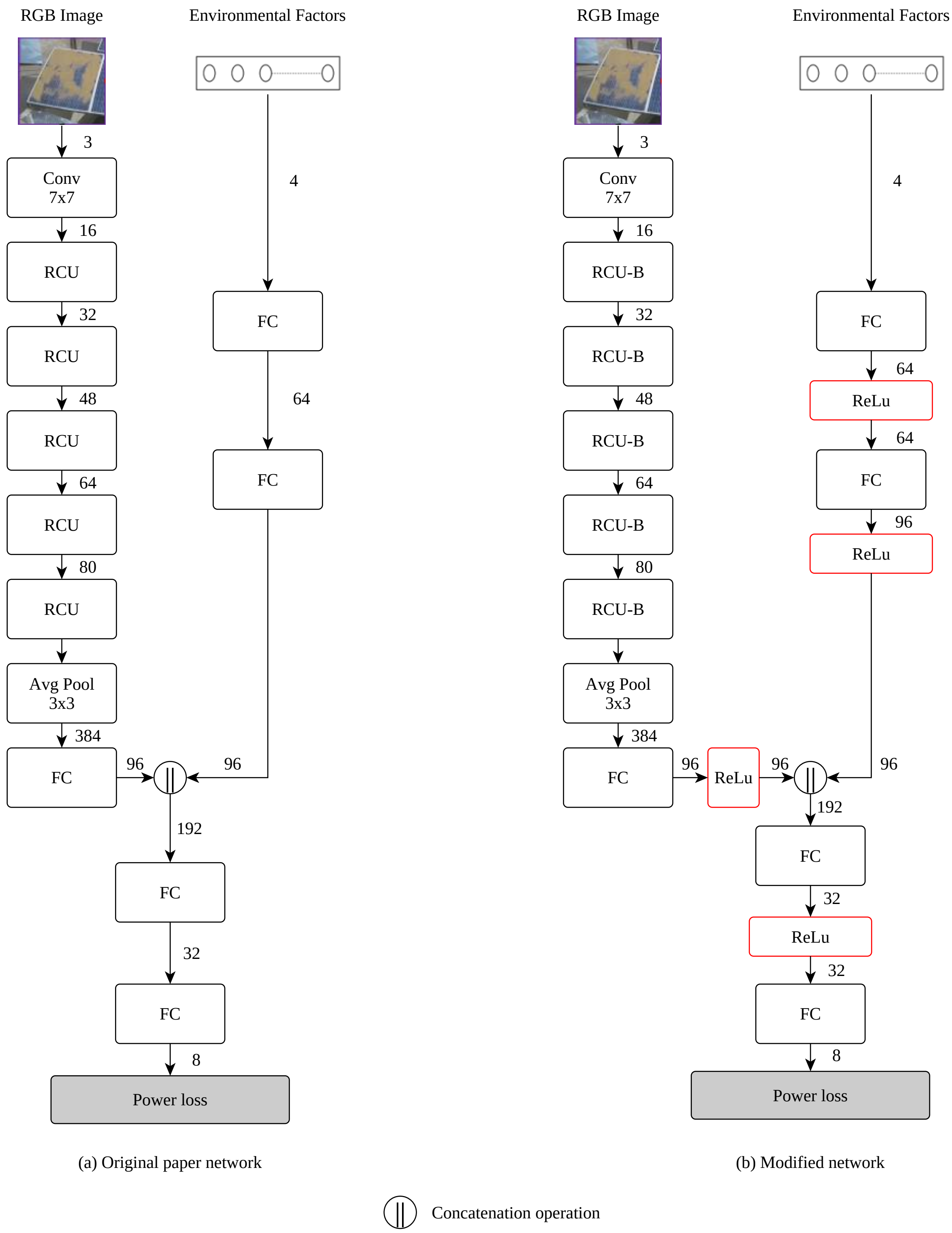
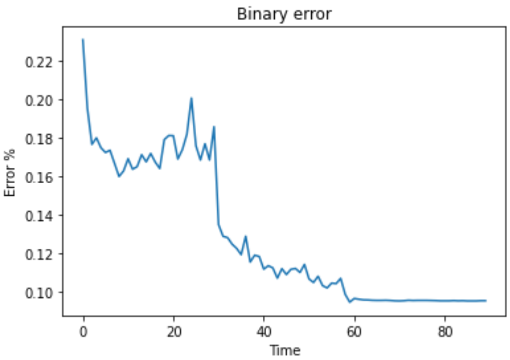


Figure 3. Structure of ImpactNet-A (a) original paper network, (b) modified network.

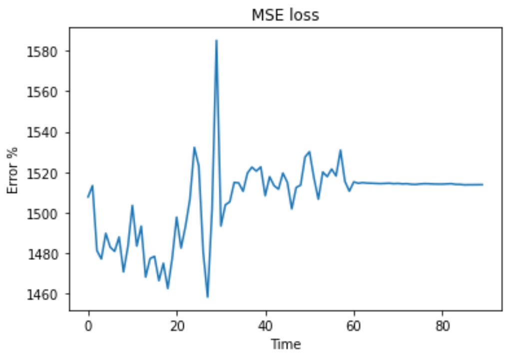
4. Experimental & Result

Based on the parameters given by [2], we train the CNN in 90 epochs, with batch size 32, and SGD with an initial learning rate of 0.01 decaying it by a factor of 10 after every 30 epochs, momentum of 0.9, weight decay of 0.0005, with random 27537 training data and 18217 testing data. We compute classification error, MSE and L1 loss at each epoch. For MSE and L1 loss, we convert the output to the numerical value by selecting the mean value of each bin, to simulate the high resolution prediction. For example, if the output is 3, the numerical value of this output is $3\times12.5+6.25=43.75$. The result is shown by Figure 4, with final error: (a) classification error is 0.09%, (b) MSE loss is 1517, (c) L1 loss is 27.3.

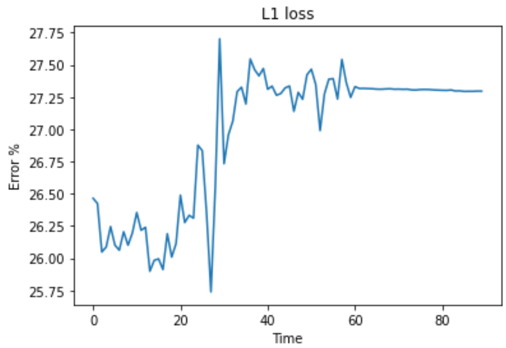
It is obvious that the model has a good performance on classification task. However, the MSE loss and L1 loss are terrible. Although the selecting of mean value of each bin is brute, it shows that directly using classification model is hard to predict power loss with high resolution, which is highly needed.



(a)



(b)



(c)

Figure 4. Result of experiment, (a) Classification error, (b) MSE, (c) L1 loss.

5. Conclusion

In this report, we reconstructed a CNN based on the work of S. Mehta et al and illustrate that the classification model performs terrible on high resolution prediction task. To be specific, we add some activate functions, ReLu, between FC layers, and in RCU to improve the non-linear transformation performance. Then we analyze the result of CNN output by indicators: MSE, L1 loss and classification error, and find that the CNN works not well for high resolution prediction. So, we conclude that using other model, like quantile regression, may have better performance.

In future work, we can modify the Impact-A net to a more complex model, like Impact-B. Moreover, we can change the output layer of CNN to implement quantile regression model, which may improve the performance of high resolution.

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