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, we build a novel model: Quantile Regression Neural Network (QRNN), by modifying the classification problem to a quantile 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), Quantile Regression Neural Network (QRNN).

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, we use Quantile Regression Neural Network (QRNN) instead of classification model to improve the resolution of prediction. The advantage of QRNN is that the outputs of CNN is the prediction of each value with confidence, which precludes a simple assessment of performance, like naively giving a binary decision. Also, we set more neural at output as more precise quantile probabilities to increase the resolution of output.

In this report, we firstly implement QRNN based on original ImpactNet-A at section 2. Then, we design quantile loss metric to evaluate ImpactNet-A model in [2] section 3. After that, we train the model based on the given data, and show the result of quantile loss at section 4. Finally, we give the conclusion that the classification model has poor performance of high-resolution prediction at section 5.

2. Implement QRNN Based on ImpactNet-A

Based on the original ImpactNet-A model, we modified the output of network by 99 neural, and each neural represents a predicted power loss (%). Quantile probabilities are from 1% to 99% with 1% increment for 99 neural. For ground truth, we copy a scalar value to a 1-by-99 tensor to match quantile probabilities, 1% to 99% with 1% increment. Figure 1 shows the implementation of QRNN.

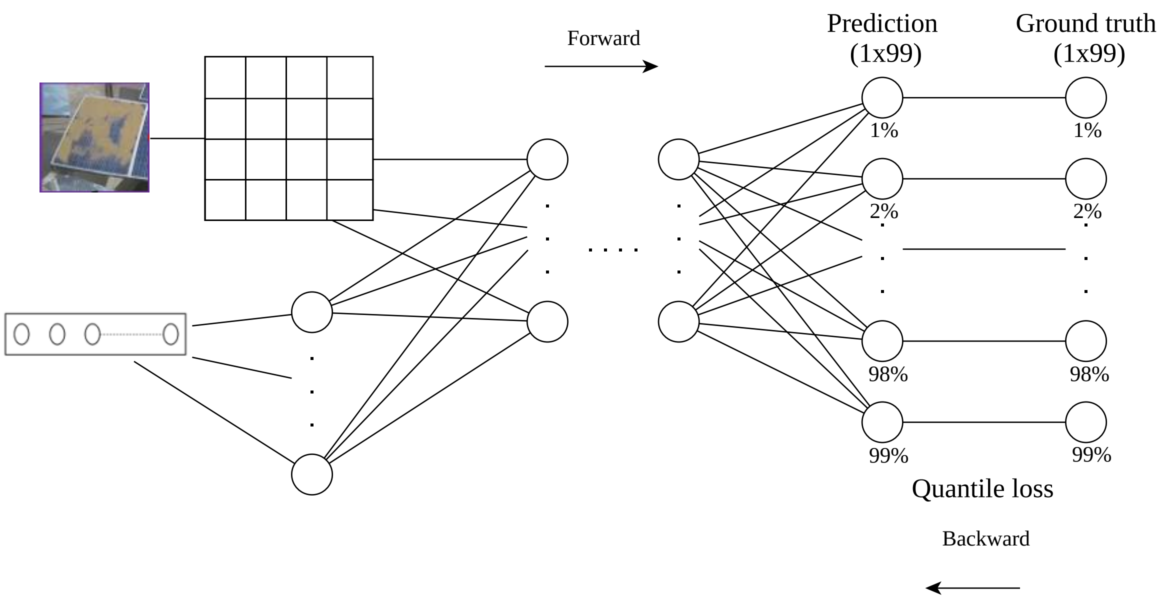


Figure 1. Implementation of quantile regression.

The loss function of QRNN is quantile loss, shown by (1 and (2 [3]:

$$\rho_\tau(u) = \begin{cases} \tau u & \text{if } u \geq 0 \\ (\tau - 1)u & \text{if } u \leq 0 \end{cases} \tag{1}$$

$$E_\tau = \frac{1}{N}\sum_{t=1}^{N} \rho_\tau\left(y(t) - \hat{y}_\tau(t)\right) \tag{2}$$

where τ is quantile probability in range 0-1, E_τ is quantile loss, N is total number of predictions, $y(t)$ is the observed value of each time t, $\hat{y}_\tau(t)$ is prediction value of each time t.

In addition, to avoid overfitting and gradient explosion, we add Batch Normalization and dropout at each layer.

3. Design of quantile loss for ImpactNet-A

Recall the classification model of ImpactNet-A by Figure 2. The output neural of the ImpactNet-A represents 8 power loss levels: 0%-100% with 12.5% increment. And each output value is a probability of the prediction falls in this bin. In this case, we can compute quantile loss as following:

(1) Convert power loss levels to 8 predictions $\hat{y}_{\tau}(t)$: 12.5%, 25%, 37.5%, 50%, 62.5%, 75%, 87.5%, 100%.

(2) Regularize output probabilities by Softmax, then compute accumulative probabilities for 8 predictions.

(3) Use accumulative probabilities represent 8 quantile probabilities τ.

(4) Compute quantile loss based on 8 predictions and 8 corresponding accumulative probabilities.

In this way, ImpactNet-A gives prediction of 8 quantile probabilities τ based on 8 determined power loss predications.

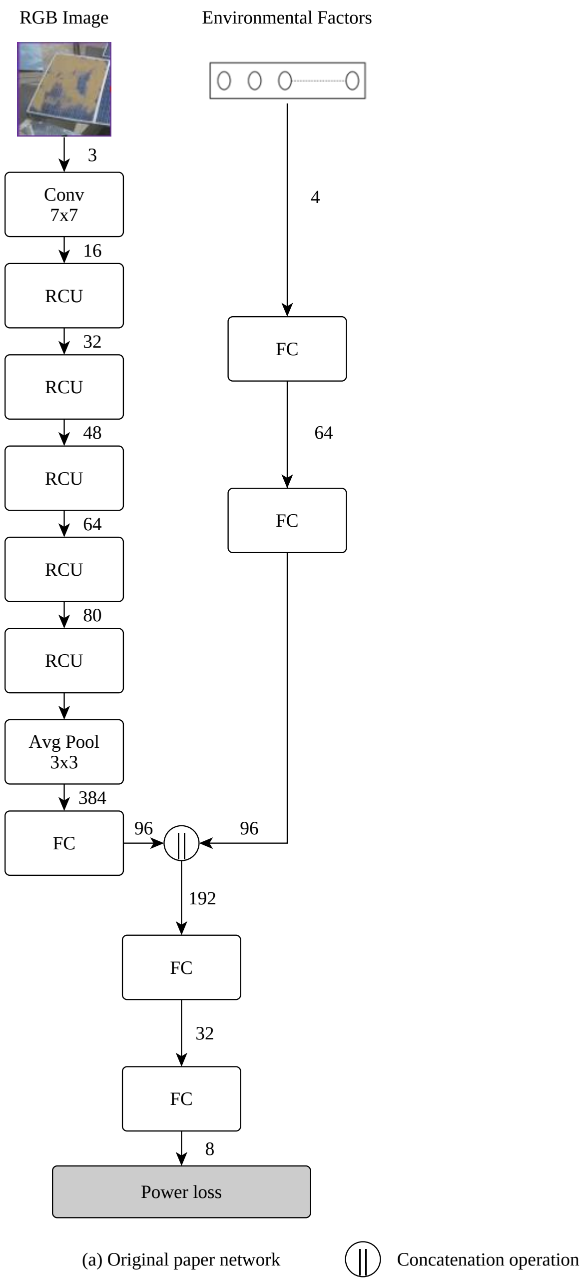


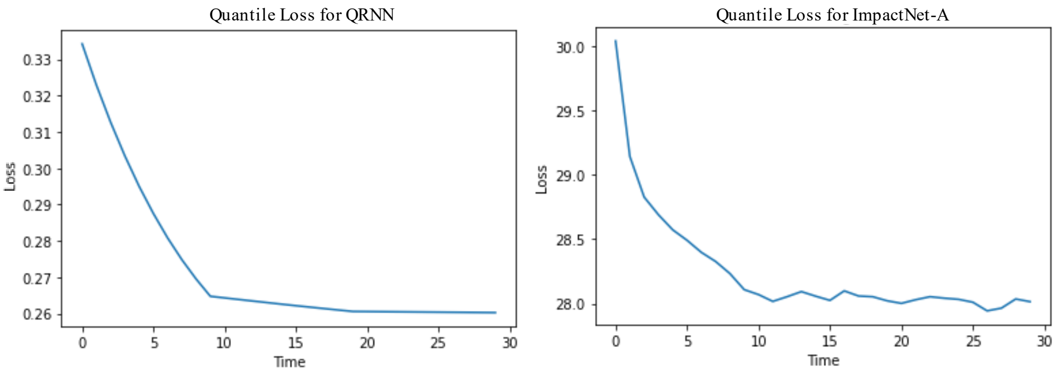
Figure 2. Structure of ImpactNet-A (a) original paper network, (b) modified network.

4. Experimental & Result

We train the CNN in 30 epochs, with batch size 32, and SGD with an initial learning rate of 0.0001 decaying it by a factor of 10 after every 10 epochs, 50% dropout for all fully connected layers and batch normalization for all convolutional layers, with random 27537 training data and 18217 testing data. We compute quantile loss at each epoch. The result is shown by Figure 3, with final error: (a) QRNN is 0.261, (b) ImpactNet-A is 27.8.

From two graphs, it is obvious that QRNN has better performance than ImpactNet-A. It is noticeable that quantile loss for QRNN is less than ImpactNet-A during the training: the range of QRNN is 0.25-0.33, while the range of ImpactNet-A is 27-30. Moreover, QRNN may have less loss if we insist the learning rate of 0.0001 while ImpactNet-A reaches optimal loss. Because losses of both models go down rapidly for first 10 iterations, then slow down the decrease speed, but QRNN keep decreasing its loss smoothly while ImpactNet-A fluctuates around 28%. This conjecture needs further experiment.

Plot of loss of ImpactNet-A shows that the compute method of quantile loss is reasonable. The reason is that even we train the model by Cross Entropy loss and evaluate by quantile loss, the quantile loss goes down well and reach an optimal value. This model indeed decreases the quantile loss.



(a) (b)

Figure 3. Quantile loss curve for (a) QRNN; and (b) ImpactNet-A.

5. Conclusion

In this report, we constructed a QRNN based on the work of S. Mehta et al, then implement a novel metric to evaluate the performance of ImpactNet-A. To avoid overfitting and gradient explosion, we add batch normalization and dropout in both models. Finally, we compare the performance of two models, and find that QRNN has higher resolution (1%-99% with 1% increment) and less quantile loss, while ImpactNet-A has low resolution (12.5%-100% with 12.5% increment) and much higher quantile loss.

In future work, we will tune the hyper parameters of QRNN to get less quantile loss, since the result of loss curve shows QRNN potentially can be further optimized.

References:

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