Attention! Is Recycling Artificial Neural Network Effective for Maintaining Renewable Energy Efficiency?

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Introduction



Renewable Energy





Type of solar panels



Monocrystalline

- Single pure silicon crystal
- Uniform dark squares
- 15~20% of conversion efficiency
- 40 years of lifespan
- More expensive

Polycrystalline

- Different Silicon Fragments
- Irregular blue squares dark squares
- 13~16% of conversion efficiency
- 35 years of lifespan
- Less expensive



Monocrystalline vs Polycrystalline Solar Panels, American solar energy society, 20 February 2021.

Efficiency of photovoltaic system



FIGURE 2: Photograph of apparatus.



Polycrystalline

FIGURE 7: Panels efficiencies ratio.



Taşçıoğlu, Ayşegül, Onur Taşkın, and Ali Vardar. "A power case study for monocrystalline and polycrystalline solar panels in Bursa City, Turkey." International Journal of Photoenergy 2016.

Solar Panels





Buerhop-Lutz, Claudia, et al. "A benchmark for visual identification of defective solar cells in electroluminescence imagery." 35th European PV Solar Energy Conference and Exhibition, 2018.

Problem and goal

- Cause of the decrease in efficiency
 - Cracks
 - Contaminations
 - No/slow response to fix the above states
- For maximizing the efficiency
 - Detect the defectives
 - Fix defectives as soon as possible



Approach



Limitations of the conventional methods

- Deep learning-based Classification method (supervised)
 - Needs one-to-one class label
 - High complexity, high power consumption

- Segmentation method
 - Needs one-to-one segmentation mask
 - Marking the defective area is unnecessary



Easy to understand



Non-defective



Defective (Crack)



Defective (Contamination)

- Is the given information sufficient? \rightarrow Yes
- Do we need high-complex model? \rightarrow Probably not



Buerhop-Lutz, Claudia, et al. "A benchmark for visual identification of defective solar cells in electroluminescence imagery." 35th European PV Solar Energy Conference and Exhibition, 2018.

Need to reduce the computational cost



- Training for the high-resolution image requires large computing power.
- Large / high-performance computing is at odds with the concept of renewable energy.





Feature Extraction



Feature	Description		
μ_{image}	Mean of whole pixel values		
σ_{image}	Standard deviation (SD) of whole pixel values		
R $$	Outlier rate that deviate from		
	the threshold, $\mu \pm 1.5\sigma$, among image		
S	Skewness of whole pixel values		
$S(\mu_{height})$	Skewness of the pixel mean along the height axis		
$S(\mu_{width})$	Skewness of the pixel mean along the width axis		
$S(\sigma_{height})$	Skewness of the pixel SD along the height axis		
$S(\sigma_{width})$	Skewness of the pixel SD along the height axis		
K	Kurtosis of whole pixel values		
$K(\mu_{height})$	Kurtosis of the pixel mean along the height axis		
$K(\mu_{width})$	Kurtosis of the pixel mean along the width axis		
$K(\sigma_{height})$	Kurtosis of the pixel SD along the height axis		
$K(\sigma_{width})$	Kurtosis of the pixel SD along the height axis		

300 x 300 pixel values \rightarrow 13 statistical features

Computational cost is reduced by 0.014%-level.



- Black: Reference
- Blue: Negative (or small)
- Red: Positive (or large)

Skewness and Kurtosis





Information emphasizing will be helpful



Information Emphasizing!



	Class Activation Map (CAM)	Attention Map (AM)
Task	Discrimination	Discrimination / Generation
Training Manner	Supervised	Supervised / Unsupervised
Label	Necessary	Optional

CAM / AM



Lee, Soo Young, et al. "Steel surface defect diagnostics using deep convolutional neural network and class activation map." *Applied Sciences,* 2019. Chen, Liang-Chieh, et al. "Attention to scale: Scale-aware semantic image segmentation." *Proceedings of the IEEE conference on computer vision and pattern recognition.* 2016.

Overall flow





Experiments



Pretrained Attention Model





LeCun, Yann, et al. "Gradient-based learning applied to document recognition." Proceedings of the IEEE, 1998.

Attention Maps Original Input Attention Map Overlap Non-defective Defective (crack) Defective (contamination)



Comparison - 1

Correlation coefficients between labels and extracted features

	Value	Original	Attention
Sign	Min	-0.937	-0.948
	Max	0.889	0.815
	Avg	0.403	0.447
	SD	0.288	0.280
Absolute	Min	0.010	0.014
	Max	0.937	0.948
	Avg	0.027	0.023
	SD	0.494	0.527

High maximum coefficient \rightarrow Setting the threshold to determine defective or not is easier.

Low average coefficient \rightarrow Each feature value is independent and meaningful info.



Comparison - 2

- DT: decision tree
- RF: random forest
- XGB: extreme gradient boosting
- LGBM: light gradient boosting machine



- Control variable
 - Feature extraction method: 13 statistical features
- Independence variable
 - Input type: original image or attention map
 - Model: decision tree, random forest, or other lightweight machine learning models



Conclusion



Conclusion

- We highly reduce the computational cost.
 - Through the proposed feature extraction method.
 - 300 x 300 pixel values \rightarrow 13 statistical features
- We propose an attention map utilization for information emphasis.
- We eliminated the cost of training a new attention model by recycling the model trained on public datasets.
 - This approach is very meaningful in the context of maximizing renewable energy efficiency.



Thank you!

