Ensembling techniques in solar panel quality classification

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ABSTRACT

Solar panel quality inspection is a time consuming and costly task. This study tries to develop as reliable method for evaluating the panels quality by using ensemble technique based on three machine learning models namely logistic regression, support vector machine and artificial neural network. The data in this study came from infrared camera which were captured in dark room. The panels are supplied with direct current (DC) power while the infrared camera is located perpendicular with panel surface. Dataset is divided into four classes where each class represent for a level of damage percentage. The approach is suitable for systems which has limited resources as well as number of training images which is very popular in reality. Result shows that the proposed method performs with the accuracy is higher than 90%.

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1. INTRODUCTION

To reduce the negative impacts on climate as well as obtain a sustainable development at the energy field, many researchers around the world are focusing on finding the new energy resources for substituting traditional ones which often emit large quantities of CO_2 to the environment. In tropical countries like Vietnam where the number of sunshine hours is about 2,000-2,600 per year, solar energy is an ideal and #promising renewable energy source which is encouraged by government for expansion and investment [1]. Photovoltaic panels are the most important component of a solar energy system. Under ideal conditions, the lifecycle of panels typically varies from 25 to 30 years [2]. However, this cycle is significantly shortened due to several environmental factors such as rain, wind, temperature, and radiation from the sun according to [3]. To limit the undesirable effects of these factors on lifespan of solar panels, material quality improvement [4], [5] is the approach which is studies by most companies. However, this approach is expensive and require strict conditions for experiment as well as costly facility. Currently to verify quality of panels and detect the crack before selling them to the market, the solar industry has applied technique, namely resonance ultrasonic vibration (RUV) to screen them [6]. According to [7], photovoltaic cell is a p-n semiconductor layer which is similar to ordinary diodes. The characteristics of these cells include absorbing sunlight and producing infrared electroluminescence (EL) when they are supplied with direct current (DC) power. Infrared light falls just outside the visible spectrum but can be observed with proper cameras. According to [8]–[10], electroluminescence image are valuable data which can be used to predict the conditions of panels. However, in their studies information of experiment preparation was not fully provided and the approaches differed from deep learning technique. Deep learning network was adopted by [11] to detect defected panels based on infrared EL images. Nevertheless, method for assessing the failure rate per panel as well as data collections were not fully described in the study.

According to industry practices, the panel is only replaced when its failure rate exceeds a threshold value. To make the research can be applied into reality, this study provides detailed descriptions of how the experiment is prepared and how the proposed study can be applied into the reality when the number of training images is limited. The backbone of our approach is the ensemble technique which is relied on three different machine learning models, namely logistic regression, support vector machine and artificial neural network (ANN). The results show that the proposed method still obtained high performance with electroluminescent images from other data sets. The rest of this study is organized as: section 2 represents the experimental setup and proposed method. Data set information and results are provided in section 3 while conclusion are presented in section 4.

2. METHOD

2.1. Experiment setup

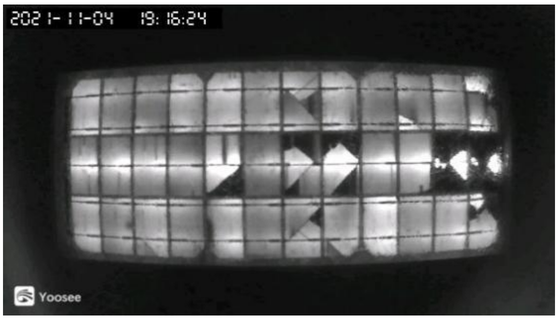
Since the solar panels emit infrared light emission when being powered by DC under the condition of lacking sunlight, the experiment is setup so that all essential factors are ideal to collect the image. The experiment was conducted in dark room and isolated from sunlight from of outdoor environment. The infrared camera with the resolution of 1,920×1,080 pixels is located vertically from the top down at a height of 45 cm. The panel is a monocrystalline photovoltaic (PV) with a maximum capacity of 10 Wp and dimensions of 44.5×19 cm. During the experiment, the voltage from the DC linear power supply is adjusted so that its value lies within the range of 18 to 25 V. The electric current is kept stable around the value of 2 A. The experiment setting is shown in Figure 1.

Figure 1. Experiment setup

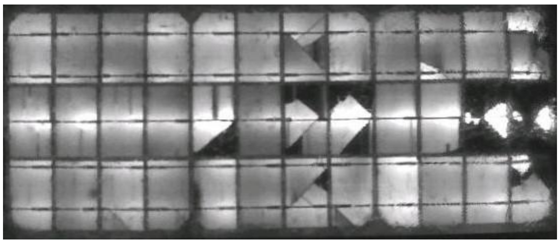
Figure 2 shows the images which are captured under different conditions. Figure 2(a) is a photo of a solar panel which was taken with a non-infrared camera. It is obvious that this photo cannot reveal any information about damage condition of the panel. Using the proposed experiment setting, Figure 2(b) provides much more details about the current situation of the panels and can be used as training data. During the capturing photo process, fixtures are also employed to locate and keep each panel at the same position. Figure 2(c) shows a typical image of a panel with damaged and functioned photovoltaic cells. In this image, functioned cells are brighter when the damaged cells include black proximities.

Furthermore, the attenuation rates within a week of these panels compared to a brand-new panel were also collected. Panels were located on the empty fields without any obstacles so that each panel had the same absorbing light conditions. Based on the attenuation rate, images are labelled as classes A, B, C and D. Panels belong to class A having the attenuation rate less than 10%, while in class B, this rate is between 10% and 20%, in class C between 20 and 30%, and the rest belonging to class D.

(a)



(b)



(c)

Figure 2. Images of solar cell (a) by non-infrared camera, (b) by infrared camera with direct current power, and (c) after affine transformation

2.2. Proposed method

To form the feature vector, the process in Figure 3 was applied. In this study, the Hough transformation approach in [12] is adopted to find the lines then the affine transformation in [13] is adopted to project the image. As a result, this process returns the feature vector of size 18×6×2 for each image. It is noted that, when the number of data is limited, sub cells can be merged into one like pooling method so that the feature vector size can be reduced. Consequently, the number of parameters in each training model can also be lower which decrease the probability of overfitting.

In this study, three methods include regression analysis [14], [15], support vector machine (SVM) [16]–[18] and neural network [19]–[22] are employed. In order to increase the accuracy of the classification process, the bagging technique of voting method is applied at ensembling stage for making final decision [23]–[25]. The label is decided by majority rule. If three models give three different output results. The label with the highest average weight is selected. Three models are applied here including logistics regression, SVM and neural network. The diagram of the proposed classification system is described as Figure 4.

The advantages of logistics regression and SVM methods are their simplicities and explanability. After being trained, these models can be deployed easily on any hardware without any special requirements since the number of parameters of these models are not high. Logistic regression and SVM are also highly explanable approaches, they can provide more insights about how a class is directly related to the feature vector. Here the neural network approach is also adopted to ensure the model does not ignore some complex functions.

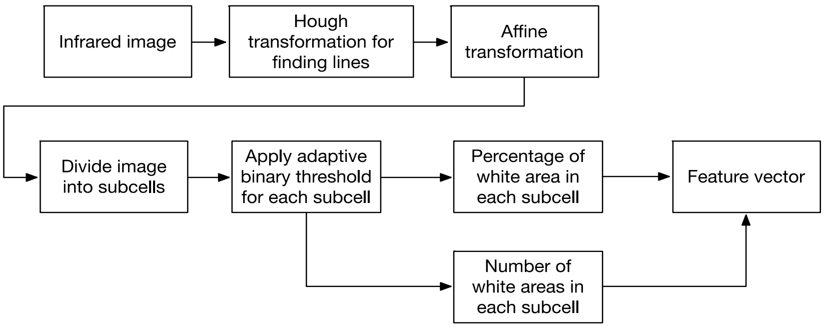


Figure 3. Feature vector forming process

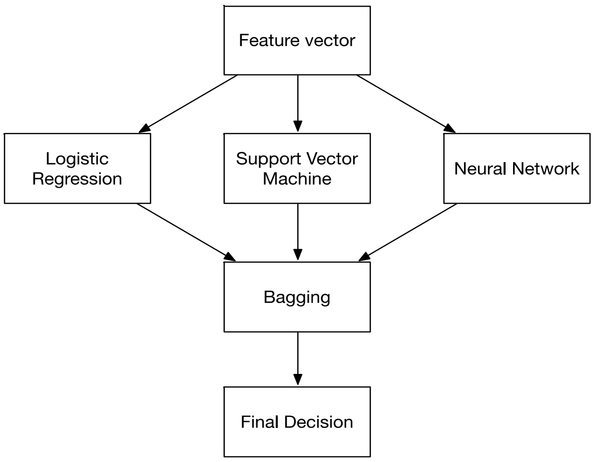


Figure 4. The proposed classification system

3. RESULTS AND DISCUSSION

The dataset, which is created by our team, includes 4 classes regarding to 4 respective outputs as described above. The number of samples for each class label in the training set is show in Table 1. Each image's resolution is 1,280×960 pixels and is then transformed to a 18×6×2 feature vector. Only 80% in each class is used for training, 20% is used for validation.

The neural network in this study comprised of one input layer, two fully connected hidden layer, and one softmax output layer. This study applied gradient descent method for training each network with a learning rate of approximately 0.001. The batch size is 30 and the number of epochs is 120. In general, the learning rate must be selected very carefully to avoid the low learning process as well as the divergence. Table 2 presents the results of the proposed system in the form of a confusion matrix. Finally, the Table 3 will summarize the performance of each model in the proposed system on the different classes of the test set.

Table 1. The characteristic of the training data set

Class	Attenuation rate(R)	Number of images
A	R<10%	225
B	10%<R<20%	225
C	20%<R<30%	225
D	The rest	225

Table 2.The confusion result matrix

Actual label	A	220	5	-	-
	B	5	212	8	-
	C	-	13	203	9
	D	-	-	12	213
		A	**B**	**C**	**D**
		Predicted label			

Table 3. Summary the performance of each model in the proposed system

Class	Total Sample	Logistic Regression	SVM	ANN	Sensitivity
A	225	90.5%	97.4%	95.4%	91.2%
B	225	89.1%	97%	94.3%	90.5%
C	225	87.7%	95.4%	93.8%	89.2%
D	225	89.8%	95.2%	91.8%	90.8%

In addition, this study also test the proposed model by pooling 4 adjacent sub cells as one. Consequently, the feature vector has the size of 9×3×2. Tables 4 and 5 present the confusion matrix and performance summary of each model regarding to this case.

It can be seen that, at both feature vector sizes of 18×6×2 and 9×3×2, the proposed system has very high sensitivity for all classes. It can be explained by the high sensitivity of each model. Given a class, if all models are assumed as independent to other networks and the sensitivity of model i is p_i, with 3 models here the sensitivity of whole system when using voting process regarding to probability theory is (1).

$$P(sys) = p_1p_2p_3 + p_1p_2(1 - p_3) + p_1(1 - p_2)p_3 + (1 - p_1)p_2p_3 \quad (1)$$

It can be seen that, this probability is much higher than probability of one model. It is obvious that the proposed system has not consumed many resources to effectively inspect the solar panel quality. Using the feature vector size of 9×3×2, the system can be easily employed for most applications without strong hardware requirement.

It can be seen from the both Tables 3 and 5, in both case of the SVM always outperform two other methods. Furthermore, the synthesis sensitivity also reduced nearly 5% when being compared with using only SVM. This phenomena occured due to the low sensitivity of the logistic regression approach. Based on the results, only SVM is enough for the classification task. Furthermore, it is somehow impossible to increase the sensitivity especially when the attenuation rate values are near the boundary values of a class. In this study, these values are 10, 20 and 30%. The wrong classifications occur more when pannels have values near them.

Table 4. The confusion result matrix

Actual label	A	222	3	-	-
	B	2	219	4	-
	C	-	3	217	5
	D	-	-	7	218
		A	**B**	**C**	**D**
		Predicted label			

Table 5. Summary the performance of each model in the proposed system

Class	Total Sample	Logistic Regression	SVM	ANN	Sensitivity
A	225	91.5%	98.4%	97.4%	92.4%
B	225	90.1%	97.1%	95.3%	91.5%
C	225	89.7%	96.4%	94.8%	90.7%
D	225	89.8%	95.5%	92.9%	91.1%

4. CONCLUSION

The study presented an approach to evaluate the quality of solar cells through image processing combined with machine learning technique. In the proposed approach, solar cells' electroluminescence images were captured inside a dark room under 18-25 voltage direct currentpower. The infrared camera is installed perpendicularly to the cell with one meter distance Images are undergone the affine transformation and feature engineering technique to extract the most effective features. These features together form a feature vectors which are used as an input to the training network. In this study, we have not used the available deep learning network which are most common in the modern approaches. There are many explanations for this choice. The first one is due to the stability of the environment during the taking photo process. In reality, setting conditions for taking photo is nearly unchanged so that the ground truth of the image can be identified easily. Secondly, through division of the whole panel into several rectangle areas, the useful local features are also extracted and utilized in the classification process. When the numbers of available images are not too many, employing the deep learning network is not an ideal choice since it requires lot of resources for training as well as easily create the overfitting phenomenon. However, due to limitations in data collections, this study has not included photovoltaic cells with long usage time, i.e., more than 1,000 hours. Study these cells will give the inspection more complete answers.

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