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Introduction to Surface Damage on Solar Panels with Feature Extraction using Statistical Methods

Pengenalan Kerusakan Pada Permukaan Solar Panel dengan Ekstraksi Fitur Menggunakan Metode Statistik

Ninuk Wiliani[1]*, Titik Khawa[2], Suzaimah Ramli[3]
[1]Departement of Informatics, Universitas Pancasila, Indonesia
[2]Computer Engineering, Asia e University, Malaysia
[3]Computer Science Engineering, National Defense University of Malaysia, Malaysia

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Abstract

Damage to the surface of solar panels, such as cracks, scratches, and stains, can reduce the energy efficiency produced. The surface of solar panels often experiences various types of damage such as cracks, scratches, stains, or being in good condition, which can affect energy absorption efficiency. The data used in this study consists of 4000 images covering various categories of surface conditions. The method used in this research is the Texture Feature Extraction Method with statistical indicators, namely Mean, Variance, Standard Deviation, Skewness, Kurtosis, and Entropy, to identify existing damage patterns. These features are then analyzed and classified to determine the type of damage on the panel surface. The feature extraction process generates data representations that depict the texture patterns of each surface condition category. This research aims to identify damage on the surface of solar panels using texture-based feature extraction techniques to support the efficient maintenance of solar panels.

Keywords: introduction to damage, solar panel surface, texture feature extraction, statistical methods, energy efficiency.

***SDGs*:**

Abstrak

Kerusakan pada permukaan solar panel, seperti retakan, goresan, dan noda, dapat menurunkan efisiensi energi yang dihasilkan. Permukaan panel surya sering mengalami berbagai jenis kerusakan seperti retakan, goresan, noda, atau berada dalam kondisi baik, yang dapat memengaruhi efisiensi penyerapan energi. Data yang digunakan dalam penelitian ini terdiri dari 4000 gambar yang mencakup berbagai kategori kondisi permukaan. Metode yang digunakan dalam penelitian ini adalah Metode Ekstraksi fitur tekstur dengan indikator statistik, yaitu *Mean, Variance, Standard Deviation*, *Skewness, Kurtosis*, dan *Entropy* untuk melakukan proses identifikasi pola kerusakan yang ada. Fitur-fitur ini kemudian dianalisis dan diklasifikasikan untuk menentukan jenis kerusakan pada permukaan panel. Proses ekstraksi fitur menghasilkan representasi data yang menggambarkan pola tekstur dari setiap kategori kondisi permukaan. Penelitian ini bertujuan untuk mengenali kerusakan pada permukaan solar panel dengan menggunakan teknik ekstraksi fitur berbasis tekstur sehingga dapat mendukung pemeliharaan solar panel secara efisien

Kata Kunci: pengenalan kerusakan, permukaan solar panel, ekstraksi fitur tekstur, metode statistik, efisiensi energi.

*Correspondence Author
email : ninuk.wiliani@univpancasila.ac.id

1. INTRODUCTION

In recent decades, the use of renewable energy, particularly solar energy, has rapidly developed as a sustainable and environmentally friendly energy alternative (Xu *et al.*, 2018). Solar panels play an important role in converting sunlight into clean electrical energy (Malof *et al.*, 2015, 2016; Barraz *et al.*, 2025). However, solar panels often face various forms of surface damage, such as cracks, scratches, and stains, due to exposure to extreme weather, dust, and other environmental factors (Musau, Ojwang and Njuguna, 2019). Such damage can reduce the effectiveness of sunlight absorption, which in turn decreases the electrical power generated by the solar panels (Zyout and Oatawneh, 2020; Subarnan, Damodaran and Madhu, 2022). This condition not only reduces energy efficiency but also increases maintenance costs and shortens the lifespan of the panels (Huang *et al.*, 2023).

As the adoption of solar panels increases in various sectors, the effort to accurately and efficiently detect and classify damage on the panel surfaces becomes increasingly urgent. Early detection of panel damage allows for timely maintenance or replacement actions, thereby helping to maintain optimal performance and maximize the panel's lifespan (Huang *et al.*, 2023). One of the methods that can be used to identify damage on solar panels is through texture feature extraction using a statistical approach. This method allows for the recognition of specific texture patterns that can indicate the type of damage on the panel's surface (Hardiyanto and Sartika, 2018).

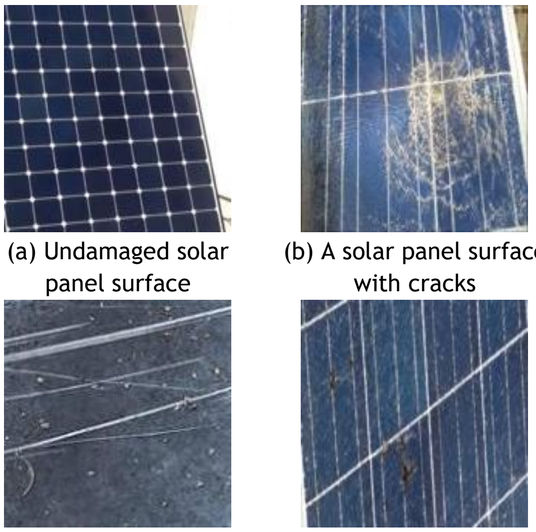
This research focuses on the application of texture-based feature extraction techniques to recognize damage on the surface of solar panels using statistical indicators, namely Mean, Variance, Standard Deviation, Skewness, Kurtosis, and Entropy (Rizki, Syaifudin and Pratiwi, 2018). The data used in this study includes 4000 images of solar panel surfaces, which are divided into four condition categories: cracks, scratches, stains, and undamaged. By analyzing these texture features, the research is expected to produce an accurate and efficient damage detection system, thereby supporting the maintenance of solar panels and increasing the energy efficiency produced (Higuchi and Babasaki, 2017).

2. METHODOLOGY

This research uses a texture-based feature extraction approach to detect damage on the surface of solar panels. The research methodology process consists of several stages, namely data collection, data preprocessing, texture feature extraction, and classification.

2.1. Data Collection

The data used in this study consists of 4000 images of solar panel surfaces with uniform resolution. These images are divided into four categories, each containing 1000 images for surface conditions that are cracked, scratched, stained, and undamaged (Higuchi and Babasaki, 2017). This dataset includes various surface characteristics commonly found on solar panels in real-world environments, thereby representing a range of damage conditions that can affect panel efficiency. In Figure 1, there are examples from the dataset of solar panel surface images, namely an image of an undamaged solar panel surface (a), an image of a solar panel surface with cracks (b), an image of a solar panel surface with scratches (c), and an image of a solar panel surface with stains (d).



(a) Undamaged solar panel surface

(b) A solar panel surface with cracks

(c) A solar panel surface with scratches

(d) A solar panel surface with stains

Figure 1. Example of image dataset.

2.2. Data Preprocessing

Before the feature extraction process, the image data undergoes a pre-processing stage to ensure consistent image quality. This stage includes adjusting the image size, converting to grayscale to reduce color complexity, and normalizing pixels to enhance the texture quality to be extracted. This pre-processing ensures that each image in the dataset has a uniform format and resolution, thereby facilitating the accurate feature extraction process (Sugiartha, 2017).

2.3. Texture Feature Extraction

Texture feature extraction is performed using six statistical indicators, namely Mean, Variance, Standard Deviation, Skewness, Kurtosis, and Entropy (Kaesmetan, 2019) as explained in Figure 2.

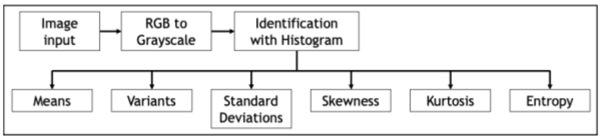


Figure 2. Feature extraction.

Figure 2 explains the feature extraction process in recognizing damage on the surface of solar panels. The part of the statistics that explains these features provides unique information about the texture characteristics of the image; The extraction of these indicators generates feature data that will be used in the classification stage, where each feature describes specific patterns of each damage category (Liantoni and Santoso, 2018).

Mean describes the average, which is a fundamental statistical measure representing the average pixel intensity value of an image. This value provides the primary measure of the distribution of brightness or intensity of the image.

Equation (1) is used to calculate the component in feature m (average intensity):

$$m = \sum_{i=0}^{l-1} i.p(i) \qquad (1)$$

Average intensity is an important statistic in image analysis, used to calculate the average brightness of an object or image. The process involves converting a colored image to grayscale, summing all the pixel intensity values, and dividing the result by the total number of pixels in the image. This average value represents the level of brightness, with higher values indicating a brighter image and lower values indicating a darker image. The average intensity is often applied to tasks such as contrast adjustment, histogram equalization, and image enhancement. Although useful, the average is sensitive to outliers, so extreme values can affect the results. Therefore, the average is often complemented with other statistical techniques to obtain a more comprehensive analysis.

Variance defined as the mean square of the signal. To measure the dispersion or spread of pixel intensities in an image, variance is a statistical metric commonly used in image analysis. Variance describes the variability or contrast of an image by calculating the average squared difference between the intensity of each pixel and the average intensity value of the image using equation (2).

$$\sigma^2 = \frac{1}{q}\sum_{i=1}^{q}\left(Y_j - M\right)^2 \qquad (2)$$

Higher variance indicates a wider range of pixel intensities, greater variability, and more detailed images, while lower variance indicates more uniform or homogeneous images with lower contrast. To calculate variance, the image is usually converted to grayscale to simplify the analysis, followed by the calculation of the average intensity. Then, the squared differences between each pixel and the average are calculated, summed, and divided by the total number of pixels in the image. The resulting value provides a measure of the spread of pixel intensity around the average, making it an important indicator for understanding contrast and detail in the image.

The standard deviation is a statistical measure used in image analysis to measure the variation or spread of pixel intensity, providing information about contrast, texture, and overall image variability using equation (3).

$$\sigma = \sqrt{\sum_{i=1}^{r}\sum_{j=1}^{t}\frac{(q(j,i)-m)^2}{rt}} \qquad (3)$$

The standard deviation value is calculated based on the average absolute difference between pixel intensity and the average image intensity value, with the result being the square root of the mean squared deviation.

A higher standard deviation indicates a more significant variation in pixel intensity, higher contrast, and a more detailed image texture, while a lower value reflects a more homogeneous image with lower contrast. In image analysis, standard deviation is often used for quality assessment, texture analysis, and image segmentation, helping to identify texture differences, important regions, and intensity variability. However, the results can be influenced by factors such as noise, resolution, and the image processing algorithms used, so they are often adjusted to meet specific analysis needs.

Skewness in the context of image analysis refers to the asymmetry or deviation from symmetry in the distribution of pixel intensity in an image. The skewness value is calculated from the third standardized moment in the pixel intensity histogram distribution using Equation (4).

$$\mathrm{Skewness} = \sum_{i=1}^{L-1}(i-m)^3 p(i) \quad (4)$$

Positive skewness indicates more dark pixels with a distribution tail extending to high intensity values, while negative skewness indicates more bright pixels with a distribution tail extending to low intensity values. A skewness value of zero reflects a symmetric distribution. Skewness analysis is often used in tasks such as contrast adjustment, image quality enhancement, and tonal distribution assessment. Factors such as lighting, image acquisition, and outliers affect the skewness value, so it is important to consider the context when interpreting it. Skewness works together with other statistical measures to thoroughly understand the characteristics of pixel intensity distribution.

Kurtosis, a statistical measure called kurtosis, is used to describe the "tail" or shape of a probability distribution and indicates whether there are outliers or extreme values calculated using Equation (5). This measure is often used to evaluate the degree of deviation of a dataset from a normal distribution. A normal distribution has a kurtosis of zero, while a distribution with positive kurtosis has thicker tails and a sharper peak (leptokurtic), whereas a distribution with negative kurtosis has thinner tails and a flatter peak (platykurtic).

$$\mathrm{Kurtosis} = \frac{M_4}{(M_2)^2} - 3 \quad (5)$$

Kurtosis is calculated as the fourth standardized moment divided by the square of the second standardized moment (variance). Interpreting kurtosis helps in assessing the density of data distribution, but it must be understood in the context of the analyzed data, considering other statistical measures for a more complete interpretation.

Entropy is a useful measure for image analysis and plays an important role in various image processing and computer vision tasks. In the context of image analysis, entropy is often used to measure the amount of information or randomness present in an image (Nasution, 2020).

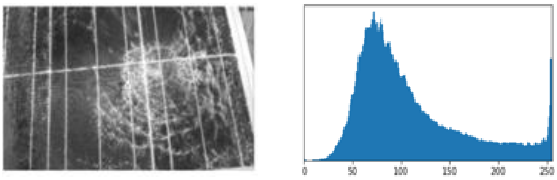
$$\mathrm{Entropy} = \sum_{i=0}^{L-1} p(i)\log_2(p(i)) \quad (6)$$

In a grayscale image, entropy is calculated based on the probability distribution of pixel intensities according to equation (6). where p(i) is the probability of a certain pixel intensity value. Images with high entropy indicate a higher level of variability, characterizing more complex or detailed textures, while low entropy indicates a more uniform or homogeneous image. Entropy is often used in image analysis tasks such as segmentation, texture analysis, and classification and helps differentiate types of textures and identify important regions in the image. The calculation of entropy can be influenced by factors such as image size, noise, and color space, so preprocessing steps are often necessary for more accurate adjustment.

3. RESULTS AND DISCUSSION

In this section, the research results are presented based on the analysis of texture features extracted from images of the solar panel surface. Each statistical feature, namely mean, variance, standard deviation, skewness, kurtosis, and entropy, is analyzed to assess its effectiveness in identifying types of damage, including cracks, scratches, stains, and undamaged conditions.

Figure 3 shows the conversion of an image into a histogram form. The image has been converted into a grayscale image. Next, the implementation of feature extraction calculations based on statistics will be shown. For example, the image has a matrix G (3X3).



(a) Grayscale (b) Histogram

$$\begin{bmatrix} 74 & 73 & \cdots & \cdots & 255 & 255 \\ 77 & 76 & \vdots & \vdots & 78 & 255 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 107 & 96 & \vdots & \vdots & 107 & 255 \\ 68 & 98 & \cdots & \cdots & 255 & 255 \end{bmatrix}$$

(c) Matrix

Figure 3. Process image to histogram and matrix.

$$G = \begin{bmatrix} 100 & 60 & 35 \\ 40 & 75 & 25 \\ 50 & 30 & 45 \end{bmatrix}$$

From the Matrix, the probability is:

$$p(i) = \frac{x}{n} = \frac{1}{9} = 0{,}111$$

$$\text{Means} = (100x0{,}111) + (60x0{,}111) + \cdots + (45x0{,}111) = 51{,}111$$

$$\text{Variance } (\sigma^2) = ((100 - 61{,}716)^2 x0{,}111) + ((60 - 61{,}716)^2 x0{,}111) + \cdots + ((45 - 61{,}716)^2 x0{,}111) = 509{,}876$$

Variance normalization = 0,00783

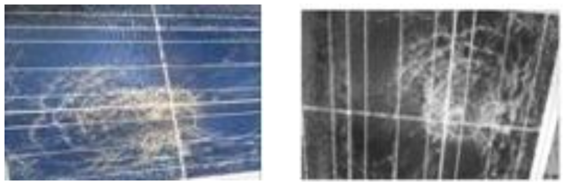
$$\sigma = \sqrt{509{,}876} = 22{,}580$$

$$\text{Skewness} = ((100 - 61{,}716)^3 x0{,}111) + ((60 - 61{,}716)^3 x0{,}111) + \cdots + ((45 - 61{,}716)^3 x0{,}111) = 10910{,}151$$

Skewness normalization = 0,1686609

$$\text{Entropy} = -1\left(\left(0{,}111x\log_2(0{,}111)\right)x9\right) = 3{,}1699$$

Figure 4 is an example of one of the images processed using Google Colab, resulting in features that have been extracted into mean, variance, standard deviation, skewness, kurtosis, and entropy. The results were obtained from the numbers found in the histogram. From the results of the texture feature extraction calculations, the results for each image as shown **Figure 4**.



(a) Original image (b) Grayscale

Mean = 102.897
Variance = 6482.891
Standard Deviation = 80.516
Skewness = 0.568
Kurtosis = -0.579
Entropy = 8.006

(c) Matrix

Figure 4. Example of image feature extraction results.

This research uses 4000 images, with details as follows: 1000 images of undamaged surfaces, 1000 images of solar panel surfaces with crack damage, 1000 images of scratched surfaces, and solar panels with spot damage. Table 1 is the result of the feature extraction calculation of the dataset from each processed image. From the results in the table, an analysis will be conducted according to the features of each image and presented using a histogram diagram, in Figure 5.

In Figure 5, a consistent pattern is obtained between the damage categories and their statistical indicator values. In general, the features mean, variance, standard deviation, skewness, and kurtosis show a significant difference in images with damaged and undamaged surfaces. In terms of skewness, all values are below zero, meaning all values are negative, which indicates that the lighting of each image is quite good. Variance and standard deviation show higher intensity variation in images with damage such as cracks and scratches compared to undamaged images.

The results of this study indicate that a feature extraction-based approach can provide significant information in identifying damage on the surface of solar panels. Features such as mean and variance have proven effective in distinguishing between damaged and undamaged surface conditions, while entropy and kurtosis play an important role in identifying the texture complexity on surfaces with specific damage. Based on these evaluation results, this statistical

Table 1. Dataset feature extraction results.

No	Mean	Variance	Standard	Skewness	Kurtosis	Entropy	Tipe
0	94.434	6118.408	78.220	-2.774	112.499	5.746	Good
1	90.552	5754.641	75.859	-1.720	2.367	6.111	Good
2	92.684	6095.754	78.075	-3.459	58.104	6.106	Good
3	76.787	4007.042	63.301	-2.239	2.454	5.981	Good
4	65.136	2117.661	46.018	0.751	5.560	5.777	Good
5	68.369	2577.956	50.773	-1.244	2.662	5.937	Good
..	...						...
998	95.251	6333.371	79.582	-2.100	7.658	6.133	Good
999	69.618	1202.660		-1.135	-0.140	5.438	Good
0	102.897	6482.891	80.516	0.568	-0.579	8.006	Crack
1	105.859	6473.843	78.839	0.969	-0.346	6.221	Crack
2	110.922	4649.498	68.187	-1.674	13.683	8.006	Crack
3	98.346	3290.075	57.359	-0.869	-0.937	5.272	Crack
4	112.798	4695.098	68.520	-2.053	19.950	6.651	Crack
5	113.289	6164.867	78.516	-1.107	0.388	6.940	Crack
.	...	...	...	...	...	...	...
998	110.957	3809.101	61.717	-0.880	9.719	7.154	Crack
999	183.096	5182.651	71.990	-2.055	17.631	6.391	Crack
0	105.326	1275.320	35.711	-0.463	-0.097	6.306	Spot
1	102.308	1413.636	37.598	-0.683	0.848	7.124	Spot
2	121.515	1422.251	37.712	-0.141	0.021	6.246	Spot
3	114.800	2427.582	49.270	-0.886	-0.835	6.345	Spot
4	109.884	1400.620	37.424	0.194	-0.082	5.823	Spot
5	123.560	1220.036	35.858	0.025	-0.674	4.001	Spot
...	...	...	...	...	...	...	...
998	98.890	1210.020	34.785	0.219	0.227	6.871	Spot
999	100.855	1419.083	37.670	-0.010	1.131	7.116	Spot
0	106.473	4690.986	68.490	0.983	3.286	5.010	Spot
1	112.841	91.235	9.551	2.860	22.266	5.493	Spot
2	94.955	486.342	22.053	1.828	29.274	5.760	Spot
3	94.255	493.708	22.219	1.696	26.346	5.706	Spot
4	112.046	90.637	9.520	2.841	10.469	5.819	Spot
5	77.006	881.861	29.696	1.565	2.944	6.127	Spot
...	...	...	...	...	...	...	...
998	45.184	836.779	28.927	0.983	2.731	5.322	Spot
999	106.473	627.732	25.054	-0.930	3.286	5.010	Spot

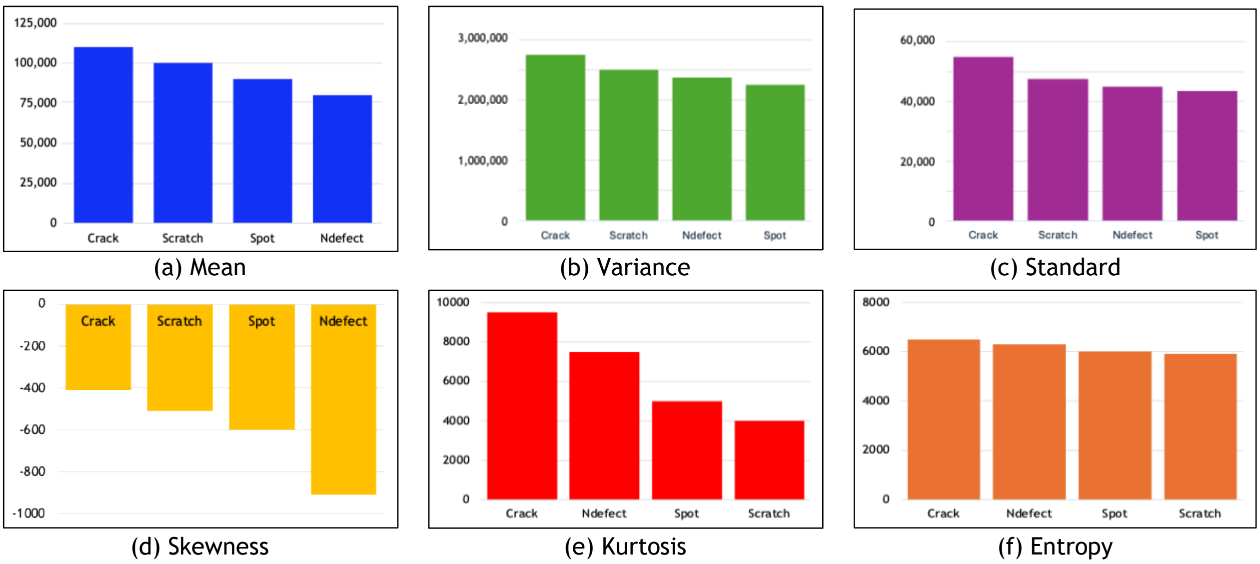


Figure 5. Results of analysis for each feature.

feature extraction method can be relied upon for implementation in an automatic solar panel damage detection system, which can enhance the effectiveness and efficiency of solar panel maintenance.

4. CONCLUSION

This research concludes that statistical-based feature extraction methods can be effectively used to detect damage on solar panel surfaces through texture analysis. By using statistical indicators such as mean, variance, standard deviation, skewness, kurtosis, and entropy, this method can detect different damage patterns, including cracks, scratches, stains, and undamaged conditions. The research results show that each indicator plays an important role in distinguishing damage categories, where the mean and variance features are effective in identifying intensity differences, while entropy and kurtosis demonstrate superiority in measuring chaos and the distribution of texture intensity on damaged surfaces.

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