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IMPROVING THE IMAGE QUALITY OF GRAYSCALE THERMAL IMAGES TAKING FROM PHOTOVOLTAIC PANEL WITH CONTRAST ENHANCEMENT METHOD

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Abstract. *The condition of photovoltaic thermal image data is crucial to a great variety of developing research and implementations since thermal images are competent in exposing meaningful unseen features for detecting hotspots as the abnormality in a photovoltaic module. However, the images may degrade from unsatisfactory image quality because several images may have too low contrast. In addition, the details are at variance with human visual perception due to limitations of the image acquisition device and diversities of the surroundings of the photovoltaic. Therefore, an image enhancement stage is needed to solve these issues. This research presents the comparison methods for the image enhancement stage that promotes the details of photovoltaic thermal images by enhancing contrast. These methods were completed using contrast-stretching and histogram equalization. The findings indicated that histogram equalization gave superior histogram and CDF properties than contrast-stretching. Additionally, it recognized hotspot cells well in quantitative analysis, with an average accuracy of 96.93% and an average F1 Score of 81.84% from 30 photovoltaic thermal images.*
Keywords: Grayscale thermal image, Photovoltaic module, Image enhancement, Contrast-stretching, Histogram equalization

1. **Introduction.** The photovoltaic solar panel system is one of the most expeditiously growing interests in renewable energy resources. The recorded market data presents that the worldwide photovoltaic (PV) market increased highly last year. The whole setup capacity for PV in 2020 acquired more than 760 gigawatts-DC [1]. Nevertheless, critical inconveniences of the utilization occur in the supervising condition of photovoltaics. A photovoltaic or solar panel may have various anomalies derived from the motives of dropping performance and the component it impacts. Specifically, faults in the semiconductors may decrease the photovoltaic cells' efficiencies. Significant anomalies, for instance, electrical disconnection, panel degradation, or hot spots under abnormal operation, and then the harm region can be exposed immediately using infrared (IR) imagery [2].

A beneficial technique for identifying the abnormalities in photovoltaics is infrared, which operates a thermal IR camera to display faults depending on their raised heat [3]. A thermal camera may benefit from showing unsafe parts emitting temperatures over their standard operating boundary and the high temperature of photovoltaic cells related to anomalies in the photovoltaic system [4]. For example, surface imperfections result

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in heated cells called hot spots on the photovoltaic module. Hotspots are regions with overheated conditions that could harm the cells or other components of the PV [5]. Therefore, thermal images from the thermal camera are used to detect even small temperature changes to provide insight into the health of a solar panel. Artificial intelligence techniques may improve the image processing of camera-generated images, eliminating the need for pricey sensors [6]. Moreover, thermal image processing is suggested to automatically and accurately recognize the anomalies of a photovoltaic module [7].

Thermal image processing has been adopted during monitoring photovoltaic or solar panel investigative projects. A substantial amount of study has recently been attracted to processing photovoltaic thermal images. Previous research used the bi-level Otsu thresholding methodology during the segmentation procedure to separate the background and foreground areas for identifying the hotspot on the PV module [8]. It converted grayscale thermal images to binary images depending on a predefined threshold and obtained an average detection accuracy of 92.16% for detecting hotspots. Nevertheless, this study examined only six manually-cropped images. Next, [9] assessed a multi-level Otsu-based image processing for segmenting and detecting hot spots in solar photovoltaic cells and achieved an average accuracy of 91.81% from 10 photovoltaic thermal images. Nevertheless, an image still suffers the wrong interpretation resulting in low accuracy.

A thermal image must be of good enough quality for further processing. If the image quality is not good, it will misunderstand image processing. Thus, in the early stage of photovoltaic thermal image processing, the preprocessing was conducted by converting the input image to a grayscale thermal image because of the restriction of the infrared approach [10], and the grayscale format is a relatively compact representation and storage [8]. Despite the benefit of the grayscale image format, thermal images may display blur details and low contrast in several conditions. These problems are considering the cameras' environment and restraints [11]. Consequently, thermal images should be enhanced with practical image preprocessing techniques to obtain better image interpretation and analysis results.

Image enhancement is an image preprocessing step that attempts to boost the feature of an image [5]. This process enhances the visual aspect of the image and provides an acceptable representation of conversions in the following image processing stages, such as segmentation, identification or recognition, and evaluation [12]. For photovoltaic thermal images, the problems are low contrast and blur details in several conditions. Thermal images with low contrast have moderately unsatisfactory quality. The thermal image information is challenging to define directly by human and computer vision. Therefore, contrast enhancement methods are applied to increasing the contrast to produce more precise details or information about the images.

Contrast image enhancement methods can be classified into two categories. The first is the linear contrast method that broadens the original image's values into a new distribution linearly. The linear technique involves the contrast-stretching method. It is the linear normalization because in contrast-stretching, the image's intensity levels are normalized by extending one arbitrary interval of the image's intensities and fitting it to another arbitrary interval. It depends only on one pixel's intensity or grey level value, not other pixels around it. The second is the non-linear contrast method that retains edges and details of images that use non-linear transformation functions from the input image's histogram. The non-linear method includes histogram equalization. Histogram equalization is the most common algorithm for non-linear contrast enhancement considering its competence and effectiveness [13]. It is a non-linear normalization because the region of the image's histogram with high abundance intensities is widened and the area with low abundance intensities is condensed.

Compared to other imaging methods' extensive applications, research on comparing photovoltaic thermal image enhancement has rarely been conducted. This work applies contrast enhancement techniques in photovoltaic thermal images to effectively interpreting the photovoltaic module's condition. Unfortunately, there is no standard regulation for deciding the proper contrast image enhancement method when performing image enhancement. The contrast enhancement is generally established experimentally and application-specific. Therefore, this study compares two contrast enhancement techniques: contrast-stretching as the linear contrast method and histogram equalization as the non-linear contrast method. The final enhanced images were evaluated using qualitative and quantitative approaches.

This article is organized in the following order. Section 2 explores the basic principle in general. Next, the approach for enhancing the images is described in Section 3. Section 4 discusses the discoveries and comments. Lastly, the concluding statements are presented in Section 5.

2. Related Theory.

This section summarizes the most often reported relevant concepts, emphasizing increasing the image quality of thermal imaging solar modules with low contrast.

2.1. Contrast enhancement method.

One of the stages in image preprocessing is removing unnecessary information such as noise, called image enhancement. Image enhancement aims to make the image ready to be processed at the next stage, such as image segmentation or pattern recognition of information in the image. This process enhances the visual aspect of the image and provides an acceptable representation of conversions in the following image processing stages, such as segmentation, identification or recognition, and evaluation [12]. It improves the image's intensity levels or customizes the histogram to be effortlessly understood by humans [14]. In this study, contrast enhancement is applied to distinguishing between the foreground and background of the image.

Contrast enhancement boosts object visibility in a scene by increasing the contrast between object or foreground and background. Contrast is the diversity in apparent representations that makes an object (or its properties in an image) detectable from the background and other objects. In a range of vision, contrast is conditional on the difference in the object's color and brightness within the same perspective. In other words, it is the diversity between brighter and darker tones or pixels of the image, if the variance is significant, the image will have high contrast, and if it is small, the image will have low contrast. Consider a low-contrast image and its enhanced counterpart, depicted in Figure 1 with accompanying notations. The terms x_i and y_i $(i = 0, 1, \ldots, N-1)$ represent the image's pixel intensities. Each image has N pixels, each with L various grey levels.

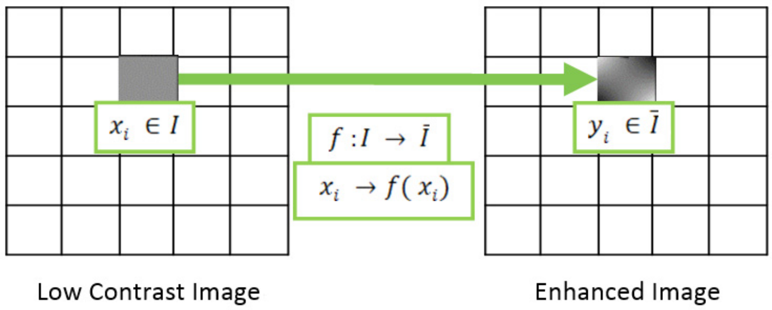


FIGURE 1. The difference between the low contrast input image and the enhanced image result by function f

In Figure 1, a low-contrast image has little contrast between its bright and dark parts, giving it a flat appearance. Moreover, high contrast or enhanced image has a spectrum of shades ranging from dark to light, with deep shadows and dazzling highlights [15]. Contrast enhancement involves image manipulation, and a certain manipulation may be specified by a function f that translates an input pixel to its matching output pixel. This function is referred to as the transformation function. The modified pixels are determined by the function f, which modifies the input image's histogram. The user should also examine the distribution of pixels in the input and output images to better understand the transformation function's impact. The distribution of pixels may be calculated using the histogram, representing the distribution of the image's grey levels (pixels). The transformation functions of contrast enhancement can be divided into linear and non-linear contrast enhancement.

2.1.1. *Linear contrast enhancement.* The linear transformation function is the most straightforward technique to manipulate an image. It changes the pixel intensities linearly – the linear processing results in more saturated pixels in the final images. From a histogram perspective, it is evident that this procedure, dubbed contrast-stretching, stretches the distribution of grey levels throughout the whole grey level range.

2.1.2. *Non-linear contrast enhancement.* The non-linear transformation function idea was applied to preventing excessive brightness in the output image. This function produces more accurate results and a slightly changed histogram than the linear transformation. Although the output of these functions is likewise dependent on the original input pixels, they do not merely scale them but rather alter them according to a predetermined function, which is selected depending on the input image.

2.2. **Image histogram and CDF plot.** The essential thing to understand about contrast enhancements is to be familiar with the theory or concept of an image histogram. An image's histogram is used to display the frequency with the intensity value of a pixel. It is depicted in the form of a two-dimensional graph. Visual observation of a histogram informs the direct contrast displayed in the image and any possible variations in the color distribution of the image elements. The histogram can be built up for a grayscale image by calculating the frequency of grayscale values in the image [16].

Histograms have grown in popularity to present image data and assist in determining specific issues in an image depending on histogram form. The histogram may be generated for a basic grayscale by calculating the number of instances of each value in the greyscale image. The x-axis indicates the grayscale value included. Furthermore, the y-axis indicates the frequency or pixel count in the image. Histograms are often displayed using a bar chart, as seen in Figure 2, with one bar for each grey level and a height proportionate to the number (or percentage) of pixels that belong to that grey level [17]. The histogram shape may be used to describe the appearance of an image. As indicated in Table 1, four histograms depend on the image's appearance or the essential greyscale intensity characteristics.

Histograms may be utilized anytime a statistical representation of an image's or video frame's grey-level distribution is sought. The histogram display aids in examining the frequency of presence of the image's various grey levels [18]. Additionally, histograms may be utilized to improve or adjust an image's qualities, most notably its contrast. Contrast is the distinction between the darkest and brightest regions of an image. A balanced histogram or high contrast has a more pleasing appearance and displays more information, as seen in Table 1. It is plausible that an image with pixels that span the

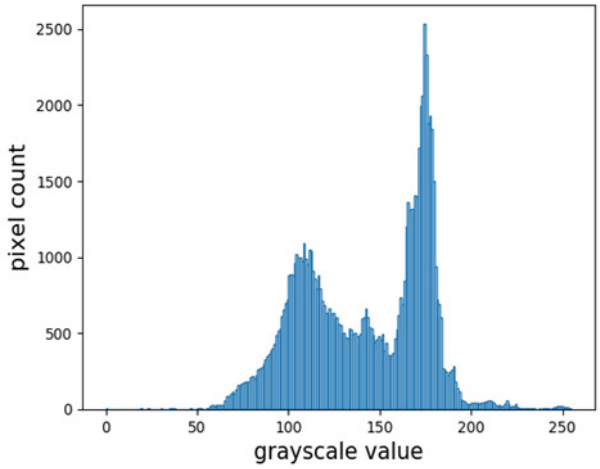
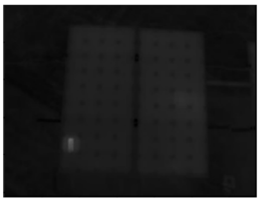
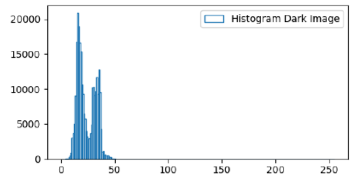
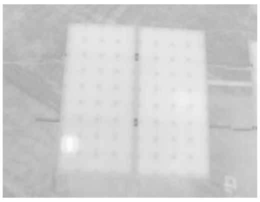
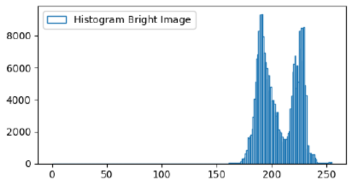
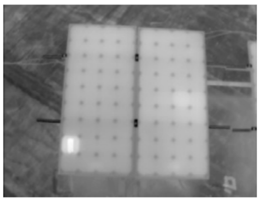
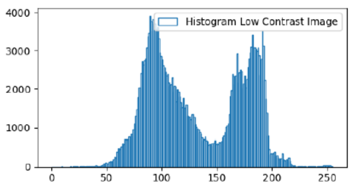
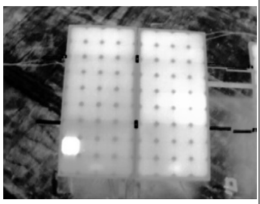
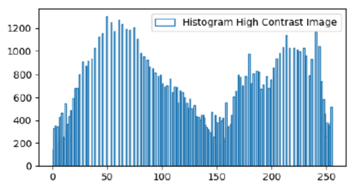


FIGURE 2. Example of image histogram

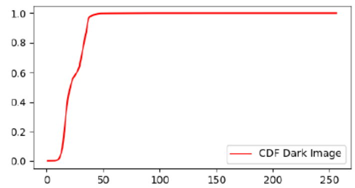
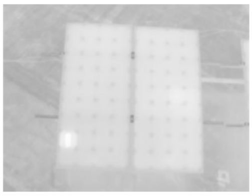
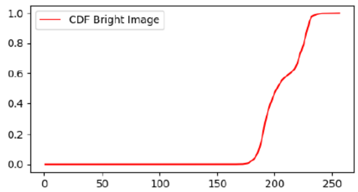
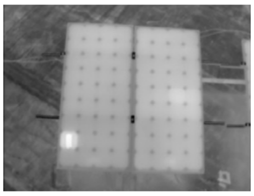
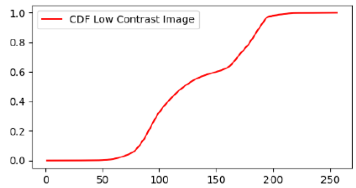
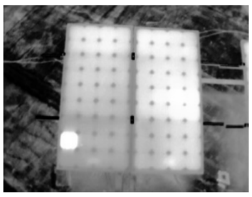
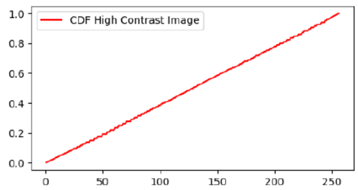
TABLE 1. Sample of grayscale image appearance and its histogram

No.	Image appearance	Image histogram	Histogram characteristic
1	 Dark Image		A cluster of bars or histogram bins is **piled on the left side of the histogram** at the lower end of the grey-level range.
2	 Bright Image		Components of the histogram are concentrated in high grayscale values **piled on the histogram's right side.**
3	 Low Contrast		The histogram is thin and is **centered in the middle of the grayscale values.**
4	 High Contrast		The histogram covers a significant chunk of the intensity scale, and the distribution of pixels is very consistent, with just a few bins much higher than the rest.

whole range of conceivable degrees of intensity and are evenly distributed would seem to have strong contrast and a wide range of grey tones in the histogram [19].

The cumulative distribution function (CDF) is another graphical depiction of the probability distribution of pixels in the image. The y-axis displays the cumulative probability of pixels' distribution, often known as the percentile. The x-axis represents the distribution values (from least to greatest). The line illustrates the probability using vertical distances. While a histogram is more straightforward when assessing image processing, the CDF is a more practical idea [4]. Slopes represent data in CDF, as seen in Table 2. Our eyes are significantly more robust at detecting slope variations, making it sometimes simpler to spot outliers in the sample.

TABLE 2. Sample of grayscale image appearance and its CDF

No.	Image appearance	CDF
1	 Dark Image	
2	 Bright Image	
3	 Low Contrast	
4	 High Contrast	

3. **Methodology.** It is sometimes difficult to acquire sufficient information from the raw image of photovoltaic modules due to image noise and poor resolution. It necessitates the employment of image processing techniques to facilitate viewing and analysis. Additionally, image processing might reveal anomalies associated with the thermal signature of equipment [20]. Since the quality of photovoltaic thermal images is needed to improve due to the low-contrast images data, a new approach based on the contrast image enhancement method is proposed in this study. The proposed method diagram is shown in Figure 3. Initially, image segmentation is applied to recognizing the photovoltaic module in the grayscale thermal images. Then, the photovoltaic module images were enhanced using

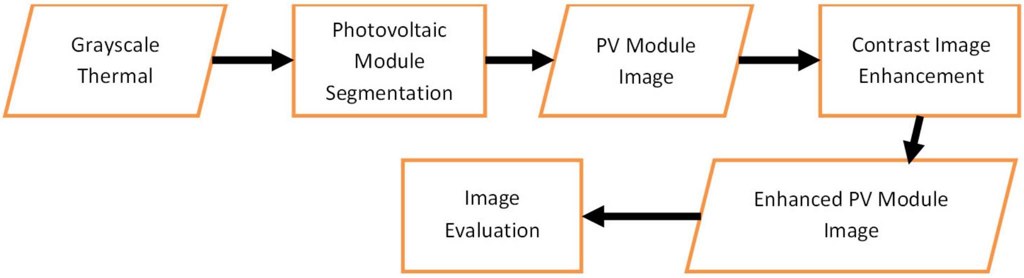
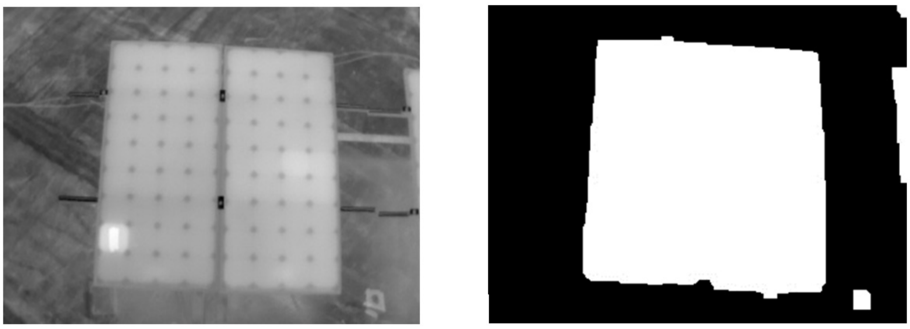


FIGURE 3. Proposed method diagram

contrast image enhancement methods. The images' enhancement results were analyzed by observing the histogram and CDF features. Finally, the masking method detects the hotspot for evaluating the contrast enhancement result to ensure the performance of the interpretation analysis. Each phase of the process is described in-depth in the following sections.

3.1. **Photovoltaic module segmentation.** PV modules, on average, have a greater pixel intensity than the surrounding areas in an infrared thermal image [21]. Before enhancing the thermal image, as seen in Figure 4(a), the photovoltaic module segmentation is necessary to focus the image processing on the PV module only. Thresholding is a general and fundamental segmentation approach in computer vision, and it enables the separation of the photovoltaic module from the grayscale thermal image background [22]. Thresholding splits an image into multiple areas having the same intensity of color or grey level [9]. *Thresholding* is the process through which an image is binarized. Generally, binarization is when a grayscale image is transformed into black and white or binary depending on a threshold value. This research used Otsu's thresholding approach to be more dynamic by automatically determining the best threshold value for each input image. Figure 4(b) depicts the outcome of this operation.

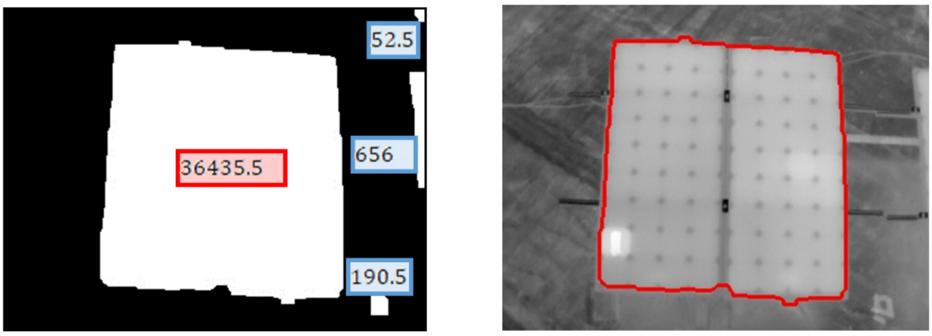


(a) (b)

FIGURE 4. Photovoltaic module image: (a) Original grayscale thermal image; (b) binary image

While the segmentation result accurately assesses the photovoltaic module as the foreground in the binary image, there are specific locations where some of the background areas remain visible or still detected as the foreground (white color). Therefore, the contour algorithm is applied to finding the contour points around the borders of these white objects. *Contours* are the lines connecting all spots along the object's boundaries with the same intensity. Contours help determine the size of all white objects and object identification.

As seen in Figure 5(a), four sizes of white areas are gained in this binary image: 36435.5, 656, 190.5, and 52.5. Visually, the most prominent white area in Figure 5(a) is the photovoltaic module. So, after finding the sizes of all white objects in the binary image, the most significant size (36435.5) is chosen as the photovoltaic module to make red contours around it, as shown in Figure 5(b).



(a) (b)

FIGURE 5. (a) Binary image; (b) detected PV module image with contours

3.2. **Contrast image enhancement.** After getting the contours around the photovoltaic module, the contour area became the region of interest and applied contrast enhancement. The primary outcome of contrast image enhancement is to reveal details hidden in the low-contrast grayscale images. Grayscale images with low contrast will look too grey and result in low quality for image interpretation. Therefore, this part aims to enhance the contrast by contrast-stretching and equalizing the histogram. Contrast image enhancement is started by calculating the histogram. Mathematically the image histogram is calculated by Formula (1).

$$h_i = \frac{n_i}{n}, \quad i = 0, 1, \ldots, L-1 \tag{1}$$

Digital images have L degrees of grey, i.e., from values 0 to $L-1$ (for example, in an image with an 8-bit grey degree quantization, the grey degree value is from 0 to 255). The value of n_i has been normalized by dividing by n. The value of h_i is in the range of 0 to 1.

3.2.1. *Contrast-stretching.* As the name implies, contrast-stretching is a technique for improving images' contrast by extending an image's intensity values to span its whole dynamic range. An image must have its upper and lower pixel value constraints defined before stretching may occur. The minimum and maximum pixel values are often used as these limitations, permitted by the image type. The minimum and maximum bounds for 8-bit grey-level images are 0 and 255. The transformation function is always linear and rising monotonically.

The following algorithm applies to contrast-stretching.

1) Determine the lower limit of the pixels by examining the histogram from the lowest grayscale value (0 to 255) to create the first pixel larger than the predefined threshold value.
2) Scan the histogram of the highest grayscale value to the lowest in the set second threshold value to determine the top boundary of pixel grouping.
3) Pixels with values less than the first threshold value are given a value of 0, while those with values more than the second threshold value are allocated a value of 255.

4) The pixels between the first and second scaled threshold values fulfill the whole range of grayscale values (0 to 255) using Formula (2)

$$x = \frac{v - v_{\max}}{v_{\min} - v_{\max}} \times 255 \tag{2}$$

where v is the region of interest's grayscale value, x is the new grayscale value, $v_{\min}$ is the pixel group's lowest value, and $v_{\max}$ is the pixel group's maximum grayscale value.

Figure 6 shows the result of the contrast-stretching method.

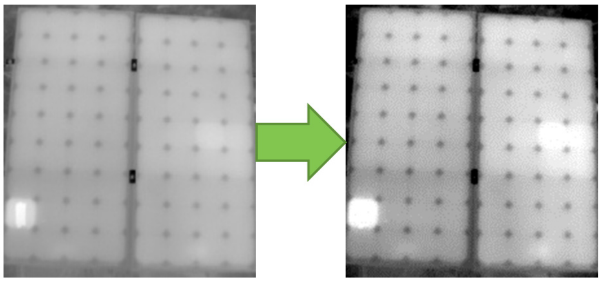


FIGURE 6. Before and after contrast-stretching applied on detected PV module image

3.2.2. *Histogram equalization.* The second contrast enhancement operation in this study is histogram equalization. The histogram equalization technique switches the image histogram to extend the histogram nonlinearly. This approach improves an image's global contrast by modifying the histogram's pixel intensity distribution. It permits regions with low contrast to have a stronger contrast in the resulted image.

Histogram equalization is accomplished in the following manner.

1) A histogram of the image's pixel intensities is computed. The histogram categorizes each pixel $f[x, y]$ as belonging to one of L equally spaced buckets $h[i]$

$$h[i] = \sum_{x=1}^{N} \sum_{y=1}^{M} \begin{cases} 1, & \text{if } f[x, y] \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

2) Compute the cumulative distribution function (CDF)

$$CDF[j] = \sum_{i=1}^{j} h[i] \tag{4}$$

3) Modify the image using CDF to produce the output image

$$g[x, y] = \frac{CDF[f[x, y]] - CDF_{\min}}{(N \times M) - CDF_{\min}} \times (L - 1) \tag{5}$$

The result of histogram equalization is illustrated in Figure 7, where the contrast is noticeably improved.

3.3. **Image evaluation.** After enhancing the PV module images, the images result or enhanced photovoltaic module images are utilized to assess the image's quality and compare the performance of contrast-stretching and histogram equalization methods using qualitative and quantitative analysis. Qualitative analysis in this study is done by identifying the image's appearance based on histogram and CDF plot. The CDF and the histogram will be investigated to see the influence of pixel intensity on each technique since they are the two common graphical representations of digital image processing [23].

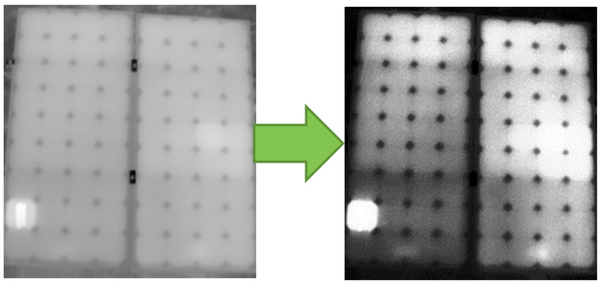


FIGURE 7. Before and after histogram equalization applied on detected PV module image

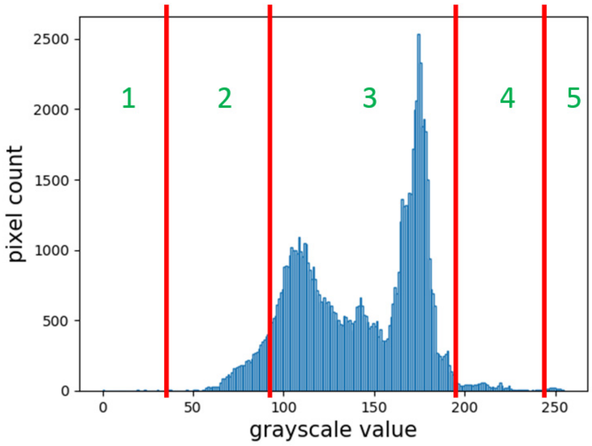


FIGURE 8. Representation of five tonal zones of an image histogram

Figure 8 illustrates the histogram's five tonal zones, corresponding to the tonal range 0-255. These zones are blacks, shadows, midtones, highlights, and whites [23].

1) Blacks – this portion is all black and has no information. Additionally, it has a minimal spectrum of tones positioned on the histogram's left side. When the histogram hits the chart's far left, it indicates that eliminations have been made to the shadows' image.

2) Shadows – while shadows are commonly confused with blacks, mainly when a deeper shadow occurs, this section has a somewhat broader tonal range than blacks. Shadows include some detail and may be enhanced to a certain amount. Typically, the image's noise manifests itself in this region.

3) Midtones – this section contains the maximum tones and pixel count spectrum. Shades will not change no matter how far the tone is stretched or pushed.

4) Highlights – this area is similar to shadows but located in a more favorable light or bright portion of the image and includes some apparent features. It may be repositioned gently to the extreme right near clipping.

5) Whites – this group is entirely white and indicated as hotspots in photovoltaic grayscale thermal images.

Moreover, the following formulas are used for quantitative analysis by assessing the accuracy, precision and F1 Score. The average accuracy and F1 Score are calculated from 30 photovoltaic thermal images for comparing methods.

$$Average\ Accuracy = \frac{\sum_{i=1}^{n} ACC_i}{n} \tag{6}$$

$$Average\ Precision = \frac{\sum_{i=1}^{n} P_i}{n} \tag{7}$$

$$Average\ F1\ Score = \frac{\sum_{i=1}^{n} F_i}{n} \tag{8}$$

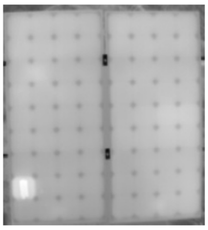
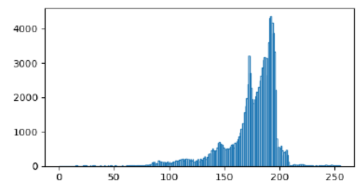
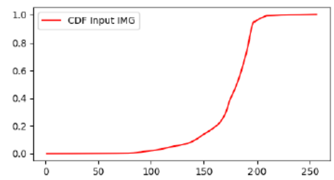
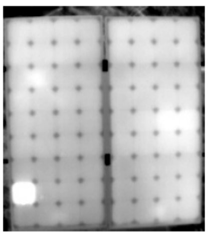
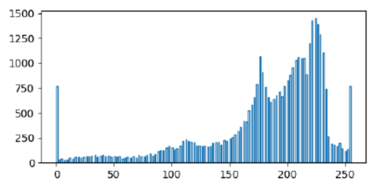
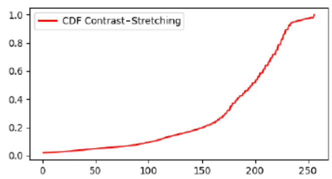
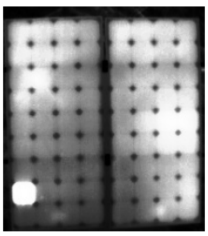
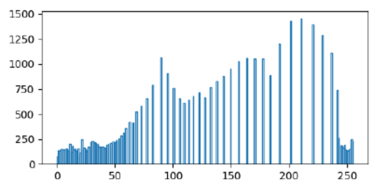
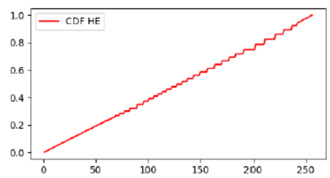
The measurement accuracy relates to how near the actual values of corrected cells detection. Precision denotes the number of correct cells in the identified hotspot. Furthermore, the F1 Score is calculated by averaging precision and recall. Consequently, this score takes consideration of both false positives and false negatives. If the pixels are an uneven distribution, F1 is more valuable than accuracy. Greater F1 Scores are typically preferable.

4. **Result and Discussion.** Results were compared based on the evaluation of qualitative and quantitative assessments.

4.1. **Qualitative analysis.** The qualitative finding evaluates something based on quality rather than quantity in its simplest form. A qualitative study examines how something is described. It employs descriptive language based on thoughts and perceptions. In this study, qualitative analysis is used by recognizing the image appearance with human visual based on histogram and CDF plot. As seen in Table 3, the histogram and CDF of the original image displayed the low contrast characteristic because the histogram is centered in the middle of grayscale values. Therefore, the contrast enhancement method is applied to improving the details of the image.

As shown in Table 3, the histogram and CDF plot results of the sample image are from the original image are compared with the contrast-stretching and histogram equalization.

TABLE 3. Result of histogram and CDF of photovoltaic grayscale thermal image

	Sample image	**Histogram**	**CDF**
Original image			
Contrast-stretching			
Histogram equalization			

The histogram of the enhanced images indicated that both the contrast-stretching and histogram equalization exhibit a better-distributed pixel intensity value than the original image.

Figure 9 shows the grayscale tonal zones of the image from the contrast-stretching method; the histogram shows a zone of small-scale shadows, indicating that the contrast-stretching image is in the neighborhood of a black section. Additionally, the midtones area contains additional information, resulting in an asymmetrical histogram. Lastly, this image has a significant amount of highlights which indicates that this image has better contrast than the original image.

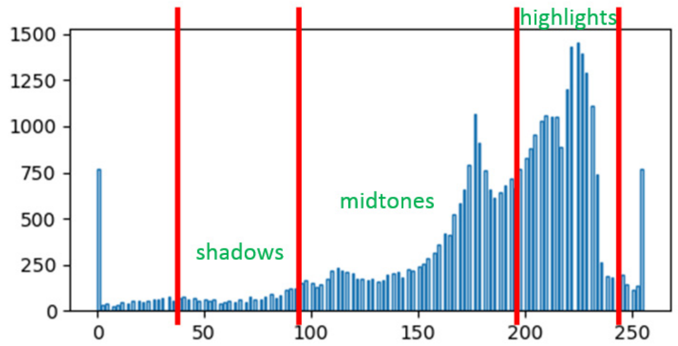


FIGURE 9. Histogram tonal zones of contrast-stretching

Figure 10 depicts a histogram with a very consistent distribution of pixels. Additionally, it demonstrates that most pixels are located between the image's midtone and highlight regions. The histogram distributed the whole range of conceivable degrees of grayscale intensity. This histogram distribution indicated that the contrast in this image is higher than in the original image and contrast-stretching.

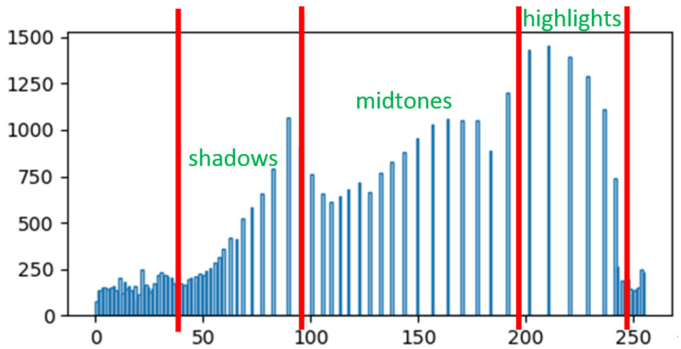


FIGURE 10. Histogram tonal zones of histogram equalization

The experiment with the sample images revealed that the proposed contrast enhancement methods are superior in detail retention and may increase image quality for the practical interpretation of the photovoltaic thermal image, especially in the histogram equalization method. The CDF comparison indicates that the contrast enhancement methods provided a more linear CDF than the original image. In terms of qualitative evaluation of the image, it is clear that the contrast is improved. The image visually shows the hotspots previously hidden in the original image. These experimental findings demonstrate that histogram equalization is a powerful contrast enhancement technique that increases image quality, facilitating the extraction of information from photovoltaic grayscale thermal images.

4.2. **Quantitative analysis.** A quantitative analysis or performance metric is a comprehensive and measurable indicator used to quantify any algorithm's performance. Three metrics are utilized to determine the method's efficiency, accuracy, precision and F1 Score. These techniques are used to assess the performances of the contrast enhancement method by calculating the correct detection of hotspot cells in the enhanced PV module images. Figure 8 shows contrast-stretching and histogram equalization performance metrics average from 30 photovoltaic thermal images.

Figure 11 summarizes the performance metrics on the contrast-stretching and histogram equalization method using average accuracy, precision and F1 Score. It demonstrates that the histogram equalization technique outperforms the contrast-stretching method alone. The average precision of contrast-stretching is higher than the histogram equalization with 96.72% and 96.46%, respectively. However, the histogram equalization beats the contrast-stretching method with 96.93% average accuracy and 81.84% average F1 Score compared to the contrast-stretching method's 94.15% average accuracy and 56.68% average F1 Score. It indicates that accuracy is improved, and the histogram equalization is exceptionally good at image enhancement on photovoltaic thermal grayscale images. The results indicate that histogram equalization is an effective strategy for enhancing contrast and improving image quality, leading to improved image interpretation, which enhances the ability to detect hotspots from photovoltaic grayscale thermal images.

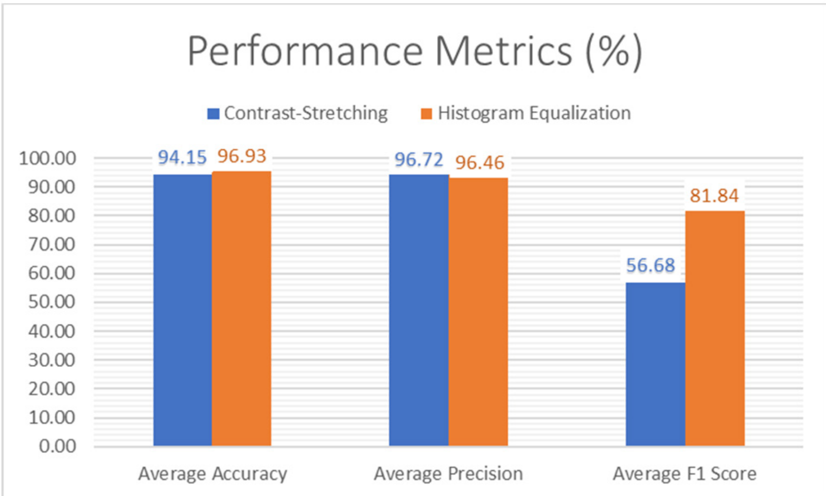


FIGURE 11. Performance metrics of hotspot cells detection with contrast enhancement methods

5. **Conclusions.** Image preprocessing is a vital technology that enables humans to recognize and interact with objective things. It is utilized in various areas, including interpreting photovoltaic grayscale thermal images for automated detection hotspots in photovoltaic modules. The photovoltaic thermal images provide considerable information during image preprocessing. Various image enhancement algorithms have been created, each with advantages and disadvantages, as image preprocessing techniques have evolved. Contrast enhancement techniques significantly increase the visibility of low contrast photovoltaic grayscale thermal images. The experimental results show that histogram equalization is a powerful contrast enhancement method that improves image quality, resulting in better image interpretation to extract information from photovoltaic grayscale thermal images. The visuals or qualitative approach analysis showed that histogram equalization provided better histogram characteristics and CDF features than contrast-stretching. In quantitative analysis, hotspot cells were detected effectively with a 96.93% average accuracy

and 81.84% average F1 Score from 30 photovoltaic thermal images. The noise expansion and detail loss phenomena will occur during contrast image enhancement. Developing an algorithm capable of these issues is an opportunity for future research improvement. Future work may design the adoption of IoT-based solar PV monitoring systems built on sensing technologies, data analysis, and communication devices to provide an effective, precise, and resilient monitoring system for the PV based on thermal image processing.

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