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Enhancing Photovoltaic Panel Inspection using RGB Image-Based Detection and Image Processing Techniques

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ABSTRACT

Photovoltaic (PV) panels have become more common in recent years due to their numerous benefits. However, ensuring that PV panels function optimally and reliably is essential for maximizing their efficiency and durability. Identifying and addressing flaws in PV panels is vital to achieving this goal. While thermographic imaging is routinely utilized for defect identification, the potential for using RGB images for this purpose is virtually untapped. This paper intends to investigate using RGB images to recognize PV panel defects, proposing a methodology that integrates image processing techniques such as K-means clustering, Canny edge detection, and grayscale conversion. The results show that defects on PV panels may be successfully discovered by applying K-means clustering and Canny edge detection to RGB images with an accuracy of 90.66%. This study sheds light on improving defect identification practices in the PV industry.

1. INTRODUCTION

Photovoltaic or PV refers to converting light into electricity using semiconducting materials that exhibit the photovoltaic effect. PV technology is commonly used in solar panels to generate electricity from sunlight. PV technology is considered a key component of renewable energy systems due to its ability to harness abundant sunlight and convert it into clean, sustainable electricity without emitting greenhouse gases or other pollutants (Obaideen et al., 2021). PV systems are widely used worldwide to help reduce reliance on fossil fuels and mitigate climate change by providing a source of clean, renewable energy (Shahsavari & Akbari, 2018). The study by Han et al. (2025) confirmed that utilizing renewable energy enhances energy resilience, whereas dependence on fossil fuels undermines long-term sustainability. The use of solar energy is increasing, including in Malaysia, and its importance needs to be widely promoted to consumers (Amali et al., 2024), as well as how it is implemented. PV panels comprise interconnected

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photovoltaic cells, typically made from silicon and other materials. These panels are commonly installed on rooftops, in solar farms, or integrated into various structures to generate renewable electricity for residential, commercial, and industrial applications.

PV technology also does not escape experiencing problems that need to be monitored and maintained, including issues faced by PV panels. Defects on PV panels refer to any abnormalities or faults on panels that can impair their performance, efficiency, or reliability (Osmani et al., 2023). These defects can manifest in various forms and may result from manufacturing flaws, installation issues, environmental factors, or degradation over time. Examples of defects are cracks, hotspots, delamination, soiling, and degradation (Afifah et al., 2021). Detecting and addressing PV defects is crucial for maintaining solar energy systems' optimal operation and longevity.

One of the simplest and most cost-effective methods for detecting defects is visual inspection, which involves manual examination for visible signs of damage like cracks, delamination, or corrosion. However, this method may overlook internal defects or those in hard-to-reach areas. Electroluminescence (EL) imaging, a non-destructive technique, captures images of PV panels under electrical excitation, revealing internal defects such as microcracks, hotspots, and cell shunts (Al-Waisy et al., 2022). Infrared (IR) thermography offers another non-destructive approach by capturing thermal images of panel surfaces to detect temperature variations indicative of localized defects like cell cracks or interconnect failures (Wang et al., 2022a). Electrical characterization techniques involve analyzing electrical parameters such as current-voltage curves and series resistance to identify deviations that may indicate the presence of defects affecting panel performance. Moreover, machine learning (ML) algorithms have emerged as a powerful tool for defect detection in PV panels, automating the identification and classification of defects with high accuracy based on datasets of defect images or electrical characteristics.

Artificial intelligence (AI) has become widely used across various fields, including image detection. However, traditional image processing remains essential for studying the features and characteristics of an image. The study by Et-taleby et al. (2025) used image processing to identify the pixel intensity levels based on the brightness of thermal images, which were then classified into whether the PV panels were damaged. For our work, we report the capability of using image processing techniques without AI assistance to identify whether a panel is defective. Subsequently, classification experiments using AI alone and combining both techniques were conducted. Defect detection using RGB images is somewhat limited, whereas these images can be captured using high-definition cameras built into drones. RGB images are more convenient for computational processes than hyperspectral images (Purwadi et al., 2023). This research examines the feasibility and usefulness of employing RGB image processing techniques to detect defects in PV panels.

Work in (Patel et al., 2020) proposed a method to detect PV defects using image processing based on RGB images. Their work uses thresholding, morphological erosion, and edge detection to detect the defect PV. For edge detection, the Kirsch operator was used to detect the edges and boundaries of the image. RGB images were turned into HSV, grayscale, and binary images for processing. Image processing has also been used by Qasem et al. (2016), where the PV images are filtered, and the pixels' lightness is differentiated to determine the dusty level that appears on the PV.

Next, Salamanca et al. (2017) proposed to detect solar panels after the image was captured by a standard camera without light restriction. In their study, they used computer vision and image processing techniques to identify if there were solar panels in the images. Guan et al. (2023) proposed a method based on the gray-level co-occurrence matrix that allows the defect to be detected based on the images captured by unmanned aerial vehicles to enhance the PV defect detection process.

Two types of images are used to detect the defect: IR and RGB in the work proposed by Kuo et al. (2023). IR imaging was used to detect PV module thermal defects, and RGB was used to detect defects on

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the panel's surface. The study used Otsu's method to determine the threshold value and used the Laplacian operator to detect the edge in the image.

Although several studies have applied advanced methods for PV defect detection, these approaches often require expensive equipment, controlled environments, or complex training datasets. Furthermore, RGB image-based methods remain underexplored, particularly for low-cost and real-time applications. This study utilizes RGB images of PV panels to determine whether a panel is defective or not after applying image processing techniques. After this introduction section, this paper will discuss the methodology used in this paper, followed by results and discussion. The final section is a conclusion.

2. METHODOLOGY

In this study, the detection of defects in the RGB image was accomplished by a series of stages that included image pre-processing, histogram analysis, and image segmentation techniques that included two methods: classical segmentation and K-means clustering, edge detection, and panel classification, as shown in Fig. 1.

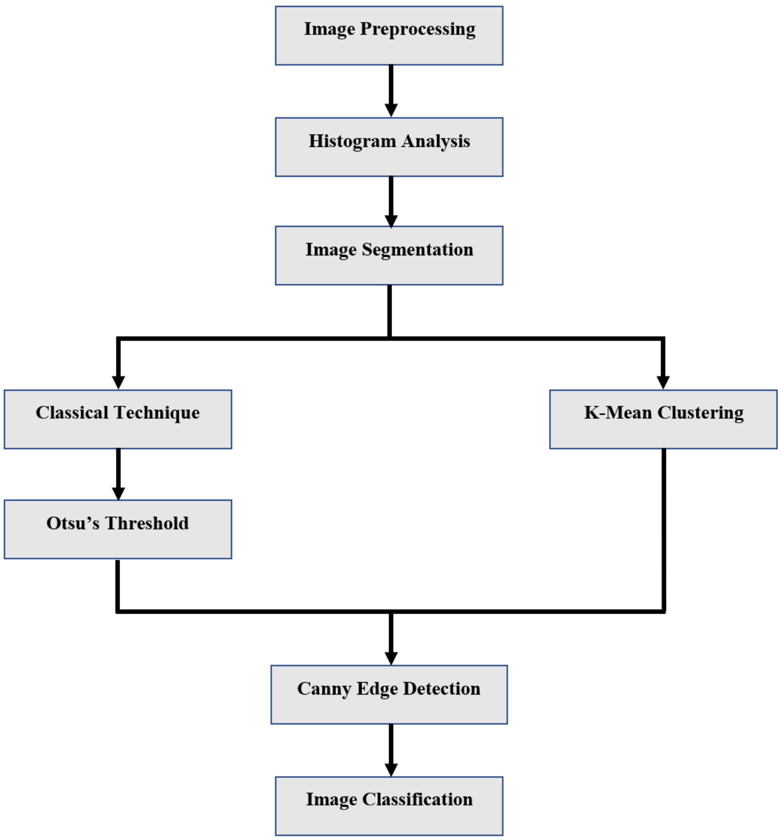

Fig. 1. Flowchart of the process to classify the images into defect and clean PV panels

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The selection of Otsu's thresholding, Canny edge detection, and K-means clustering in this study is driven by their proven effectiveness in various image processing applications, particularly in segmentation and edge detection tasks. Otsu's thresholding is a widely used global binarization method that automatically determines the optimal threshold to distinguish foreground from background in grayscale images. Canny edge detection is chosen due to its robustness in detecting sharp intensity changes, which is essential for outlining defect boundaries on PV panels. Meanwhile, K-means clustering is a simple yet powerful unsupervised learning algorithm that segments image regions based on color or intensity similarities, enabling the separation of defective areas from clean regions. These methods are also computationally efficient and adaptable to different image types.

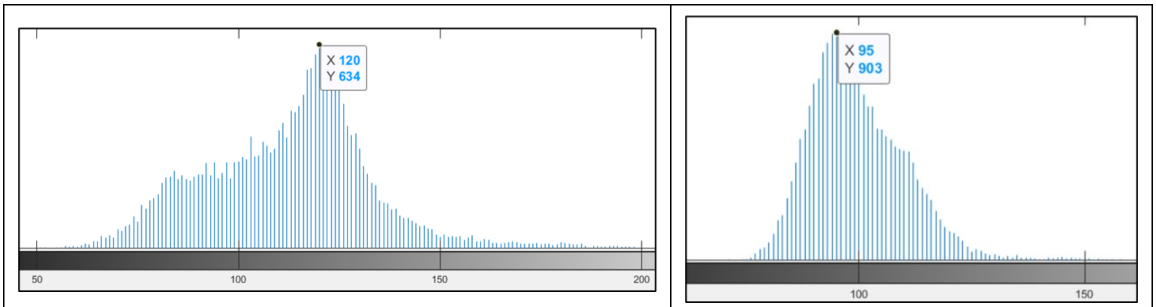
2.1 Image pre-processing

The image data used in this study are publicly available and were obtained from Kaggle. The dataset consists of RGB images of photovoltaic (PV) panels with varying conditions, including clean and defective panels. These images were used to evaluate the effectiveness of image processing techniques for defect detection.

At this preliminary step, the image will go through image cropping and resizing. In this case, the raw image of a panel needs to be cropped and resized to eliminate the background image, leaving only the image of the panel itself. The initial stage of image preprocessing, which involves cropping and resizing images, is designed to optimize the image for further processing. It aims to increase image quality, clarity, and accuracy (Wang et al., 2022b; Zyout & Oatawneh, 2020). During the image preprocessing stage, the background was removed through a cropping process, then the image dimensions were resized from 136 × 160 pixels to 132 × 156 pixels.

2.2 Histogram analysis

Image histogram analysis is important in image processing techniques for detecting defects in PV panels (Ali et al., 2020; Prabhakaran et al., 2023). An image's histogram represents the distribution of pixel intensities across the image. Several key insights can be derived from analyzing the histogram, which is helpful for flaw detection in PV panels. The dynamic range of pixel intensities in the image is shown through histogram analysis. Adjusting the contrast based on the histogram might make defects more visible, making them easier to notice. This modification entails expanding or equalizing the histogram to use the entire intensity range of the image. Fig. 2 shows the results of histogram analysis with examples of defective and clean panel images. Regarding light intensity range and the highest pixel, the clean panel image and the defective panel image provide distinct results.



(a) Histogram of defect panel image

(b) Histogram of clean panel image

Fig. 2. Histogram analysis of defect and clean panel images

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2.3 Image segmentation

Image segmentation refers to splitting the PV panel image into meaningful and distinct parts or segments, depending on specific features, when detecting defects on PV panels. It is an important stage in defect identification since it separates the faults from the background and other normal sections of the panel. In this section, the methods that will be tested on the images are the classical technique (grayscale technique) and k-means clustering.

2.3.1 Otsu's threshold

After the preprocessing stage, the RGB image will be transformed into a grayscale image. The transformed grayscale image simplifies the analysis by lowering the image to a single channel intensity value. The image is then segmented into regions of interest using Otsu's thresholding technique, which is determined by maximizing the inter-class variance. This aids in recognizing faults from normal and background areas (Patel et al., 2020; Espinosa et al., 2020). After thresholding, the Canny edge detection approach is implemented to recognize the edges of the defect image. The study by Fadzli et al. (2024) concluded that the Canny operator emerged as the most effective and comprehensive edge detection technique. Canny edge detection identifies sharp intensity shifts typically associated with defect boundaries. Potential fault areas are identified by recognizing these edges, providing crucial information for the next stage. The grayscale threshold obtained from Otsu's approach is stacked with the edges obtained by Canny edge detection to improve the visualization of the reported faults. This overlay combines binary defect segmentation with edges to produce a more realistic picture of fault boundaries. Fig. 3 depicts the process.

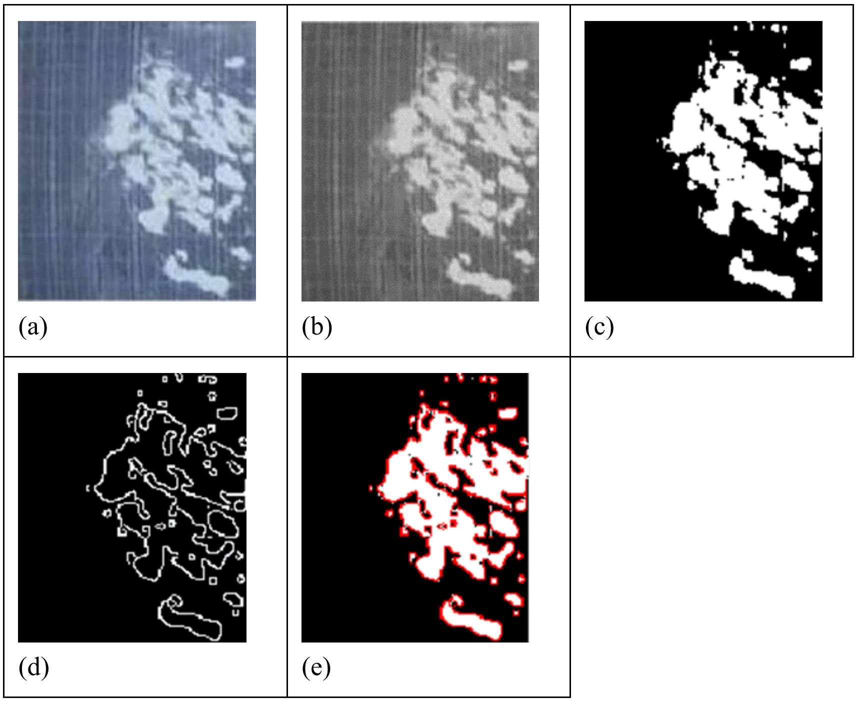

Fig. 3. Image segmentation using Otsu's threshold method. (a) The original image (b) The grayscale image (c) After applying Otsu's threshold method (d) Edge detection using Canny operator (e) Overlay image of (c) and (d)

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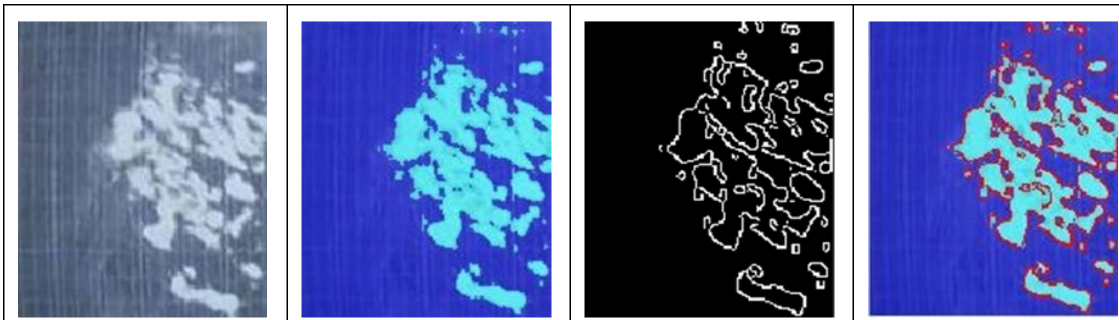
2.3.2 K-mean clustering

Clustering divides a given set of data points into K unique groups based on similarity or closeness. K-means clustering is used in image processing to group pixels in an image into K clusters, allowing the identification of various regions or objects within the image. In this project, the value of cluster K is set to 2, as the approach of this clustering technique is to separate the image into two clusters, potentially separating defective areas from the rest of the panel. Following the K-means clustering process, the Canny edge detection technique determines the image's edges. Edge detection detects areas with significant intensity shifts, frequently indicative of probable defective areas. The K- means the clustered image is overlaid with the edges acquired from the Canny edge detection to improve the visualization of the discovered defects. This approach aids in separating defects from the background and graphically shows probable defect borders, making future defect analysis and characterization easier. Fig. 4 depicts the entire process.



(a) (b) (c) (d)

Fig. 4. Image segmentation using the K-means method. (a) The original image (b) K-mean clustering is applied to the image. (c) Edge detection (d) Overlay image of (b) and (c)

2.3.3 Image classification

The number of edge pixels is calculated after applying the classical technique, which includes grayscale conversion, Otsu's method thresholding, and Canny edge detection, as well as the K-means clustering technique, which includes K-means clustering, Canny edge detection, and overlaying the clustered image with the detected edges. Calculating the number of edge pixels offers a quantitative measure of the detected edges, allowing the severity or extent of faults in the PV panel image to be assessed. By comparing the number of edge pixels between a clean PV panel image and a defective PV panel image, it is possible to evaluate the panel as clean or defective by counting the number of edge pixels within the segmented defect regions obtained from either the classical technique or the K-means clustering technique. The number of edge pixels is obtained by traversing the image and counting the pixels detected as edges during the Canny edge detection step when each technique was overlaid. The count is computed within defective areas segmented using either a classical grayscale technique or K-means clustering approaches.

3. RESULTS AND DISCUSSION

In this research, Otsu's threshold and K-means clustering techniques were employed to effectively visualize and analyze defects observed in PV panels using RGB images. By extracting the number of edge pixels from these images, valuable insights into the condition of the panels were obtained. A systematic

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comparison of the edge pixel counts between clean and defective panel images established a robust threshold for distinguishing between the two states. This threshold functions as a classification criterion, facilitating the automated recognition and categorization of newly captured images. The findings contribute to the ongoing analysis of PV panels and informed decision-making regarding maintenance and repair strategies.

A dataset of RGB images featuring both clean and defective panels was employed to achieve this purpose. The inquiry began with an initial analysis of the dataset, with a focus on the histogram analysis and the number of edge pixels in each K-means clustering image, as it shows a clearer visual of separating the defective area and the normal area. During the project's preliminary phase, the defect panel image had a low maximum pixel value but a wide light intensity spectrum. In contrast, the clean panel had a high maximum pixel but a small light intensity spectrum. Then, a separate test was done on a dataset of 15 images containing both clean and defective panels before running the images in the graphical user interface developed using MATLAB, as shown in Fig. 5. The objective was to measure the number of edge pixels in each image and provide a preliminary observation. The dataset was purposefully chosen to include many clean and defective panel conditions.

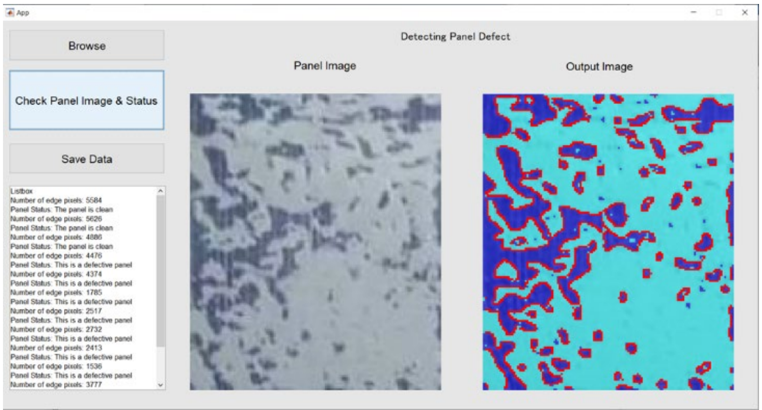

Fig. 5. Graphical User Interface designed using MATLAB for the PV panel detection

After analysing the 15 images, a distinct pattern emerged. The number of edge pixels in clean panel images was consistently 4500 or higher, but the number of edge pixels in defective panel images was 4500 or below. This preliminary discovery gave critical information about the expected distribution of edge pixel counts between clean and damaged panels. The detection and classification were then evaluated on the 610 sample images. The status of defect detection in each image was compared to the 610 sample images labeled as ‘actual status’ with ‘predicted status’ as in Table 1 to evaluate the accuracy, precision, and sensitivity of the algorithm used for defect identification in PV plant panels based on RGB images. Positive is classified as a clean panel image, while negative is classified as a defective one.

The data of the total count of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) is in Table 2. The data analysis from Table 3 gives important predictive performance and the actual condition of the panel images. The algorithm achieves an accuracy of 90.66%, indicating that 90.66% of all panel images were correctly classified. This high accuracy demonstrates the algorithm’s ability to differentiate between defective and clean panels using RGB image data. The true positive rate or recall is 95.45%, reflecting the algorithm's ability to identify 95.45% of defective panels correctly.

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Table 1. Comparison of predicted and actual status in PV panel defect detection

	Predicted Status	**Actual Status**
True Positive (TP)	Clean	Clean
True Negative (TN)	Defect	Defect
False Positive (FP)	Clean	Defect
False Negative (FN)	Defect	Clean

A high recall value indicates that the system effectively minimizes missed detections of defective panels, thereby enhancing reliability. Similarly, the true negative rate representing the specificity is 90.28%, signifying that 90.28% of clean panels were correctly identified. This high specificity suggests a low false positive rate, reducing the likelihood of misclassifying clean panels as defective. The positive precision is 43.30%, representing the proportion of correctly classified defective panels out of all panels predicted as defective. The relatively lower precision suggests that a significant number of clean panels were misclassified as defective. This could be attributed to an imbalance in the dataset, where defective panels constitute a smaller proportion of the total samples, leading to a higher false positive rate. Conversely, the negative precision is 99.61%, indicating that 99.61% of the panels predicted as clean were indeed clean. This high precision highlights the algorithm's effectiveness in correctly identifying clean panels while minimizing false positives.

Table 2. Total counts of classification results

Total TP	42
Total TN	511
Total FP	55
Total FN	2

Table 3. Evaluation metrics for classification performance

Accuracy	90.66%
True Positive Rate	95.45%
True Negative Rate	90.28%
Positive Precision Value	43.30%
Negative Precision Value	99.61%

4. CONCLUSION

The focus of this research was to detect defects in PV panels using image processing techniques based on RGB imagery. The algorithm separated the RGB images into distinct regions using image processing, allowing the identification of probable defects. Furthermore, the number of edge pixels was used to characterize the existence of defects. The significance of this study lies in its potential to revolutionize defect detection practices in PV plants and significantly impact the solar energy industry. This study makes

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several important advances by utilizing RGB image processing techniques for identifying defects in PV panels. For future development planning, the use of AI can be a valuable addition to improving the defect detection system, as proposed by (Othman et al., 2024). By introducing AI into the defect detection system, it is possible to achieve even higher accuracy rates and improve the overall performance of the algorithm. It can also address the dataset imbalance issue identified in this study. This may include applying data augmentation, synthetic image generation, or resampling methods to improve model robustness when classifying underrepresented defective panel images.

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6. CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of the paper.

7. AUTHORS' CONTRIBUTIONS

Suhaili Beeran Kutty: Conceptualisation, methodology, writing, analysis, formal analysis, and project administration; **Mohamad Ad-Fadhil Musa**: Data processing, analysis, and formal analysis; **Murizah Kassim**: Review, editing, and proofreading; **Puteri Nor Ashikin Megat Yunus:** Review, editing, and proofreading.

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