An Integrated Fuzzy Logic and Support Vector Machine–Based Framework for Automated Defect Detection in Photovoltaic from Thermal Infrared Imaging

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Abstract: This study aims to develop an automated and reliable framework for detecting and classifying defects in photovoltaic (PV) panels operating within solar arrays. As PV systems are increasingly deployed worldwide, early and accurate fault diagnosis has become essential to maintain efficiency, reduce energy losses, and lower maintenance costs. To address this need, the proposed approach integrates thermal infrared (IR) imaging with advanced image processing and machine learning techniques. Initially, thermographic images are preprocessed using a fuzzy logic–based edge detection method to suppress background noise and enhance defect boundaries. The Hough Transform is subsequently applied to localize panel structures and extract geometric features. Relevant attributes are then organized into a labeled feature matrix and used to train a Support Vector Machine (SVM) classifier with a fine Gaussian kernel. Model performance is validated using ten-fold cross-validation. Experimental results demonstrate that the proposed framework effectively identifies multiple PV panel defects, including hotspots, delamination, cell damage, and surface contamination, achieving a classification accuracy of 91%. The findings confirm the robustness and reliability of the integrated method. Practically, the system offers a cost-effective and intelligent tool for real-time fault monitoring, enabling improved maintenance planning, enhanced operational reliability, and optimized performance of large-scale PV installations.

Keywords: Photovoltaic Panels; Thermal Infrared Imaging; Defect Detection; Fuzzy Edge Detection; Hough Transform.

Introduction

The rapid expansion of photovoltaic (PV) installations has intensified the need for reliable [1] and efficient [2] fault detection mechanisms to ensure optimal energy yield and system longevity. Thermal infrared (IR) imaging has emerged as a practical non-invasive technique [3] for identifying defects such as hotspots [4], delamination [5], cell damage [6], and surface contamination [7]. However, accurate interpretation of thermographic data remains challenging due to background noise [8], environmental variability [9], and complex panel geometries [10]. Existing studies often rely on conventional edge detection or standalone machine learning models, which may struggle to distinguish true defect signatures from irrelevant thermal patterns. These limitations highlight the need for a robust, automated framework capable of enhancing defect features while maintaining reliable classification performance under real operating conditions.

To address these challenges, this research proposes an integrated defect detection framework that combines fuzzy logic–based edge detection, Hough Transform–based panel localization, and Support Vector Machine (SVM) classification. The innovation of the study lies in the synergistic use of fuzzy membership functions to improve edge precision, coupled with geometric line detection to eliminate background interference and determine module orientation. Extracted features are systematically organized into a labeled matrix and used to train an optimized SVM model with a fine Gaussian kernel and ten-fold validation. This integrated methodology enhances both localization and classification accuracy, offering a practical and intelligent solution for automated PV panel fault diagnosis in real-time operational environments.

Method and Models

This research presents an automated framework (as shown in Figure 1) for detecting and classifying defects in photovoltaic (PV) panels using thermal imaging and machine learning. Infrared (IR) images of PV modules are first acquired using a thermal camera with Wi-Fi capability. The images undergo preprocessing through fuzzy edge detection to enhance defect boundaries and suppress background noise. In the development phase, relevant features are extracted from the processed images to construct a labeled feature matrix. These features are then used to train a Support Vector Machine (SVM) classifier, with optimized parameters to improve classification performance. The Hough Transform is additionally applied to improve panel localization and structural line detection. Once trained, the SVM model is deployed in an online framework for automated defect detection and classification. The proposed system enables accurate identification of PV panel faults, improving reliability, maintenance efficiency, and overall solar array performance through intelligent, data-driven analysis.

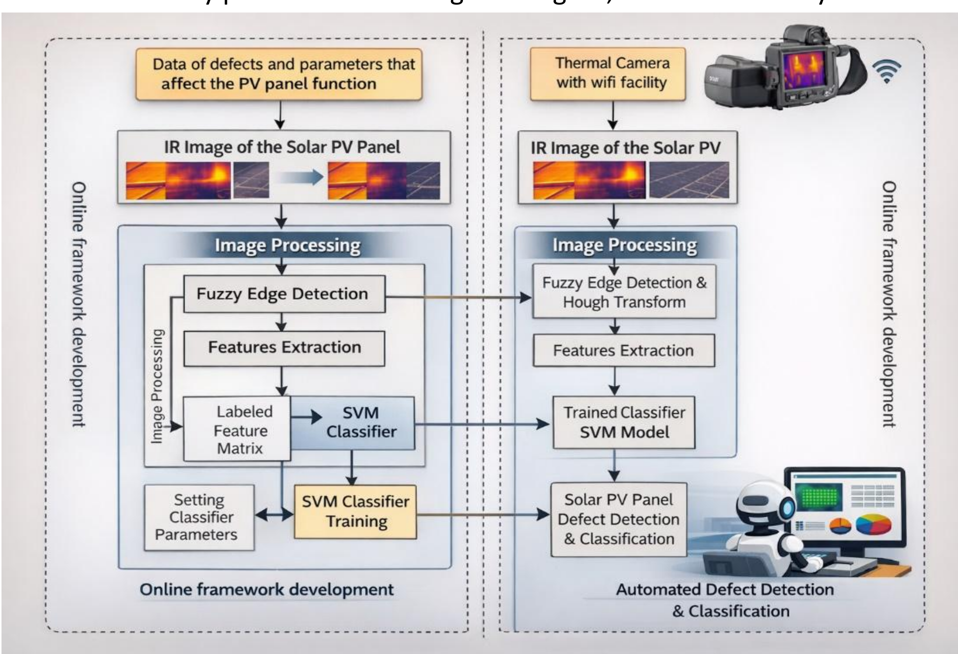

Figure 1. Research method.

Experiments and Results

Figure 2 presents the infrared (IR) image captured under specified site conditions, highlighting multiple photovoltaic (PV) panel defects. Fault (F1) is identified as a localized hotspot caused by improper maintenance and partial shading. Fault (F2) results from an air bubble in the back-sheet, disrupting heat dissipation and producing thermal irregularities. In Fault (F3), failed cell damage is evident through abnormal temperature distributions. Fault (F4) indicates delamination, likely linked to a short-circuit effect that intensifies heating. Fault (F5) shows bird droppings that obstruct irradiance and cause uneven temperature rise. All thermograms were recorded during real-time system operation.

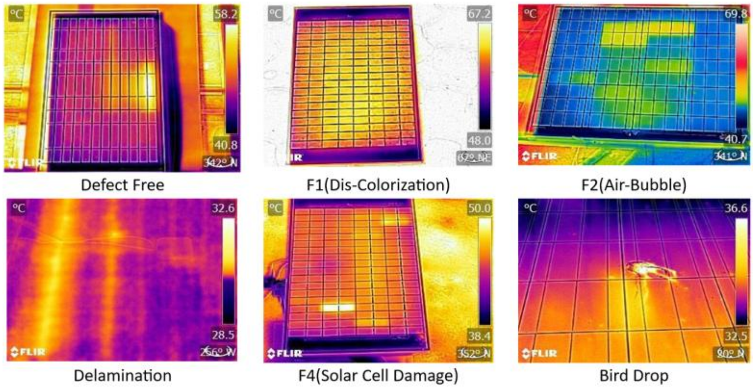

Figure 2. Thermal image of the defective PV panel for test case.

Grayscale images derived from the thermal data were first converted into two-dimensional (2-D) image arrays to facilitate detailed analysis. The image gradients in the horizontal (x) and vertical (y) directions were then computed using a double-matrix approach to enhance edge and defect detection. This was accomplished by convolving the grayscale image with appropriate gradient filters, and the resulting gradient values were normalized within the range of −1 to 1 to ensure analytical consistency. As shown in Figure 3, the thermal image is decomposed into its horizontal and vertical gradient components. Edge features were subsequently extracted using a fuzzy logic–based method, where membership functions evaluated pixel transitions between homogeneous regions and edge regions.

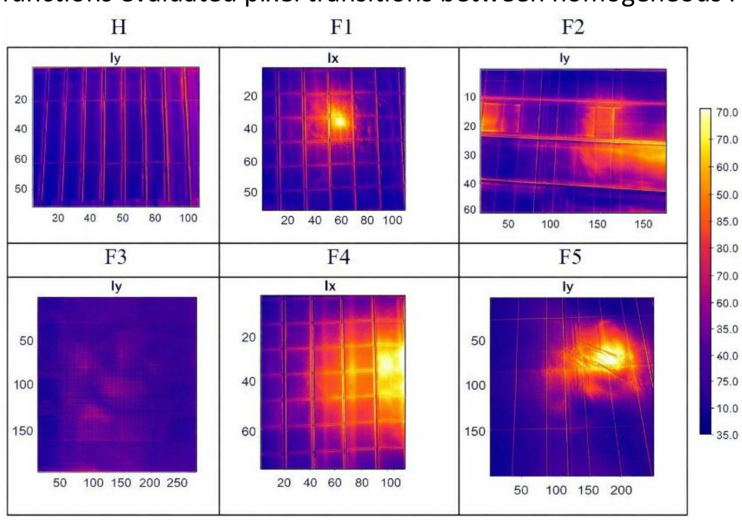

Figure 3. 2D gradients of the IR image in x and y-axis.

The first-order derivative (i.e., gradient) of the image forms the fundamental basis for defining the input membership functions. When the gradient value of a pixel is equal to zero, a Gaussian membership function (MF) with a degree of one is assigned, indicating maximum belongingness to a non-edge region. The standard deviation, set at 0.1, plays a critical role in regulating the performance of the edge detector. Increasing the standard deviation beyond this value reduces the sensitivity of the fuzzy system, thereby diminishing its ability to accurately identify edge features. For the output variable, triangular membership functions are employed to facilitate clear identification of the onset, peak, and recognition of edges. This configuration enables a more precise classification of pixels into edge and non-edge categories. Figure 4 presents the resulting edge-detected images corresponding to the input thermograms, along with the defined membership functions for both input and output variables.

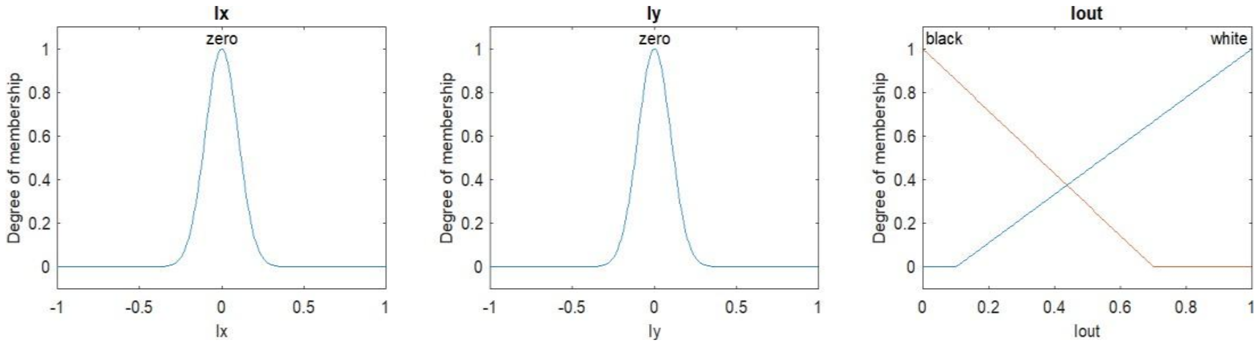

Figure 4. Input and output Fuzzy membership function.

When the gradient of a pixel is zero in both the horizontal and vertical directions, the pixel is classified as belonging to a homogeneous region and, according to the defined criteria, is assigned a white value. Conversely, if the gradient in either direction deviates from zero, the pixel is identified as part of an edge and is consequently represented in the darker region of the output image. The boundaries of the acquired thermal image are extracted using the fuzzy-based image processing approach illustrated in Figure 5. This rule-based fuzzy edge detection method generates an 8-bit grayscale output image with intensity values ranging from 0 to 255. The resulting image effectively delineates all panel borders and successfully highlights various defects and irregularities present on and around the panel surfaces.

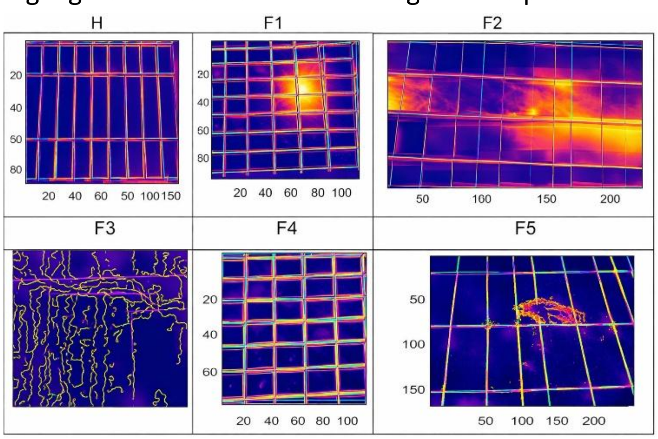

Figure 5. Edge detection using fuzzy logic of defective PV panel IR image.

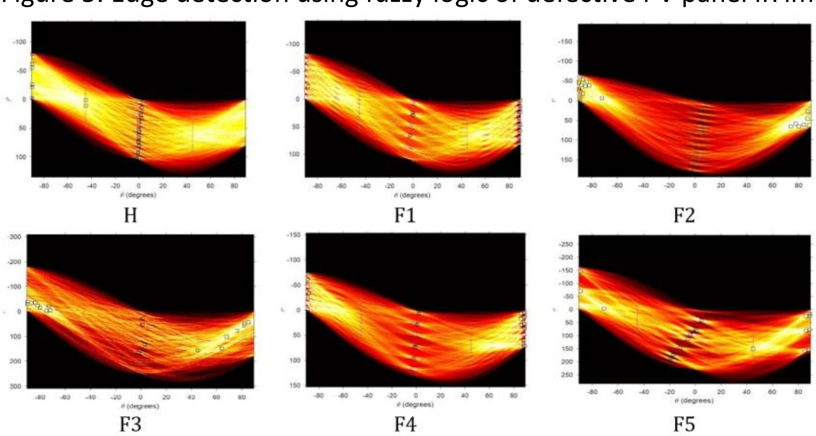

Figure 6. Hough transform of defective PV panel IR image.

The coordinates of detected edges in the photovoltaic (PV) panel image are obtained using the Hough Transform (HT). A numerical matrix of the binary image in the h and θ domains maps spatial edge points into parameter space, where prominent peaks indicate dominant panel lines and boundaries. As shown in Figure 6, the HT effectively highlights extracted linear features.

Figure 7 illustrates the spatial arrangement of the detected Hough lines and corresponding peaks used to determine the coordinates of the solar photovoltaic (PV) image. In the figure, the starting point of the PV module region is marked with a yellow “X,” while the end point is indicated by a red “X,” clearly defining the spatial extent of the module area. The identified Hough lines are represented in cyan and green. The green lines delineate the perimeter of the panel region, thereby outlining its structural boundaries, whereas the cyan line corresponds to the longest detected Hough line within the image. This distinction facilitates precise geometric interpretation of the panel layout. By applying this approach, extraneous background features present in the edge-detected image are effectively eliminated, enabling accurate localization of the panel within a larger array. Furthermore, the method provides valuable information regarding the orientation of the module, thereby enhancing the robustness of panel detection and alignment analysis.

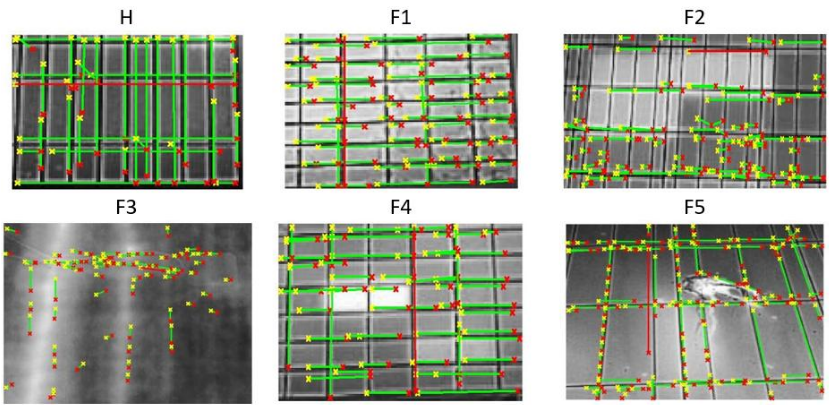

Figure 7. Hough transform lines and peaks of defective PV panel IR image.

Conclusions

In this study, a defect detection system for photovoltaic (PV) panels operating within a solar cell array was developed and systematically evaluated. The proposed approach was tested using diverse samples of unlabeled data and demonstrated a strong capability to learn distinctive fault patterns and accurately classify various types of PV panel defects. To enhance defect visibility and minimize background interference, the thermal infrared (IR) images were first processed using a fuzzy-based edge detection technique. This method effectively suppresses background noise while preserving critical edge information, enabling precise identification of defect boundaries based on pixel intensity variations. The application of fuzzy logic in edge detection proved particularly advantageous, as it provides a flexible and robust mechanism for distinguishing meaningful structural features from irrelevant image artifacts. Following feature extraction, the derived attributes were used to construct a classification framework based on a Support Vector Machine (SVM) model. A fine Gaussian kernel was selected to optimize decision boundaries, and model performance was validated using a ten-fold cross-validation strategy. The results indicate that the proposed classifier achieved a training accuracy of 91%, demonstrating its reliability and effectiveness in identifying and categorizing PV module faults.

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