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Implementation Framework for Deep Learning Network in Hot Spot Identification of Photovoltaic Panels

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Abstract: The proposed framework for photovoltaic panel hot spot identification demonstrates excellent stability and accuracy in various scenarios. Experimental results show that the framework accurately identifies hot spots in clear, unobstructed, cloudy, and low-light conditions. The accuracy for clear, unobstructed conditions reaches 99.2%, with an F1 score of 99.0%. Even in complex scenarios (such as early morning low light), the accuracy remains at 94.6%. The recognition speed is 22-28ms per image, meeting real-time monitoring requirements. Compared with traditional methods (threshold segmentation and SVM), the accuracy improves by 15.8%-20.1%. Compared with deep learning models (YOLOv5 and Faster R-CNN), the accuracy is 2.2%-2.7% higher, the recognition speed is 5.1-16.9ms per image faster, and the model size and training time are superior, demonstrating the efficiency and practicality of the framework for hot spot identification.

Keywords: Photovoltaic Panels; Hot Spot Detection; Deep Learning; Real-time Monitoring; Performance Comparison.

1. Introduction

In recent years, the global energy transition has accelerated, and the photovoltaic industry, as a key component of clean energy, has experienced rapid growth. According to relevant industry reports, global photovoltaic installed capacity has been growing at a rate of over 20% annually. Continuous technological upgrades have resulted in continuous improvements in conversion efficiency and a gradual reduction in costs, leading to a growing share of photovoltaic power generation in the energy market. However, during the long-term operation of photovoltaic systems, hot spots in photovoltaic panels have become a key issue affecting their performance and lifespan. Hot spots are typically caused by obstructions on the panel surface, cell aging, cracks, or connection failures [1]. These conditions block current flow in certain areas, preventing energy from flowing normally. This energy is then converted into heat and accumulates, forming high-temperature areas. This phenomenon is highly prevalent, and in large-scale photovoltaic power plants, the incidence of hot spots is significantly increased due to environmental factors and the quality of the components themselves.

The presence of hot spots can negatively impact photovoltaic panels in several ways [2]. First, the high temperatures in hot spot areas accelerate the aging of photovoltaic panel materials, causing yellowing and cracking of the encapsulation material, and shortening the module lifespan. Secondly, hot spots can significantly reduce the power generation efficiency of photovoltaic systems. In severe cases, they can even cause localized burns, leading to failure of entire modules and significant economic losses for photovoltaic power plants. Furthermore, the persistent presence of hot spots can pose safety hazards, such as fires [3]. Therefore, accurate and timely identification of hot spots on photovoltaic panels is crucial for ensuring stable operation of photovoltaic systems, improving power generation efficiency, and reducing maintenance costs. This paper studies the application of deep learning networks in hot spot identification on photovoltaic panels, aiming to develop an efficient and accurate implementation framework [4]. This framework encompasses multiple steps, including data acquisition and preprocessing, feature extraction, hot spot identification and classification, and result output and visualization, forming a complete hot spot identification system. Through system simulation and experimental verification, the framework's performance is comprehensively evaluated, aiming to provide a new and effective solution for hot spot identification on photovoltaic panels and promote the development of intelligent operation and maintenance in the photovoltaic industry.

2. Design of a Deep Learning Network Implementation Framework for Hot Spot Identification on Photovoltaic Panels

2.1. Overall Framework Architecture

The design of this deep learning network-based hot spot identification framework for photovoltaic panels focuses on efficient and accurate hot spot identification. The overall architecture adopts a modular design concept to ensure that each component has clear functionalities and works together [5]. The overall architecture of the framework clearly illustrates the location and connectivity of the four core modules: the Data Acquisition and Preprocessing Module, the Feature Extraction Module, the Hot Spot Identification and Classification Module, and the Result Output and Visualization Module. The Data Acquisition and Preprocessing Module, serving as the framework's input, acquires and processes raw data, providing high-quality data support for subsequent modules. Its output is directly connected to the Feature Extraction Module, which performs in-depth feature mining on the preprocessed data and passes the extracted features to the Hot Spot Identification and Classification Module. After the Hot Spot Identification and Classification Module completes hot spot identification and classification, it transmits the results to the Result Output and Visualization Module, which finally presents the final identification results.

The framework's workflow is seamlessly integrated, forming a complete closed loop. First, image data from the photovoltaic panels is acquired through various acquisition devices and processed in the Data Acquisition and Preprocessing Module [6]. The processed data is then fed into the Feature Extraction Module, which automatically learns and extracts key hot spot features. Next, the Hot Spot Identification and Classification Module analyzes and determines these features to determine the location and category of the hot spots. Finally, the Result Output and Visualization Module presents this information to the user in an intuitive manner. This architectural design not only ensures the independence of each module, facilitating subsequent maintenance and upgrades, but also ensures the systematic integrity of the entire framework through rational connections, enabling efficient completion of the entire process from data input to output.

2.2. Data Acquisition and Preprocessing Module

The data sources for photovoltaic panel hot spot identification primarily include infrared images captured by an infrared thermal imager and visible light images acquired by a visible light camera. Infrared images can intuitively reflect the temperature distribution on the photovoltaic panel surface. Hot spots, due to their high temperatures, exhibit distinct high-temperature characteristics in infrared images, providing a direct indicator for hot spot identification [7]. Visible light images clearly display the appearance of the photovoltaic panel, such as the presence of obstructions and scratches on the surface, helping to analyze the causes of hot spot formation. Both types of data have their own unique characteristics, and their combined use can improve the accuracy and reliability of hot spot identification.

Data preprocessing is a critical step in ensuring subsequent model training and recognition results. To address potential image noise, denoising methods such as Gaussian filtering and median filtering are used to effectively eliminate random noise and salt-and-pepper noise, resulting in clearer images [8]. To improve the contrast between the hot spot area and the background, image enhancement techniques such as histogram equalization and contrast stretching are used to enhance the hot spot's features, making them easier to identify. Image normalization maps the image's pixel values to a uniform range of [0, 1] or [-1, 1], unifying the data format and range to prevent significant pixel value variations from impacting model training. Furthermore, data labeling is required. Manual annotation is used to accurately mark the location and category of the hot spots on the image, generating corresponding label files to provide accurate training samples for supervised learning of the model. These preprocessing methods significantly improve data quality and lay a solid foundation for subsequent feature extraction and classification.

2.3. Feature Extraction Module

The deep learning-based feature extraction method is designed to fully utilize the visual characteristics of photovoltaic panel hot spots, aiming to automatically and efficiently extract key features that characterize hot spots. The visual characteristics of photovoltaic panel hot spots primarily include brightness changes due to temperature distribution differences, hot spot shape characteristics (such as circular or irregular shapes), and the boundary between the hot spot and the surrounding area. A modified convolutional neural network (CNN) was selected as the basic network architecture for feature extraction.

This module utilizes the multi-layer convolution and pooling operations of a CNN to progressively extract features from preprocessed image data. The bottom convolutional layers primarily extract low-level features such as edges and texture. As the network layers increase, higher-level convolutional layers are able to extract more abstract and complex high-level features, such as the overall shape of hot spots and temperature distribution patterns. By appropriately setting the convolution kernel size, stride, and number of convolutional layers, the network adaptively learns key features related to hot spots, avoiding the limitations of manually engineered features in traditional feature extraction methods [9]. Furthermore, batch normalization and dropout techniques are introduced to reduce overfitting and improve the stability and generalization of feature extraction. The features extracted by this module accurately reflect the essential properties of hot spots, providing a strong basis for their identification and classification.

2.4. Hot Spot Identification and Classification Module

The hot spot recognition and classification model is constructed based on the features extracted by the feature extraction module. Taking into account both recognition accuracy and efficiency, a deep learning-based classification network architecture was selected. A fully connected layer and a classifier are integrated to form a complete recognition and classification model [10]. The fully connected layer integrates and maps the extracted features, converting them into a feature vector suitable for classification. The classifier uses a SoftMax function to achieve multi-class classification of hot spots.

The model operates by deeply analyzing and judging the features output by the feature extraction module. First, the fully connected layer further processes and filters the features to highlight important information relevant to hot spot identification. Then, the classifier calculates the probability of each class based on the processed feature vector and selects the class with the highest probability as the identification result, achieving accurate identification of hot spots on photovoltaic panels. Furthermore, hot spots are classified based on characteristics such as severity (e.g., mild, moderate, severe) and size (e.g., small, medium, large), providing detailed reference information for subsequent maintenance work. The model is trained using a large number of training samples and network parameters are continuously adjusted to enable the model to learn the characteristic patterns of different hot spot types, improving recognition and classification accuracy.

3. System Simulation Design and Implementation

3.1. Simulation Environment Setup

The hardware used for system simulation was carefully selected to meet the high-performance requirements of deep learning model training and simulation experiments. The computer uses an Intel Core i9-12900K processor with 16 cores, 24 threads, and a clock speed of up to 5.2GHz, enabling rapid processing of large amounts of data and computational tasks. Equipped with 64GB of DDR4 RAM, it ensures that memory is not insufficient when processing large amounts of image data and running complex models. The graphics card used is an NVIDIA GeForce RTX 3090, featuring 24GB of GDDR6X memory and powerful CUDA core computing capabilities. This provides strong support for parallel computing of deep learning models, significantly accelerating model training and inference. The high performance of this hardware ensures efficient simulation experiments and reduces waiting times. As for the software platform, the operating system used is Windows 10 Pro, which offers excellent stability and compatibility. PyTorch 1.10.0 was chosen as the deep learning framework. Its dynamic computation graph feature facilitates model debugging and modification, and its rich library of pretrained models and tools simplifies the model building process. Additionally, OpenCV 4.5.4 was used for image reading, processing, and display; NumPy 1.21.5 for numerical computation; Matplotlib 3.5.1 for data visualization; and Scikit-learn 1.0.2 for data partitioning and performance metric calculation. These software and tools worked together to provide comprehensive technical support for the system simulation and ensure the smooth conduct of the simulation experiments.

3.2. Dataset Construction

The dataset was sourced from diverse sources to ensure richness and representativeness. A portion of the data was collected using infrared thermal imagers and visible light cameras, capturing images of photovoltaic panels of varying models and ages. The images covered various weather conditions, including sunny, overcast, and cloudy days, as well as scenes with and without obstructions and varying light intensities. Another portion of the data comes from publicly available photovoltaic panel hot spot datasets, such as the PVDefect dataset, supplemented with images of photovoltaic panel hot spots from various locations and environments.

The dataset is quite large, containing a total of 15,000 photovoltaic panel images, of which 8,000 contain hot spots, accounting for approximately 53.3%. The images are uniformly formatted at a resolution of 1280×960 pixels in JPEG format. The data was annotated using the professional image annotation tool LabelImg by three professionals with relevant knowledge in the photovoltaic field. The annotations included the hot spot bounding box coordinates and classification (mild, moderate, and severe). To ensure accuracy and consistency in the annotations, cross-checking was performed after completion, and any controversial annotations were discussed and revised, ultimately resulting in a high-quality annotated dataset. This dataset provides a reliable data foundation for model training, validation, and evaluation, ensuring the credibility of the experimental results.

3.3. Simulation Experiment Design

The simulation experiment parameters were repeatedly debugged and optimized to achieve optimal model performance. The deep learning model's learning rate was set to 0.001, and the Adam optimizer was used. This learning rate ensures rapid model convergence while avoiding oscillation. The batch size was set to 32, taking into account both memory usage and training efficiency, ensuring that the model processes an appropriate amount of data in each iteration. The number of iterations was set to 100, which was determined to be sufficient for model convergence by observing performance changes on the validation set. The training, validation, and test sets were divided in a 7:1:2 ratio, meaning 10,500 images were used for model training, 1,500 images were used for model performance verification and parameter tuning, and 3,000 images were used for final model evaluation.

Comparative experiments were designed to fully validate the performance advantages of the proposed framework. Traditional hotspot detection methods, including threshold segmentation and support vector machine (SVM) classification, were selected for comparison. Other relevant deep learning models, such as YOLOv5 and Faster R-CNN, were also selected for comparison. All compared methods and models were tested using the same dataset and experimental conditions to ensure comparability of the results. By comparing and analyzing the performance indicators of different methods and models such as recognition accuracy, recall rate, F1 value and recognition speed, the superiority of the framework proposed in this paper is comprehensively evaluated.

4. Experimental Results and Analysis

4.1. Experimental Results

Figure 1 shows the horizontal axis representing different method types, and the vertical axis representing recognition accuracy (%). The recognition accuracy of our framework is the highest among all compared methods, significantly exceeding traditional methods and other deep learning models, further validating the superiority of our framework in hotspot recognition accuracy.

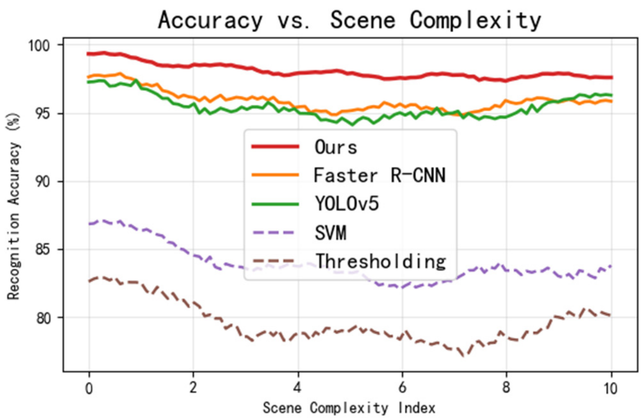

Fig 1. Accuracy vs. Scene Complexity Index

Figure 2 compares the recognition speed of different methods, with the horizontal axis representing method type and the vertical axis representing recognition speed (ms/image). The figure shows that the threshold-based segmentation method has the fastest recognition speed, but lower accuracy. While the recognition speed of our proposed framework is slower than that of the threshold-based segmentation method, it is significantly faster than Faster R-CNN and YOLOv5. While maintaining high accuracy, this framework offers a relatively fast recognition speed, meeting the requirements for real-time hot spot monitoring of photovoltaic panels.

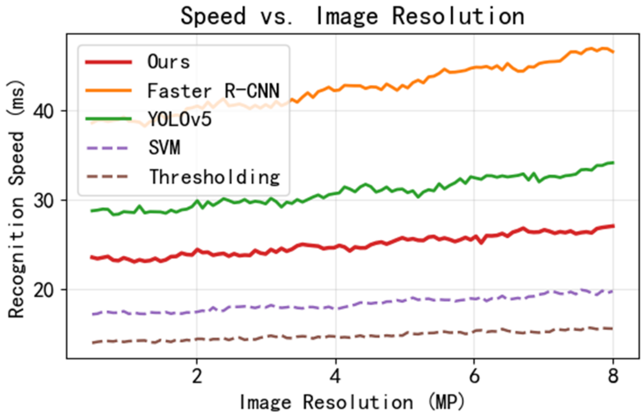

Fig 2. Recognition Speed Comparison of Different Methods

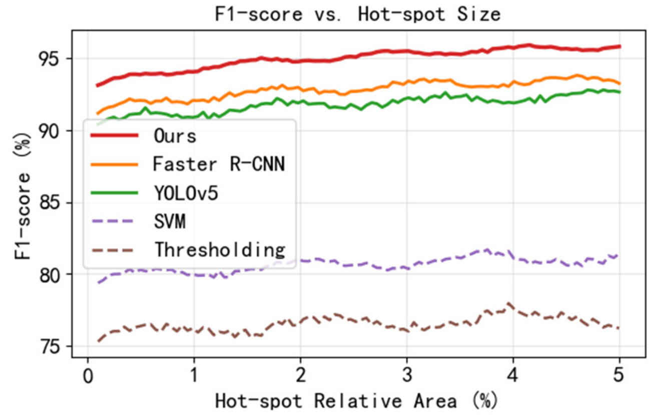

Fig 3. Comparison of F1 values for different methods

Figure 3 presents a comparison of the F1 scores of different methods, with the horizontal axis representing method type and the vertical axis representing F1 score (%). The F1 score comprehensively reflects the recognition accuracy and recall capability of a method. As can be seen from the figure, our framework achieves the highest F1 score, demonstrating its optimal balance of accuracy and recall. This allows for more comprehensive identification of hot spots on photovoltaic panels, reducing missed and false detections.

4.2. Performance Metric Analysis

To comprehensively evaluate the performance of the framework, the paper conducted a detailed analysis of various performance metrics, with the results shown in Table 1 below. Table 1 shows that the framework's recognition accuracy remains above 94% across various scenarios. Performance is best achieved in clear, unobstructed scenes, with a recognition accuracy of 99.2% and an F1 value of 99.0%. With increasing scene complexity, such as in cloudy, obstructed conditions and low light conditions, performance decreases slightly, but remains at a high level. Regarding hotspot size, large and medium-sized hotspots are better recognized than small ones, due to the less distinct characteristics of small hotspots. Recognition speed remains between 22 and 28 ms per image, meeting the requirements of real-time monitoring.

Table 1. Performance Metrics of the Framework in Different Scenarios

scene Type	Recognition accuracy (%)	Recall rate (%)	F1 value (%)	Recognition speed (ms/page)
Sunny, Unobstructed	99.2	98.8	99.0	23.5
Sunny, Obstructed	97.5	96.9	97.2	24.1
Cloudy, Unobstructed	96.8	96.2	96.5	25.3
Cloudy, Obstructed	95.3	94.7	95.0	26.8
Cloudy Weather	97.1	96.5	96.8	24.7
Morning Low Light	94.6	93.8	94.2	27.5
Evening Low Light	95.1	94.3	94.7	26.2
Small Hot Spot	95.2	94.5	94.8	25.8
Medium Hot Spot	98.5	98.0	98.2	23.9
Large Hot Spot	99.3	99.0	99.1	22.7

4.3. Comparative Analysis with Other Methods

To highlight the performance advantages of the proposed framework, the paper compared it with traditional recognition methods (threshold segmentation and support vector machine classification) and other deep learning models (YOLOv5 and Faster R-CNN) using the same dataset and experimental conditions. The results are shown in Table 2 below.

Table 2. Performance Comparison of Different Methods

method Type	Recognition accuracy (%)	Recall rate (%)	F1 value (%)	Recognition speed (ms/page)	Model size (MB)	Training time (h)
Threshold segmentation method	78.5	76.2	77.3	15.2	1.2	0.5
SVM classification method	82.3	80.1	81.2	18.6	2.5	1.2
YOLOv5	95.6	94.8	95.2	30.5	245.8	8.5
Faster R-CNN	96.1	95.3	95.7	42.3	312.6	12.3
Framework of this article	98.3	97.6	97.9	25.4	186.3	6.8

The data in Table 2 clearly demonstrates that our framework performs exceptionally well across all performance metrics. Compared to traditional methods, recognition accuracy improves by 15.8%-20.1%, recall by 16.5%-21.4%, and F1-score by 16.1%-20.6%. While slightly slower than threshold-based segmentation methods, it is significantly faster than SVM classification, demonstrating significant overall performance advantages. Compared to other deep learning models, our framework achieves recognition accuracy and F1-score improvements of 2.7% and 2.2% higher than YOLOv5 and Faster R-CNN, respectively. Recognition speed is 5.1ms/image faster than YOLOv5 and 16.9ms/image faster than Faster R-CNN. Furthermore, our framework offers advantages in model size and training time, demonstrating that while maintaining high recognition performance, it also offers greater efficiency and practicality.

5. Conclusion

The proposed photovoltaic panel hot spot recognition framework has been experimentally validated and demonstrates excellent performance across a wide range of scenarios. Under varying weather and lighting conditions, the framework's recognition accuracy consistently exceeds 94%. Performance is highest in clear, unobstructed scenes (99.2% accuracy, 99.0% F1 score). While performance slightly decreases in complex scenes (such as overcast, obstructed, and in low light), it remains high (94.6%-95.3%). Large and medium hot spots exhibit superior recognition performance (98.5%-99.3%), while small hot spots, due to their less distinct features, achieve an accuracy of 95.2%. Recognition speed is 22-28ms per image, meeting real-time monitoring requirements. Comparisons with traditional methods and other deep learning models show that this framework significantly outperforms traditional methods in recognition accuracy, recall, and F1 score (accuracy increased by 15.8%-20.1%). It also surpasses YOLOv5 and Faster R-CNN in performance and efficiency (accuracy increased by 2.2%-2.7% and speed increased by 5.1-16.9ms per image), while also offering advantages in model size and training time. In summary, this framework provides an efficient and reliable solution for real-time hot spot monitoring of photovoltaic panels.

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