Defect Detection of Solar Panels Based on UAV Perspective

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Abstract: The global energy structure is rapidly transitioning towards clean energy, and the solar power generation industry is developing quickly. If solar panels have defects, their power generation efficiency decreases, maintenance costs increase, and safety incidents may even occur. Therefore, this study proposes a scheme for detecting defects in solar panels by integrating drone technology, deep learning algorithms, and multi-source data processing. Using the drone's flight control system and optimised path planning system, images of large-scale panels are efficiently collected. With the improved YOLOv8 algorithm and multispectral image processing technology, even tiny defects such as hairline cracks can be accurately identified. Combined with 5G real-time transmission and distributed cloud storage, a comprehensive data management system is established. Experiments show that under different lighting conditions and terrains, the system achieves a defect detection accuracy of 92.3% and a recall rate of 87.6%. Its efficiency is more than 15 times higher than manual inspection and can reduce maintenance costs by 30%, thereby providing the industry with an intelligent and cost-effective solution.

Keywords: Drone; Solar Panels; Defect Detection; Deep Learning; YOLOv8; Multispectral Imaging

1. Introduction

Driven by the 'dual carbon' goals, solar energy has become an important component of clean energy, and the global photovoltaic installation capacity is also growing rapidly. According to data released by the China Photovoltaic Industry Association, the global solar photovoltaic installation capacity had already exceeded 2TW in 2024, with China contributing more than half. Currently, large ground-mounted photovoltaic power stations and distributed rooftop photovoltaics have become the main application scenarios for solar photovoltaic.

1.1 Research Background

Over long periods of operation, solar panels are easily affected by environmental and manufacturing process factors, leading to defects such as cracks and hot spots. If a panel develops a hot spot, its power generation efficiency can decrease by fifteen to thirty per cent, and in severe cases, it may even cause a fire, rendering the entire array inoperative.

Currently, traditional inspections mainly rely on manual patrols and fixed sensor monitoring. During manual inspections, personnel need to climb scaffolds or roofs, which results in low work efficiency, with an average daily inspection area of less than 10,000 square metres, and there are also safety risks such as falling from height and electric shock. Although fixed sensors can monitor in real time, their coverage is very limited, making it difficult to detect minor defects, and the deployment costs are high. Nowadays, with the rapid development of drone technology and artificial intelligence, drone-based inspection solutions have become an important method for addressing challenges in traditional inspections, offering the advantages of "high-altitude coverage, flexibility, and low cost".

1.2 Research Significance

The value of this study lies in the construction of a full-process intelligent detection system of 'collection - processing - recognition - feedback', with the following three advantages: In terms of efficiency, with the collaboration of UAV swarms and autonomous path planning, more than 100,000 square metres of solar panels can be inspected daily, making it an order of magnitude more efficient compared to manual inspection; in terms of accuracy, by integrating multispectral imaging and deep learning algorithms, it not only overcomes the limitations of visible light but also accurately identifies hidden defects, with a false detection rate below 8%; in terms of cost, due to savings in labour and equipment deployment, the full lifecycle operation and maintenance costs are reduced by 30% - 40%, and early warning can reduce power generation losses by 5% - 8%.

1.3 Research Content and Framework

The study focuses on three modules: 'drone system design, image processing algorithms, and data management platform'. In terms of the drone detection system, we optimised flight control and path planning to achieve high-precision positioning, ensuring the stability of image acquisition. The defect detection algorithm establishes a three-tier system of 'preprocessing, feature extraction, and classification recognition', which enhances recognition accuracy and improves generalisation ability. The data management platform utilises 5G and distributed storage technologies to achieve real-time data transmission, secure storage, and visual feedback.

2. Current Status of Domestic and International Research

2.1 Progress of Domestic Research

Since 2015, domestic research has combined drones with solar panel inspections [1], and a collaborative model of 'universities responsible for R&D and enterprises for application' has now been established. At the technical application level, top photovoltaic companies such as Longi and Jinko have conducted pilot drone inspections, using a combination of 'infrared thermal imaging and high-definition visible light'[2] cameras to detect obvious defects such as hot spots and damage. Its detection efficiency is 5 to 8 times higher than manual inspection, but the recognition rate for microcracks smaller than 0.1mm is less than 70%. In terms of algorithm research, a team from Guizhou University proposed an algorithm based on SVM for defect classification, which extracts image texture features to classify hot spots and damage, achieving an accuracy rate of 85%, though in some complex environments, the accuracy can drop below 65%. In terms of system integration, the 'drone plus IoT' platform developed by Nanjing University of Aeronautics and Astronautics enables data connectivity, but cannot resolve path conflicts in multi-drone fleets, which limits efficiency in large-scale applications.

2.2 Progress of Research Abroad

European and American countries are relatively advanced in the industrial application of drone detection technology, with the core breakthroughs being 'multi-source data fusion' and 'intelligent decision-making'. In terms of hardware, the American company PrecisionHawk launched the SolarInspect drone system, equipped with a high-resolution multispectral camera with a wavelength range of 400 - 1700nm, and also fitted with LiDAR to simultaneously obtain optical and three-dimensional information of the solar panels. In terms of algorithms, the German Fraunhofer Institute proposed an end-to-end defect detection model based on CNN, using ResNet50 as the backbone network and trained with 100,000 labelled samples, achieving a defect recognition accuracy of 90%. However, due to the large size of the model, real-time operation on the drone end is challenging. In terms of applications, the EU's 'SolarDrone' project incorporates digital twins, but the deployment cost of its system is relatively high, making it difficult to widely promote in small and medium-sized power plants.

2.3 Research Gaps and Development Trends

Current research mainly has three limitations: first, the established models have poor generalisation ability. Many algorithms perform well in good weather conditions and flat station environments, but their accuracy significantly decreases in more complex settings; second, the real-time performance is relatively poor, as many deep learning models require cloud computation, making it difficult to meet instant feedback requirements; third, cluster cooperation technologies are still imperfect. When multiple drones are operating, issues such as overlapping paths or omissions often occur, affecting detection efficiency.

The future development shows three major trends: first, the level of intelligence will be enhanced, moving beyond the stage of defect identification to further defect prediction, using big data to analyse the ageing patterns of battery panels, thereby identifying potential problems 6 to 12 months in advance; second, the integration of multi-source data will be realised, combining data from various modalities such as visible light and infrared to transition from two-dimensional image detection to three-dimensional structures with optical features; third, deep integration of the Internet of Things will be achieved, relying on 5G and edge computing [3] to enable real-time interconnection of devices, establishing a complete closed-loop system for detection, diagnosis and maintenance.

3. Research Content and Technical Plan

3.1 UAV Detection System Design

Drone systems play a role in defect detection similar to the human 'eye' and must meet the three requirements of 'high-precision positioning, stable flight and high-quality imaging'. The specific design details are as follows.

3.1.1 Flight control system optimisation

To improve positioning accuracy, we adopted a solution combining 'GPS and Beidou dual-mode positioning with an MU inertial measurement unit', using the Kalman filter algorithm to correct any positioning errors; when the drone hovers 1 to 3 metres above the battery panel array, its positioning error can be controlled within ±0.1 metres, ensuring complete image acquisition.

In terms of flight stability control, we designed an adaptive PID controller based on outdoor wind disturbances ranging from 0 to 10m/s to adjust its roll and pitch angles in real time, keeping attitude fluctuations within ±2° to avoid image blur.

In terms of emergency handling mechanisms, we have set up low battery automatic return and obstacle avoidance functions, detected through TOF sensors, which automatically navigate around obstacles when the distance to them is less than one metre.

3.1.2 Intelligent path planning algorithm

Based on two different types of photovoltaic power plants, ground and rooftop, we have designed two path planning schemes:

For ground power plants, a grid coverage algorithm optimised by the A* algorithm is used to divide the power plant into several rectangular grids, allowing the drone to fly close to the edges of the grids. According to the camera's field of view, we set the spacing between adjacent flight paths to 1.5 metres to ensure full coverage.

For rooftop power stations, we use a contour tracking algorithm to allow drones to scan the contours of the roof to generate paths for irregular areas; then we use the RRT* algorithm to avoid various obstacles to ensure that path planning takes less than 5 minutes per 10,000 square metres.

3.1.3 Selection and integration of image acquisition devices

The core equipment for this study selected the DJI Matrice 350 RTK drone, while also using a variety of sensors. We used the DJI Zenmuse P1 as a multispectral camera, which can perform 4K visible light and near-infrared imaging, with a frame rate of up to 30fps. If there are defects, its reflectivity will decrease by 10% to 20%. The infrared thermal imager we used was the FLIR Vue Pro R, with a resolution of 640×512 and a temperature measurement range of -20°C to 150°C, capable of detecting hot spot defects. Synchronous flight and photography were triggered using the SDK interface, taking one photo every 0.5 seconds, with an image overlap of no less than 20%.

3.2 Image Processing and Defect Detection Algorithms

Image processing and related algorithms are equivalent to the 'brain' of the entire system, and need to achieve the transition from 'raw images' to 'clearly identifying the defect type and specific location'. Its processing workflow is as follows:

3.2.1 Image preprocessing

The original image is affected by lighting, shaking and noise, requiring preprocessing:

In terms of geometric correction, because the drone is capturing images in an inclined state, the captured images may be distorted. In this case, we need to use a perspective transformation algorithm to correct the originally inclined image into an orthophoto, ensuring that the error during the correction process is within ±1 pixel.

In terms of image preprocessing, colour images are converted to grayscale to reduce data volume, and contrast is enhanced using histogram equalisation; backlit images use CLAHE [4] to suppress overexposed areas, thereby highlighting specific details of dark defects.

For noise removal, a combination of median filtering and Gaussian filtering is used. Median filtering is primarily for removing salt-and-pepper noise, while Gaussian filtering targets Gaussian noise. After processing, the signal-to-noise ratio can be improved by more than 20dB.

3.2.2 Defect feature extraction

According to different defect types such as cracks, hot spots, and damage, we extract features from both visual and spectral as well as temperature aspects. In terms of visual features, for visible light images, the edges of cracks are extracted using the Canny edge detection algorithm [5], and a series of morphological operations are used to connect broken edges to form a complete contour; in terms of spectral and temperature features, hot spots are extracted by obtaining the temperature from infrared images, setting a temperature threshold, with areas above the threshold identified as hot spots, and hidden cracks are extracted in near-infrared images by their reflectivity, with regional reflectivity being 15%-25% lower than normal, which is located using threshold segmentation.

3.2.3 Deep learning defect classification model

To improve defect detection accuracy and generalisation capability, the YOLOv8 [6] model was modified. In the backbone network, the original CSPDarknet was replaced with EfficientNet-B0, reducing the parameter size from 60MB to 35MB and achieving a real-time running frame rate of 15fps on the drone. The loss function adopts the CIoU method, which effectively mitigates the excessive sensitivity of traditional IoU to overlapping areas, thereby enhancing localisation accuracy.

During the model training and validation phase, we constructed a dataset containing over 5,000 annotated samples with six defect types. There were 2,000 normal samples and 3,000 defective samples, which were divided into training, validation, and test sets in a 7:2:1 ratio. Then, by using techniques such as rotation, flipping, and brightness adjustment, the training set was expanded to 20,000 images. Using the Adam optimiser with an initial learning rate of 0.001 and a batch size of 16, after 50 epochs of training, the test set achieved an accuracy of 92.3% and a recall rate of 87.6%, showing a significant improvement compared with before.

3.3 Data Processing and Management Platform

To achieve real-time transmission, secure storage, and efficient utilisation of detection data, we have established a corresponding data management platform. In terms of real-time data transmission, UAV detection data is divided into dedicated network slices through 5G slicing technology, ensuring a bandwidth of no less than 100Mbps and a latency of less than 50ms, allowing images and detection results to be transmitted to the cloud in real time.

For big data storage, the Hadoop distributed storage architecture [7] is used, with HDFS mainly responsible for storing raw images, each 4K image being about 10MB, resulting in a daily storage volume of approximately 100GB. HBase is used to store detection results, including defect types, locations, and other information, supporting fast queries of data at the tens of millions level. In terms of data security and privacy protection, TLS1.3 protocol is used for transmission encryption to prevent data theft, and AES-256 algorithm is used to encrypt more sensitive data during storage. Access control is implemented through the RBAC model, assigning permissions according to different roles to avoid data leakage.

4. Experiments and Results Analysis

4.1 Experimental Environment and Parameter Settings

4.1.1 Experimental site

We selected two different photovoltaic power stations as test scenarios. The first is a large ground-mounted power station in Xuzhou, Jiangsu Province, with an installed capacity of 50MW. The solar panel arrays are arranged in a rectangular layout, measuring 1000 metres in length and 500 metres in width, with a total of 150,000 panels. The terrain is very flat, with no significant obstacles. The second is a rooftop distributed power station in an industrial park in Nanjing, Jiangsu Province, with an installed capacity of 1MW. The panels are installed on the roofs of the factory buildings, which range in height from 10 to 15 metres, and there are obstacles nearby such as air conditioning units and skylights.

4.1.2 Experimental equipment and software

In terms of hardware, the equipment we use includes the DJI Matrice 350 RTK drone, the Zenmuse P1 multispectral camera, and the FLIR Vue Pro R infrared thermal imager, and it is also equipped with a high-performance server with an NVIDIA A100 GPU and an Intel Xeon Gold 6348 CPU.

In terms of software, Python 3.9, PyTorch 2.0, OpenCV 4.8 (for image processing) and Hadoop 3.3 (for distributed storage) were used.

4.1.3 Evaluation criteria

We use four indicators to evaluate the performance of the system. The first is detection efficiency, which refers to the area of solar panels that can be inspected per hour, measured in ten thousand square metres per hour. The second is accuracy, which is the percentage of correctly identified defects out of the total identified defects. The third is recall rate, which is the percentage of correctly identified defects out of the actual number of defects. The fourth is localisation error, which is the distance between the algorithmically marked position and the actual defect location, measured in metres.

4.2 Experimental Results and Analysis

It can be seen from Table 1 that when using three drones for swarm collaboration, the detection efficiency is more than 15 times higher than manual inspection, especially with a more prominent efficiency improvement at rooftop power stations, where the intelligent path planning algorithm avoids rooftop obstacles and reduces ineffective flight time.

Table 1. Comparison of Detection Efficiency

Detection scheme	Scenario 1 (ground power station)	Scenario 2 (rooftop power station)	Average efficiency improvement
Manual inspection	8,000 square metres/hour	5,000 square metres/hour	-
Traditional drone (single)	52,000 square metres/hour	31,000 square metres/hour	6.5 times
This system (3 clusters)	125,000 square metres/hour	78,000 square metres/hour	15.2 times

The analysis results in combination with Table 2 show that:

1. There is a significant advantage in detecting tiny cracks, with an accuracy 12.7% higher than traditional YOLOv8, due to the CBAM attention mechanism enhancing the ability to detect small targets.
2. The accuracy of hot spot detection is the highest, reaching 95.6%. The temperature features presented in infrared images are not affected by lighting, making them easy to identify.
3. The average recall rate is 87.6%, higher than the 85.3% achieved by manual inspection, which can prevent missed detections during manual inspections.

Table 2. Comparison of Defect Identification Accuracy

Defect Type	This System (YOLOv8 Improved)	Traditional YOLOv8	Manual Identification
Cracks (width < 0.1mm)	89.2%(accuracy)	76.5%	82.1%
Hotspot (temperature difference 5-10℃)	95.6%(accuracy)	90.3%	88.7%
Damage (area < 10cm²)	94.3%(accuracy)	89.8%	91.5%
Average recall rate	87.6%	79.2%	85.3%

4.3 Positioning Error Test

Based on the positioning errors of 100 defect samples, it is known that 82% of the samples have a positioning error of no more than 0.1 metres, while 95% of the samples have a positioning error within 0.2 metres, with the maximum error being 0.25 metres. The current positioning accuracy meets the requirements for operation and maintenance, allowing personnel to quickly locate defects according to the system's annotations, avoiding secondary inspections.

4.4 System Stability Testing

Testing the system's stability in different environments: on sunny days, the accuracy is 92.3% and the recall rate is 87.6%; on cloudy days with insufficient light, the accuracy is 89.5% and the recall rate is 84.2%; in dusty weather with image noise, the accuracy is 86.7% and the recall rate is 81.5%. The system performs well in complex environments and can operate all day.

5. Innovations

5.1 Detection Technology Innovation: Multimodal Fusion Lightweight Models

Multispectral and infrared fusion detection effectively compensates for the limitations of visible light detection alone. Subtle hidden cracks that are not easily noticeable can be identified through near-infrared images based on differences in reflectivity, while early-stage hotspots can be detected using infrared images based on temperature differences, allowing precise defect localisation from both "optical" and "thermal" dimensions. The YOLOv8 model is lightweighted by replacing the original backbone network, reducing the model's parameters by 41.7% and enabling real-time operation at 15 frames per second on the drone.

5.2 Drone Application Innovation: Swarm Collaboration and Adaptive Path Planning

In multi-drone cooperative operations, MESH self-organising network technology[8] is introduced to enable 3 to 5 drones to work together, using a task allocation algorithm to divide inspection sub-areas and avoid overlapping paths, improving efficiency by 2.4 times compared to a single drone. Scenario-adaptive path planning can switch between different algorithms based on the terrain of ground or rooftop power stations, with planning time for every 10,000 square metres being under 5 minutes, demonstrating good environmental adaptability.

5.3 Data Processing Innovation: Real-Time Cloud-Edge Collaboration Defect Prediction

5G combined with edge computing uses a cloud-edge collaborative architecture, where drones serve as edge nodes responsible for image preprocessing and preliminary recognition, while the cloud is used for big data storage and model optimisation. This architecture significantly improves processing efficiency, with real-time performance three times better than full cloud processing. The defect prediction model is built based on historical data and operated using LSTM[9], capable of providing a six-month advance warning of potential hot spot defects, with an accuracy rate of 82%. This method achieves a shift from a 'passive detection' mode to a 'proactive prevention' mode.

6. Conclusion and Prospect

6.1 Research Conclusions

This study, based on defect detection of solar panels, has established a fully automated system covering the entire process of "drone collection, algorithm recognition and data management". According to experimental results, in terms of efficiency, collaborative operation using multiple drone swarms [10]increased detection efficiency by more than 15 times compared to manual inspection, fully meeting the needs of large-scale power plants during surveys; in terms of accuracy, the improved YOLOv8 model achieved an average precision of 92.3% and a recall rate of 87.6%, performing better than traditional detection methods and manual inspection; in terms of cost, the entire lifecycle operation and maintenance reduced costs by 30% to 40%, while also reducing power generation by 5% to 8%.

6.2 Future Prospects

This research requires optimisation from multiple aspects. In terms of multimodal data fusion, it is necessary to introduce LiDAR data to construct 3D point cloud models to identify surface flatness defects, achieving a comprehensive inspection effect of '2D images plus 3D structures'. Regarding the defect prediction model, the dataset should be expanded to 100,000 labelled samples, and by integrating meteorological and ageing data, the aim is to improve prediction accuracy to over 85%. For industrial application and promotion, the low-cost hardware solution developed in collaboration with photovoltaic enterprises needs to keep the total cost within 50,000 yuan to suit small and medium-sized power stations. This research provides intelligent solutions for the operation and maintenance of new energy equipment and holds significant value for the solar industry and new energy equipment inspection.

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