Fire Recognition for Photovoltaic Panel Fire Fighting UAV Based on Machine Vision

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Abstract. Photovoltaic (PV) power generation has been widely promoted due to the increased demand for clean energy in recent years, but the fires it generates are often prone to cause large negative impacts. Therefore, a machine vision-based fire recognition algorithm for PV panel fire-fighting UAVs is proposed in this research. The algorithm consists of image preprocessing, feature extraction and CNN-based recognition in three parts. Firstly, the image preprocessing stages are innovatively designed, including RGB operation, filtering operation and morphological processing. Then the feature extraction of the connectivity characteristics and the number of sharp corners of the suspected flame region after processing is carried out. Through a number of image preprocessing sessions and feature extraction sessions on the processed image information, the information of the ingested range with the dataset that combines the image information and feature information are represented. Finally, the data set of the photographed area is put into a well-trained neural network to determine. The improved CNN neural network makes the overall photovoltaic panel fire fighting UAV fire recognition algorithm reach 96.67% accuracy and more than 96.25% anti-jamming accuracy, which can complete the photovoltaic fire recognition task in an excellent way.

Keywords: Flame Recognition, Machine Vision, Neural Networks, UAV

1 Introduction

Photovoltaic power generation is a technology that utilizes the photovoltaic effect at the semiconductor interface to directly convert light energy into electricity, but its power generation process, such as MC4 connectors and other photovoltaic components in the critical contact will produce a flash-off phenomenon, which is very likely to cause the PV panels to catch on fire, resulting in ecological damage and significant economic losses. Therefore, in order to prevent the occurrence of fires in PV panels, it is particularly important to recognize the fire conditions for PV power generation fires [1-3].

Combining the results of past research, proven drone technology has been able to be applied in many areas of fire suppression. Ghali, et, al. applied two deep learning models to realize the recognition of forest wildfires by aerial photography, whose main

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recognition mechanism is visible and infrared light detection [4]. Rjoub et al. also proposed a novel UAV system for wildfire detection, whose principle is based on air quality detection and light detection [5]. The above flame recognition system is built for the application of aerial photography for photovoltaic panel flame recognition has an important guide, but taking into account the forest fire and photovoltaic panel flame in the recognition of recognition factors and interference factors are different, so this paper recognition algorithms using machine vision to detect visible light with the neural network learning way to build. Sherstjuk et al. have proposed a fire intensity evaluation method based on the forest fire monitoring system, in which two back propagation neural networks are used for identification and the training method of flame colour features and edge change features, which also has a better identification effect when coping with the photovoltaic fire identification [6]. In addition, this study also refers to and learns from the research ideas of researches in flame recognition and fire detection, and realizes the construction of the recognition algorithm of this paper under many experimental and testing environments [7-9].

In order to realize as clear and comprehensive PV panel fire recognition as possible under UAV load-permitting conditions, this paper specifically proposes a targeted fire recognition algorithm. The subsequent sections describe the algorithm design, flame characterization, recognition network construction and performance evaluation, respectively. Through the image processing of the UAV collected images, and through a series of image processing links to enhance the flame characteristics of the captured images, the final set of processed image information was submitted to the bp neural network and convolutional neural network for training, and the integrated photovoltaic panels flame colour, saturation, boundary shape and other characteristics of the fire recognition situation to make a final decision.

2 Drone Recognition Algorithm

Enter methodology section here. In order to build a fire recognition algorithm for photovoltaic panel fire-fighting UAVs that can accurately detect fires with excellent stability and robustness, this paper specifically designs the image preprocessing, flame feature extraction and flame recognition neural network construction and other links, and optimizes the parameter configurations of each link through several experimental simulations and research. The overall recognition algorithm schematic diagram is shown in Fig. 1.

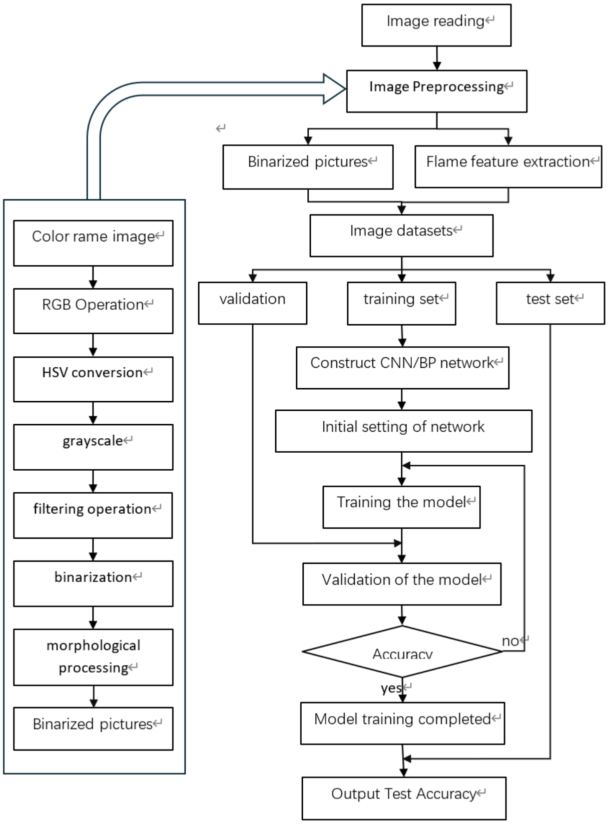


Fig. 1. Schematic diagram of the principle of the recognition algorithm

2.1 Image Preprocessing

In order to improve the recognition accuracy of the overall algorithm, image preprocessing is required to highlight the flame characteristics of the UAV-collected images. Firstly, the UAV samples the monitored PV panel area by shooting with a high-definition camera, and then performs RGB operation, HSV conversion, grayscaling operation, filtering operation, binarization operation, and morphological processing on the obtained colour frames in order, and finally obtains a binarized black and white image that excludes environmental interferences and has obvious flame features. The overall image preprocessing result is shown in Fig. 2 below.

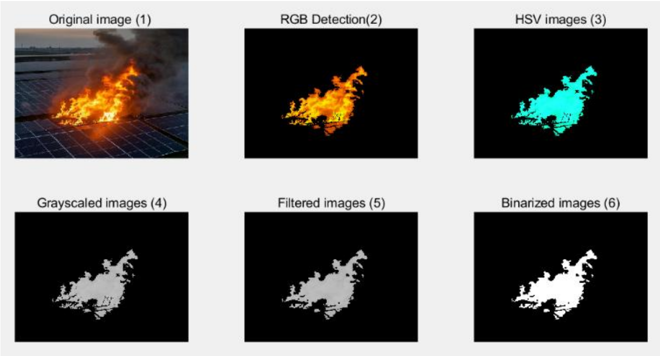


Fig. 2. Diagram of image preprocessing process

2.1.1 Perform RGB operations on the image.

In order to exclude the interference of non-flame regions on the image, and improve the accuracy and robustness of the overall image recognition. After conducting research and experiments on the RGB attributes of the flame colour of PV panels, this algorithm makes the following requirements for analysing the RGB value of the pixels in each flame region: the red channel is larger than the threshold value of 190, the red channel is larger than the green channel, and the green channel is larger than the blue channel. For the flame region that meets the above requirements to retain the pixel points, and for the region that does not meet the requirements of the RGB value is set to 0, that is, the non-flame region for the blackening operation. In order to achieve the purpose of highlighting the flame characteristics and excluding other interferences.

At the same time, in the actual test of PV panel flame colour frame image RGB attributes found that the flame characteristics are mainly determined by the red channel and the green channel, and the PV panel's background colour blue has nothing to do with the overall flame recognition. Therefore, the value of the blue channel of the image pixel point is often set to zero in order to exclude interference and highlight the flame characteristics.

2.1.2 HSV transformation of images.

As the HSV model has the advantage of better handling light changes and specific colour tasks, this algorithm carries out HSV operation on the processed images in the previous session in the image preprocessing session. The S component in the HSV model better reflects the eye-catching of the colour, thus reducing the impact of light changes on image recognition, which has a great advantage in recognizing the flame with uneven luminous intensity. At the same time the HSV colour model (hue, saturation, luminance) is able to better simulate the way the human eye perceives colour, which makes the colour detection and classification work more accurate. For example, it is easy to find a particular colour in a picture, such as the red part. Therefore, to improve the overall algorithm recognition accuracy, the colour frame picture operation is added.

2.1.3 Graying of images.

In order to make the processed image in the basic preservation of the original characteristics of the case fully reduce the amount of computer operations. At the same time, filtering some of the environmental factors interfere to reduce the shooting by the equipment and weather. Therefore, in order to simplify the image matrix, improve computational efficiency and stability, this algorithm adds a colour image grayscaling operation.

2.1.4 Filtering operation on images.

In order to effectively remove the noise in the image, and at the same time can well protect the shape, size and specific geometric and topological structure features of the image target, this algorithm carries out filtering operation on the processed grayscaled image.

After many experimental attempts, this algorithm finally adopts a median filter with a size of 3 × 3 for filtering to achieve the purpose of removing the noise, and at the same time, it is added to the original image for bootstrap filtering in order to retain the boundary features of the flame.

2.1.5 Binarization of images (threshold segmentation).

In order to distinguish the detected flame target from the background of PV panels more clearly, enhance the contrast features of the image, highlight the edges of the flame in the image, connectivity and other features, and at the same time to improve the efficiency of computer operations, this algorithm performs a binarization operation on the processed image.

After several simulations and comparisons, this algorithm uses the Otsu image threshold segmentation algorithm to calculate the global threshold based on the grayscale image. The Otsu method selects a threshold K to minimize the intra-class variance of the thresholder black and white pixels. For the input grayscale image, one of the pixel points is preferentially acquired and its grayscale value is compared with the threshold value K. If the grayscale value of the pixel point is greater than the threshold value, then its grayscale value is adjusted to 225, otherwise its grayscale value is set to 0. Repeat the above operation until all the pixel points of the image are traversed, and at this time, the output image is the binarized image.

2.1.6 Morphological processing of images.

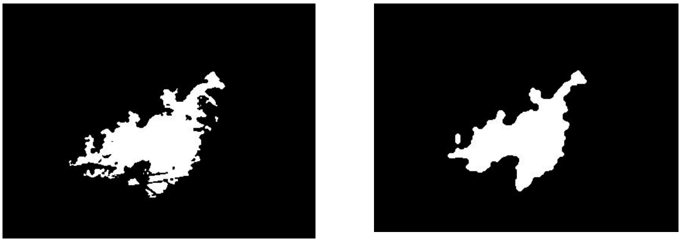
Morphological processing of binarized images targeting the recognition of flames can effectively improve the shape and characteristics of the flame region, highlight features such as the flame area and the shape of the boundary, and enhance the subsequent recognition effect. The morphological processing operation designed in this recognition algorithm is divided into 4 steps, namely, closed operation, erosion operation, filling and reverse filling operation and edge expansion operation. The specific filling effect is shown in Fig. 3 below.

1) Closed operation: the morphological closed operation is to expand first and then erode, and these two operations use the same structural elements. This algorithm creates a disk-shaped planar structural element with a radius of 3, and performs the closed-computing operation on the binary image to initially fill the gaps in the image and exclude some of the interference in the recognition, in order to achieve the purpose of morphologically coarser processing of the image being processed.

2) Erosion operation: the erosion operation reduces the boundaries of foreground objects in the image. For flame images, it removes small noise points and burrs while preserving their boundary features.

3) Fill and reverse fill operation: In order to prevent interference with features such as flame area and connectivity when flame features are extracted next, some non-flame areas, and voids in the internal areas of the flame are filled by fill and reverse fill operation. That is, the black non-flame area of white holes filled with black, the white flame area of the internal black holes filled with black.

4) Expansion operation: The expansion operation increases the boundary of the foreground objects in the image. Expansion after erosion restores the size of the flame area and fills in some small voids.



(a) *(b)*

Fig. 3. Morphological processing effect. (a) Binarized image, (b) Filled images

2.2 Flame Feature Extraction

In order to make the overall algorithm to recognize the flame accuracy, stability and robustness is higher, flame feature extraction is an essential part of the recognition algorithm. The specific flame feature elements are as follows:

1) Count the number of pixels with a value of 1 and the number of pixels with a value of 0

2) Find connected regions and count the number of connected regions

3) Count the number of pixels (area) of each connected area, i.e. flame area feature

4) Count the flame tip characteristics

2.3 Flame Recognition Neural Network Construction

This article refer to Shaojun Zeng et al. research results in designing the neural network and finally choose CNN neural network and BP neural network for the recognition experiments [10].

2.3.1 Convolutional Neural Network Construction.

Convolutional neural network is a class of feed-forward neural networks that contain convolutional computation and have a deep structure, which is one of the representative algorithms for deep learning. Schematic diagram of convolutional neural network construction, as shown in Fig. 4. The design elements of the overall convolutional neural network mainly include the number of network layers, convolutional kernel parameters, pooling layer settings, the number of neurons and excitation functions, etc. The specific network design process is as follows:

(1) The number of network layers: this algorithm builds a CNN network with the help of Matlab tools, and the overall architecture is divided into input layer, convolutional layer, pooling layer, fully connected layer and output layer.

2) Input signal: The input layer of convolutional neural network usually receives image information. The input image size of this algorithm is 300×400, which is reconstructed as a new multi-channel data, which is used as the input signal of the neural network.

3) Output signal: the network training objective of this algorithm is to determine whether there is a flame in the image or not, so the output signal has only two identification results, i.e., with flame and without flame.

(4) Convolutional kernel parameters and pooling layer settings: In the convolutional layer, this algorithm chooses a convolutional kernel of size 3×3, which is designed to capture the detailed local features in the image, in order to dig deeper into the complex features of the image, and to enhance the network's capability of extracting image features.

5) Pooling layer settings: the pooling layer adopts maximum pooling, the pooling window size is set to 2×2, and the step size is 2. The output of the convolutional layer is downsized to reduce the amount of data and computation, and at the same time prevent overfitting.

6) Activation function: for this binary classification task, this algorithm uses the commonly used ReLU function as the activation function. The simpler calculation makes ReLU extremely efficient in large neural networks. At the same time, the ReLU function makes a part of neurons not activated when the input is negative, which helps to reduce the computation and memory consumption of the network, thus improving the training and operation efficiency of the network.

After determining the key elements of the convolutional neural network such as the input signal, convolutional layer, pooling layer, hidden layer, and output signal through the above steps, the convolutional neural network algorithm can be applied to solve the optimal weights of each layer. The trained network is utilized to identify the unknown image and thus determine whether a fire has occurred in the image captured by the UAV.

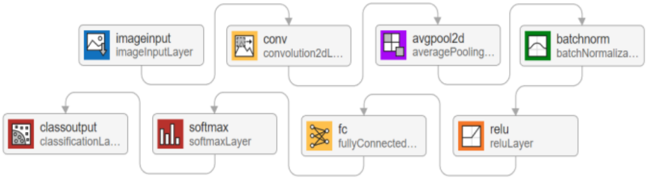


Fig. 4. Flowchart of convolutional neural network construction

2.3.2 bp neural network construction.

The overall bp neural network design elements mainly involve the number of network layers, the number of neurons and excitation function, etc. The specific network design process is as follows:

(1) The number of network layers: this algorithm is based on Matlab tools to build bp network, the overall division into three parts: input layer, hidden layer and output layer, and all are single-layer structure.

(2) Input signal: The input layer in the neural network is often input image information, but because the input image size of this algorithm is 300×400, containing too many pixels, making the overall computing rate is very slow and has high requirements on computer memory, so the input image downsampling, discrete cosine transform and other dimensionality reduction algorithms. At the same time, in order to ensure the accuracy of the overall network recognition, the flame feature parameters extracted from each photo and its dimensionality reduction of the image pixel information together with the reconstruction of the new vector, the vector elements that is the input signal of the neural network.

(3) Output signal: This algorithm network is trained to recognize whether there is a flame or not, so the output signal is the flame and no flame recognition results.

(4) Number of neurons: After several simulations, the original image pixels are downsampled with a scaling of 24, and the network with higher recognition accuracy and stability can be obtained when using the nearest-neighbor interpolation downsampling method. Currently, there are 224 input signals containing flame feature parameters and image pixels, so the input layer unit is set to 224 and the hidden layer size is set to 18.

5) Excitation function: for binary classification, this algorithm adopts the common sigmoid function as the excitation function, which is utilized for solving the optimization parameters and gradient descent.

After determining the input signal, hidden layer, output signal and other elements in the bp neural network through the above method, the bp neural network algorithm can be used to find the optimal weights of each layer, and the trained network can be used to identify the unknown image, so as to determine whether the image captured by the UAV is on fire.

3 Recognition Algorithm Network Performance Evaluation

3.1 CNN network performance evaluation

In this CNN network building, this paper applies the ROC evaluation model to test the convolutional neural network. The results show that the model performs well in distinguishing between positive and negative examples. Fig. 5 shows the results of the convolutional neural network Roc measurements The AUC value of 0.96667 is close to 1, which indicates that the convolutional neural network has strong classification ability and can accurately identify the target category. The ROC curve is smooth and close to the upper-left corner, which indicates that the model can maintain a high accuracy under different thresholds.

However, there are still some minor deviations, and further optimization of the network parameters and training data is needed to enhance the performance of the model so that it can play a better role in practical applications.

3.2 bp network performance evaluation

Figure 6 shows the BP neural network Roc measurement results. In this paper, the ROC model is used to evaluate the performance of the BP neural network. From the generated ROC curve, the area under the curve AUC is 0.925, which indicates that this BP neural network performs well in the classification task and has a strong ability to distinguish between positive and negative examples. The rapid rise at the beginning of the curve implies that a high true positive rate can be achieved with a low false positive rate. However, as the false positive rate increases, the rising trend of the curve slows down, indicating that there is still room for optimization, and the model performance can be further improved by adjusting the network parameters or increasing the amount of training data.

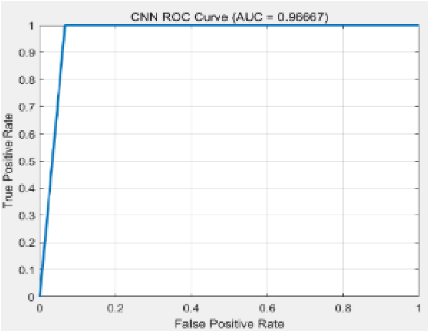


Fig. 5. Convolutional neural network ROC evaluation plot

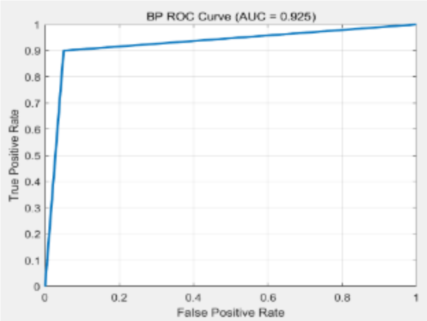


Fig. 6. BP neural network ROC evaluation plot

4 Results

4.1 Test Set Construction

The dataset contains 200 photos of PV panels with flames and 200 photos of PV panels without flames, in which the photos are obtained by internet download, video interception, field shooting and AI generation, etc. With the overall dataset as the target, 30 photos of PV panels with flames and 30 photos of PV panels without flames are randomly selected as a test set for testing the recognition accuracy. The overall database image is shown in Fig. 7 below.

Fig. 7. Schematic diagram of the overall data set.

In addition, a confusing dataset containing interference elements such as sunlight and lights is additionally constructed by field shooting and AI generation, in which there are four kinds of image interference elements, namely: photovoltaic panels reflecting sun rays, workers' yellow-orange warning clothes, ground lights, and sun rays in direct sunlight, and there are 10 images of each interference element for a total of 40 images. This image set is used as a test set for conducting anti-interference verification experiments. The interference-prone image is shown in Fig. 8 below.

(a) *(b)*

Fig. 8. Partial display of interference-prone pictures. (a) Disturbing element: direct sunlight, (b) Disturbing elements: yellow-orange warning suits

4.2 Identify flame simulation results

In order to verify the feasibility of the algorithms designed in this paper, the results of two types of recognition, namely, direct recognition by image processing and neural network recognition, are selected for comparison. The test set is selected for testing the recognition accuracy, and the accuracy test of the above two neural networks is repeated 10 times, and the average value is taken to get a more stable and reliable recognition accuracy value.

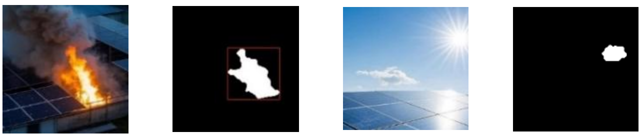
Table 1. Flame recognition simulation results

No.	Type of identification	Recognition method	Recognition accuracy	time-consuming
1	Direct image processing for recognition	Binary Threshold Detection Recognition	68.33%	-
2	neural network recognition	convolutional neural network recognition	96.67%	20s
		bp neural network recognition	93.33%	24s

As can be seen from Table 1: the recognition accuracy of direct image processing is only 68.33%, which is much lower than that of the two kinds of neural network recognition, while the recognition accuracy of cnn neural network and bp neural network can reach more than 93%, which basically meets the requirement of accurate recognition of flame. For the comparison of two neural network recognition, the total recognition time and recognition accuracy are relatively close, in which the convolutional neural network recognition is slightly better than the bp neural network recognition in these two aspects with 4 seconds and 3% respectively. The above simulation results prove the reliability and accuracy of neural network recognition of photovoltaic panel flame, and proves that the combination of cnn neural network recognition and image processing technology is a more reliable and efficient recognition program.

4.3 Anti-interference verification

To verify the stability and robustness of the recognition of the whole algorithm, an anti-interference test was designed, i.e., the simulation was verified by inputting the trained network with pictures containing interference-prone elements such as sunlight and lights. The recognition accuracy of the lowest item is higher than 90%, and the overall average recognition accuracy is as high as 96.25%, which proves the strong anti-interference, stability and robustness of the overall network, thus further proving the feasibility and reliability of the overall algorithm. The final recognition result map is shown in Fig. 9, where special markings are made for the recognition of flames. And the results of the interference experiment are plotted in Table 2 below.



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

Fig. 9. Algorithm Recognition Schematic. (a)(b) Recognizing the presence of fire. (c)(d) No flame condition identified

Table 2. Results of anti-interference experiments

serial number	Interference with picture elements	CNN recognition accuracy	BP recognition accuracy
1	Photovoltaic panels reflect the sun's rays	90%	90%
2	Worker's yellow-orange warning suit	100%	100%
3	Ground lighting	100%	95%
4	direct sunlight	100%	95%

5 Discussion

The overall algorithm recognition accuracy still has room for improvement. Secondly, the overall recognition algorithm is now more efficient for recognizing the fire photovoltaic panels with obvious flames, and the algorithm should do more for the abnormal photovoltaic panels about to catch fire without seeing the recognition of open flames in the early warning. Under certain circumstances, it is allowed to recognize the unfired photovoltaic panels as fire, and it is strictly prohibited to recognize the fire photovoltaic panels as normal, but the current algorithm does not fully meet the above requirements.

By increasing the infrared camera and other devices, the infrared situation, light source acquisition contrast and other data capture, through the above means of image capture to obtain a number of data values of the scene within the scope of the camera, and the data as the flame characteristics of the image of the region set up, combined with the original image features into an array with enhanced features, and the array into the neural network training to improve the overall algorithm operation of the accuracy, stability and robustness of the overall algorithm. At the same time, more reasonable and efficient image processing measures will be further explored, and the selection of neural networks and the configuration of network parameters will be further optimized to ultimately reduce the overall recognition algorithm time-consuming and improve the overall recognition accuracy of the algorithm.

6 Conclusion

By obtaining the ground photovoltaic panel images from the UAV at high altitude and applying the image preprocessing technology for photovoltaic panels combined with the neural network model, this paper designs and builds a machine vision-based fire recognition algorithm for photovoltaic panel fire extinguishing UAV. And after the simulation test on the dataset, it proves that the algorithm is real and effective. It has a high recognition accuracy for the photovoltaic panel flame situation, at the same time in the face of sunlight, lights and other similar fire source of interference has a high stability and anti-interference ability, and for the poor lighting and other environmental interference has a sufficient filtering function. In conclusion, the machine vision-based PV panel fire drone fire recognition algorithm designed in this paper can more accurately detect fire, with superior robustness and stability, can provide reliable protection for the fire safety of photovoltaic power stations, and provide key technical support for responding to fire accidents.

For the future, there is still room for improvement in the overall recognition accuracy of the algorithm. It is hoped that by adding other feature capture devices, further enriching the image processing measures, and optimizing the configuration of the god-general network, the overall recognition algorithm can ultimately achieve the purpose of reducing the overall recognition algorithm time-consuming and improving the overall algorithm recognition accuracy. Finally, in order to effectively deal with the fire hazards in the PV panel area, all efforts will be explored to create a more complete fire recognition algorithm for PV panel fire drones and build a solid line of defense for the safe operation of PV power plants.

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