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Real-time Welding Machine Status Recognition using Embedded Perceptron Color Classification Model

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Abstract

This paper aims to utilize the perceptron model in machine learning to achieve precise classification of the working status of welding machines by analyzing image data. We collected static images of welding and non-welding operations, extracted the R, G, B color values of the images, and labeled them accordingly (+1 for welding status, -1 for idle status). By employing the stochastic gradient descent method for training the perceptron model, we obtained the weights w and bias b of the model under the condition that all data points in the training set are correctly classified. The model's recognition accuracy was validated on the test set. Ultimately, we applied this model to the STM32f103zet6 microcontroller chip and successfully achieved real-time recognition of the welding machine's operational status during the welding process via a camera. Through testing, the classification accuracy reached 83.6%. Further optimization of classification criteria can be combined with relevant expert suggestions, providing a reference solution for monitoring and identifying the working status of welding machines in steel pipe production.

Keywords

MATLAB; Color Classification; Perceptron Model; Machine Learning; Embedded Development.

1. Introduction

Precise monitoring of equipment status is crucial for improving efficiency, reducing downtime, and minimizing losses in manufacturing enterprises [1]. Traditional monitoring methods typically rely on sensor data collection, with preliminary rule processing performed by edge computing devices. This often necessitates the installation of multiple sensors and edge computing gateways to ensure accurate monitoring of production status. For instance, J. Halme et al. specified gateway devices to process massive data flowing through edge gateway devices and monitored equipment usage and status using cloud computing [2]. Similarly, M.A. Fabricio deployed sensors on industrial electrical equipment in production lines to collect relevant data on an IoT platform, thereby achieving status monitoring of the industrial electrical equipment [3]. However, these monitoring methods often require the deployment of numerous gateway devices and sensors, significantly increasing retrofitting costs.

With the widespread use of surveillance cameras in manufacturing enterprises, this paper explores a feasible solution for monitoring the working status of welding machines based on the scene differences during the welding process. Classifying and monitoring states based on color models is common, such as identifying seed varieties based on seed coat color in agriculture [4], judging welding conditions based on weld seam color [5], and automatically identifying and sorting products based on different colors [6]. In various fields, the R, G, B colors are extracted using machine learning perceptron models, and the collected color data is divided into training and testing sets. Initially, the perceptron model is initialized with model parameters w and b, followed by iterative optimization of weights and bias values using stochastic gradient descent, resulting in final w and b values. These parameters are then applied to the perceptron classification model to verify its accuracy on the testing set [7].

By capturing real-time welding scene images of welding machines and automatically monitoring and identifying the welding machine's operating status, this paper proposes a binary perceptron model solution based on color to distinguish between welding and non-welding states. The model can output the working and non-working durations of the welding machine and calculate its utilization rate. It can also provide an intelligent solution for automatic monitoring of equipment usage status according to the requirements of expert systems, efficiently monitoring equipment status using image data captured by cameras.

2. Relevant Methods

2.1. Introduction to Welding Machine Operation Status

In large-scale wind turbine tower manufacturing, the welding machine is a core piece of equipment, and the presence or absence of welding sparks reflects the operating status of the welding machine. By analyzing the color of welding sparks using a machine learning perceptron model, we have achieved intelligent monitoring of the welding machine's operational status. This method not only accurately determines whether the welding machine is in operation but also outputs usage time and operating duration, providing an efficient means for production management.

2.2. Perceptron Classification Model

The perceptron model is a linear binary classification model consisting of input and output layers, lacking hidden layers. This limitation makes it less effective in solving complex nonlinear problems. The model utilizes an activation function to judge inputs and provide feedback. By training and adjusting weights and biases, the model can correctly classify training data. The training process employs stochastic gradient descent (SGD) by initializing weights (w) and biases (b), continuously updating them until all training samples are correctly classified, meeting the stopping criteria. This approach offers an effective means for solving simple classification problems.

2.3. Stochastic Gradient Descent (SGD)

Stochastic Gradient Descent (SGD) is commonly used to minimize the loss function of perceptron classification models by reducing the sum of distances from misclassified points to the classification hyperplane. Its randomness is manifested in updating parameters using small batches of samples in each iteration, thereby avoiding getting stuck in local optima and accelerating convergence. By computing the gradient of the loss function and updating parameters, SGD achieves effective adjustment of the model, thereby improving classification performance. The stochastic nature of this method during the training process enhances its efficiency [8].

2.4. Color Component Extraction

The RGB color model, representing the primary colors red (R), green (G), and blue (B), combines them in varying degrees to represent any color. The intensity values of each color typically range from 0 to 255, and this model is formed through additive color mixing. Colors are represented as (R, G, B), where each component denotes the intensity of red, green, and

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blue, respectively. This forms a three-dimensional color space with red, green, and blue as the coordinate axes, as shown in Figure 1. Table 1 illustrates the main eight colors and their corresponding R, G, B component values. In the paper, the RGB color model is utilized to extract the color components of welding machine operation and idle states, enabling intelligent monitoring of the welding machine's operational status.

Table 1. RGB Component Values of Major Colors

Color	RGB Components	Color	RGB Components
Black	(0,0,0)	Cyan	(0,255,255)
Red	(255,0,0)	Blue	(0,0,255)
Yellow	(255,255,0)	Magenta	(255,0,255)
Green	(0,255,0)	White	(255,255,255)

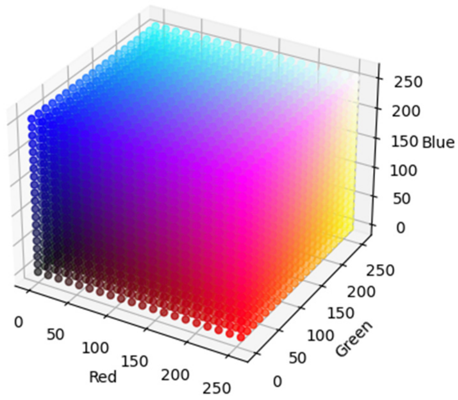

Figure 1. Distribution of Color Components in Three-Dimensional Space

3. Welding Machine Operation Status Recognition Classification Algorithm

3.1. Dataset Collection

Different welding processes use different welding electrode materials, but the material of the welding electrode has little influence on the color of the arc and sparks produced. Instead, it mainly depends on the material and composition of the workpiece being welded. In this paper, the welding material is alloy steel. During welding, the steel plate is heated to high temperatures, causing the color of the arc and sparks to change accordingly. Typically, the arc in the high-temperature welding zone emits white, light yellow, or blue light, while the color of the metal oxides produced at the welding edges is usually red, orange, brown, or black. Therefore, in the welding process, the R value is generally large, while the values of G and B can vary between 0 and 255, depending on the collected pixel data.

This paper focuses on arc welding methods and collects images of the welding machine during welding and when idle. To extract key features, several critical position pixel points of the welding machine during operation and at rest were selected, with a pixel size of 20*20 as the baseline. These pixel points were processed using Matlab to extract the R, G, and B color components. Figure 2 shows some characteristic pixel points on the left side representing the welding machine in operation and on the right side representing it at rest. This step provides crucial data support for the intelligent monitoring of the welding machine's operational status.

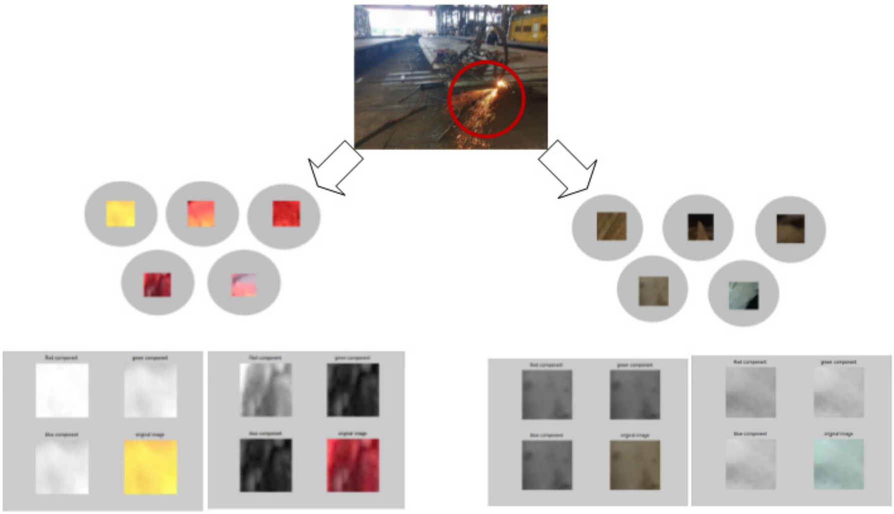

Figure 2. Extraction of Color Components from Welding Machine Operation Images

Further processing of the data involved extracting the values of each color component into an Excel spreadsheet. The data labels were assigned as follows: a label of 1 was assigned to the data representing the welding state with sparks, while a label of -1 was assigned to the data representing the idle state. The RGB data extracted from the example feature images in Figure 2 were divided into training and testing sets, with the training set comprising 70% of the total data and the testing set comprising 30%. Table 2 shows the color component data for the training set during welding, while Table 3 shows the color component data for the training set during idle states. This step provided labeled training data for establishing the perceptron classification model.

Table 2. Partial Training Set Data of Color Components When Welding Machine is Working

Sample	R	G	B label
Sample 1	115	11	15 -1
Sample 2	141	11	16 -1
Sample 3	92	8	16 -1
Sample 4	143	13	20 -1
Sample 5	83	6	10 -1
Sample 6	153	12	19 -1
Sample 7	133	12	18 -1
Sample 8	133	5	15 -1
Sample 9	253	229	96 -1
Sample 10	255	238	104 -1
Sample n	**--**	**--**	**-- -1**

During the stage of testing the perceptron classification model's performance, the testing set data was selected. Table 4 presents the information of color component data for the testing set during idle states of the welding machine, while Table 5 shows the color component data for the testing set during the working states of the welding machine. This step aimed to validate the accuracy of the model in classifying new data, providing crucial support for the credibility of the final experimental results.

Table 3. Partial Color Component Training Data of Welding Machine when Not Working

Sample	R	G	B label
Sample 1	98	76	48 1
Sample 2	99	78	50 1
Sample 3	100	77	56 1
Sample 4	96	73	50 1
Sample 5	12	10	12 1
Sample 6	14	10	11 1
Sample 7	14	10	11 1
Sample 8	16	12	11 1
Sample 9	16	12	11 1
Sample 10	19	14	11 1
Sample n	--	--	-- **1**

Table 4. Partial Color Component Test Dataset When Welding Machine is Not Working

Sample	R	G	B	Label
Sample 1	93	80	64	1
Sample 2	101	81	44	1
Sample 3	127	112	79	1
Sample 4	142	136	120	1
Sample 5	83	78	59	1
Sample 6	87	80	61	1
Sample 7	94	86	99	1
Sample 8	92	86	86	1
Sample 9	83	91	104	1
Sample 10	206	224	238	1
Sample n	--	--	--	**1**

Table 5. Partial Color Component Test Dataset When Welding Machine is Working

Sample	R	G	B	Label
Sample 1	213	158	77	-1
Sample 2	214	158	84	-1
Sample 3	203	168	92	-1
Sample 4	185	121	25	-1
Sample 5	227	216	132	-1
Sample 6	215	171	79	-1
Sample 7	193	129	45	-1
Sample 8	212	162	50	-1
Sample 9	208	158	73	-1
Sample 10	202	138	69	-1
Sample n	--	--	--	**-1**

3.2. Perceptron Classification Algorithm based on Color Components

To gain a clearer understanding of the distribution of color components in the three-dimensional color space for welding machine in different operating states, we visualized the color components separately in the three-dimensional space for both working and non-working states. Figure 3 illustrates these distributions. Through such visual presentation, we can intuitively observe and comprehend the spatial distribution characteristics of color components in different states. This aids in the in-depth analysis of data properties during the training process of the perceptron model.

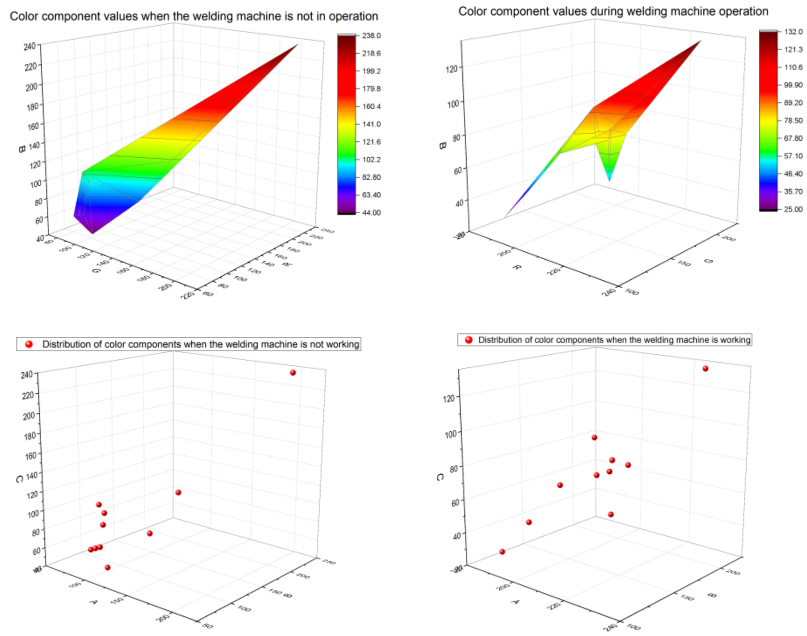

Figure 3. Spatial Distribution of Color Components in Different States of the Welding Machine

In the following steps, we mapped the color components of the welding machine in different states to the same three-dimensional space, as shown in Figure 4. By observing the distribution in the figure, it is evident that the welding machine exhibits distinct distribution characteristics in the three-dimensional color space under different working states, with clear boundaries between these distributions. The color components under different states have minimal chance of mixing together. This implies that, with a sufficiently high model accuracy, a binary classification model based on color components can successfully differentiate between different working states of the welding machine. This observation provides intuitive data support for the subsequent training of the perceptron model

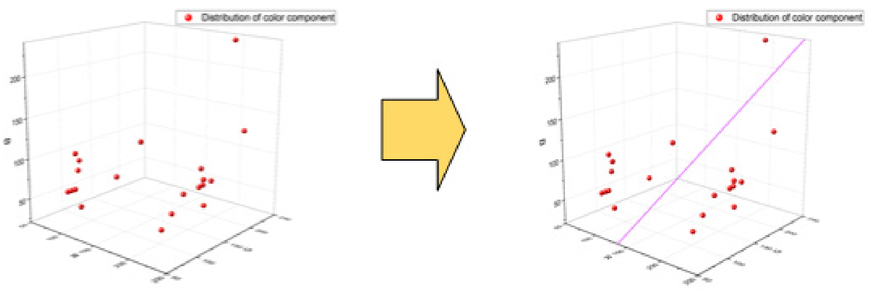

Figure 4. Classification Effect of Different State Components in Color Space

The perceptron model, proposed by Rosenblatt in 1957, is a linear binary classification model. In this model, the color components serve as feature vectors input, while the classification label serves as output. To obtain an optimal classification effect for multidimensional feature vectors, weights (w) and biases (b) need to be continuously iterated to solve, achieving the best classification performance. The model from the input space to the output space of the perceptron can be represented as:

$$f(x) = sign(w \cdot x + b)$$

In the equation, the value of sign(x) is as follows:

$$sign(x) = \begin{cases} -1, & x < 0 \\ +1, & x \geq 0 \end{cases}$$

Based on the data extracted from the collected welding machine working status images, let's set up sample (x_i, y_i). In this sample, input vector x_i represents a three-dimensional color vector, and input vector y_i corresponds to the identification of input vector x_i, which can be either +1 or -1. The perceptron classification model is then updated as follows:

$$f(x) = sign([w_{i1}, w_{i2}, w_{i3}] \cdot [x_{i1}, x_{i2}, x_{i3}] + b)$$

To minimize the sum of distances from misclassified samples to the hyperplane during the training process, the calculation of its loss function can be performed as follows:

$$L(w_i, b) = -\sum_{[x_{i1}, x_{i2}, x_{i3}] \in M} y_i([w_{i1}, w_{i2}, w_{i3}] \cdot [x_{i1}, x_{i2}, x_{i3}] + b)$$

First, the initialized weights $[w_{i1}, w_{i2}, w_{i3}]$ and bias b are given. Then, data points $([x_{i1}, x_{i2}, x_{i3}], y_i)$ from Tables 2 and 3 are selected to determine if these data points are misclassified by the current model. The weights and bias are updated as follows:

$$[w_{i1}, w_{i2}, w_{i3}] = [w_{i1}, w_{i2}, w_{i3}] + \eta y_i [x_{i1}, x_{i2}, x_{i3}]$$

$$b = b + \eta y_i$$

Here, η represents the model's learning rate. Following this, the weights w and bias b are continuously updated according to the aforementioned method, selecting data points from the training set one by one, until there are no misclassified points in the training set. The initial model of the perceptron is illustrated in Figure 5:

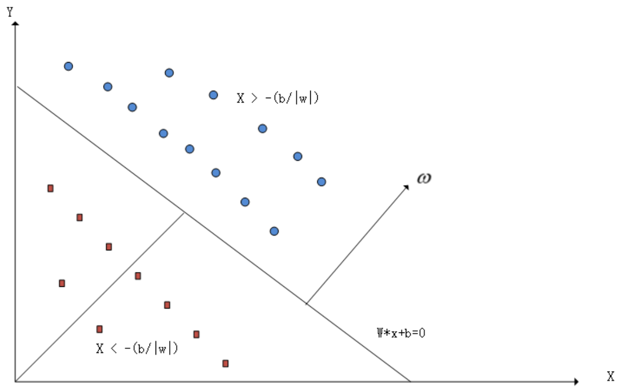

Figure 5. Classification Hyperplane of Traditional Perceptron Model

After iterative updates using stochastic gradient descent with a learning rate of η = 0.6, we obtained the weight values w = [57, 43.8, 28.8], and the bias b = 0.6 for the perceptron model. Therefore, the expression of the perceptron binary classification model is:

$$f(x) = sign(57x_1 + 43.8x_2 + 28.8x_3 + 0.6)$$

Through the training of the perceptron model, we obtained a model that can perfectly classify the training set. This indicates that the model can establish clear boundaries in the color component space, allowing the data points of different states, such as welding and idle states, to be distributed in distinct regions. This provides a reliable foundation for effectively classifying the data in the test set.

Combining Tables 4 and 5 with Figure 3, it can be observed that there are distinct differences in the distribution of R, G, and B channel data between welding and idle states. According to the theoretical calculations mentioned earlier, it is found that this classification model exhibits a clear linear boundary. This observation is presented in Figure 6, where the color component space of the welding machine's different operating states shows evident clustering and separation.

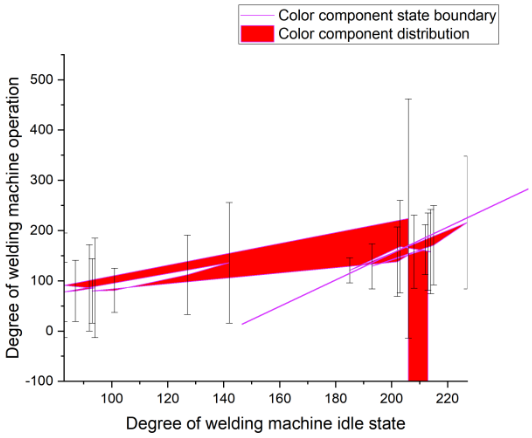

Figure 6. Classification Effect in Stacked 2D Space

3.3. Simulation State Recognition Experiment

3.3.1. Hardware and Software Equipment

In this experiment, we chose STM32f103zet6 as the main control chip, equipped with an OV7725 camera as the external device for real-time recognition of welding machine status, as shown in Figure 7. To complete the code download and debugging, we used ST-Link as the program burner, and selected Keil 5 as the development environment.

Figure 7. Software and Hardware Setup

Based on the obtained perceptron model, the design for classifying and recognizing welding machine states based on RGB color components was conducted. Tests were conducted separately for welding status and idle status welding effects, and the final achieved results are as follows:

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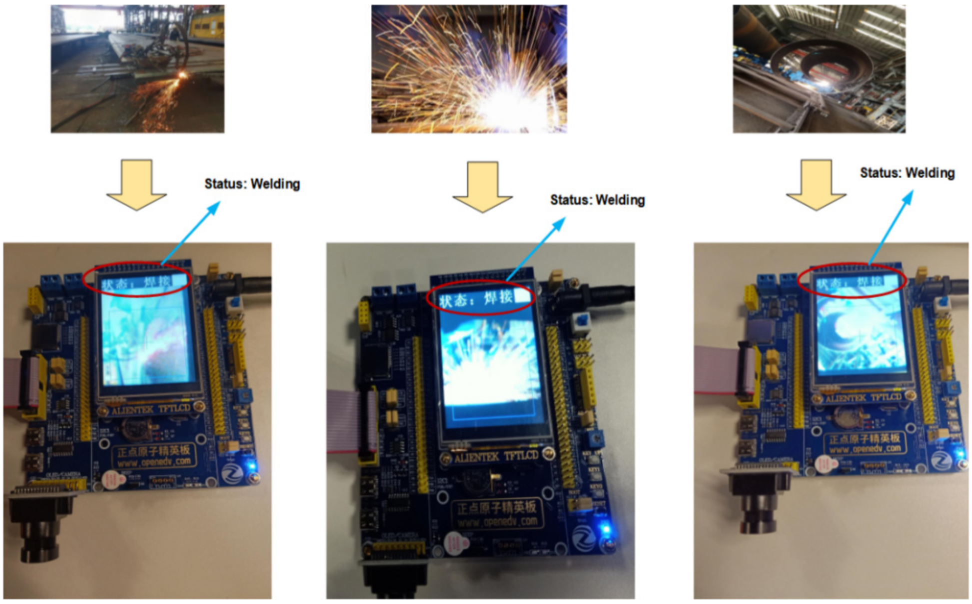

Figure 8. Welding Machine Working State Recognition Result

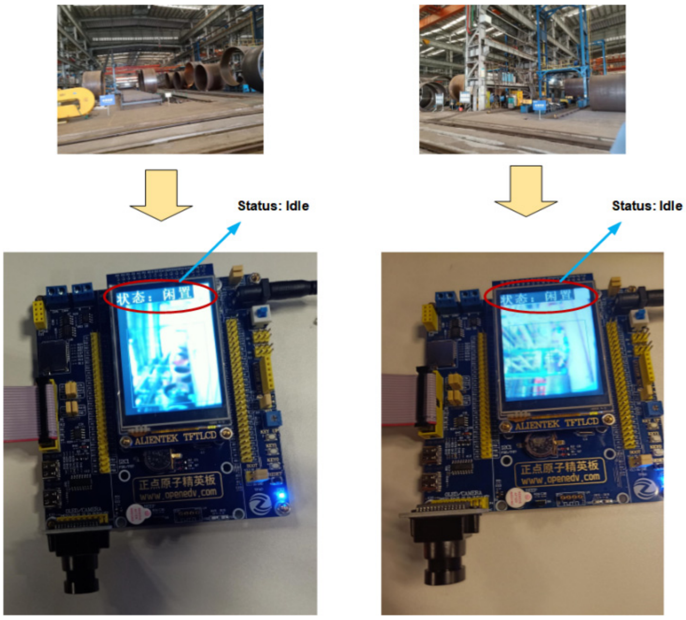

Figure 9. Welding Machine Idle State Recognition Result

The experimental results above reveal that during the welding process, the welding machine generates a large number of sparks while active, whereas no sparks are observed when idle. Following extensive training on a dataset with numerous added labels, the perceptron color classification model successfully categorizes the working status of the welding machine based on stacked color space boundaries, achieving accurate recognition of its state. Validation results from 200 sets of test data are as follows: the average recognition accuracy of the color classification model for identifying the working status of the welding machine in this paper can reach 85.78%.

Typically, welding machines emit a significant number of sparks during normal operation, with minimal sparks usually occurring at the beginning or end of the welding process. Therefore, in the process of identifying the working status of the welding machine, this paper temporarily disregards the presence of minimal sparks at the beginning or end of the welding process, focusing solely on the occurrence of numerous sparks. This paper provides a color classification model for identifying the working status of the welding machine for reference purposes only. For a more precise identification of different welding states, adjustments to the color classification model can be made based on the actual production conditions on-site and requirements proposed by experts to achieve greater accuracy in classifying the working status of the welding machine.

4. Conclusion and Future Perspectives

With the continuous advancement of technology, surveillance cameras have become increasingly common in industrial production sites. By utilizing surveillance devices to identify the working status of equipment with obvious color differences (such as welding machines), the need for replacing intelligent welding machines or adding sensors can be avoided, significantly reducing the cost of enterprise renovation. The application of this technology can enhance economic benefits for enterprises and inject new impetus into future green and sustainable development.

Future research could focus on finer recognition and classification of color components based on cameras, enabling the determination of various equipment states, including different welding scenarios. This is expected to promote the widespread application of cameras in various fields, achieving the goal of multiple uses for a single camera. The expansion of this technology will provide more possibilities for intelligent monitoring systems and production automation, promoting further development in the industrial sector.

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