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Research of Fire Detection System Based on Video of Ship Cabin

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Abstract

Once a fire breaks out on a ship, it will directly threaten the lives of the people on board, the safety of the ship and the cargo carried, and even may cause incalculable environmental damage. Therefore, it is necessary to research a feasible and efficient ship fire detection system Therefore, it is necessary to research a feasible and efficient ship fire detection system to protect the life and property of ship operators. Due to the special environment of ships, the traditional sensor-based fire detection system is prone to miss and false alarm. In recent years, some researchers have combined computer image processing technology and deep learning technology with fire detection, i.e., video-based fire detection algorithm, which has greatly promoted the development of fire detection systems. The video-based fire detection system has the advantages of large monitoring range, high intelligence, not easily affected by the surrounding environment and easy to query the video afterwards. In this paper, a deep learning algorithm is used for the final recognition of smoke, using 8-layer Convolutional Neural Networks (CNN) and DenseNet-121 models are used to train the smoke dataset respectively. The trained The smoke detection model and the candidate smoke selection cascade were cascaded together, and the 9 videos collected, including 6 smoke videos and 3 smoke-free videos, were analyzed. The smoke detection model and the candidate smoke selection are cascaded together, and the 9 videos collected, including 6 smoke videos and 3 smoke-free videos, are detected. The detection results were evaluated using three metrics: accuracy, detection rate and false detection rate. The three metrics were compared with other classical video-based smoke detection algorithms. The results show that the smoke detection algorithm proposed in this paper is more accurate than other classic video-based smoke detection algorithms. The results show that the smoke detection algorithm proposed in this paper improves the accuracy of fire detection, reduces false alarms, and can be used in the early detection of fires. The results show that the proposed smoke detection algorithm improves the accuracy of fire detection, reduces false alarms, and can be applied in the early detection of fires to minimize fire hazards.

Keywords

Vessel, Fire detection, Smoke features, Convolutional neural network.

1. Causes of ship fires

The causes of fires in ships over the years are summarized and statistics, they can be broadly divided into the following aspects [1].

(1) Open flame fire or fire caused by shade combustion

Life in the fire of burning matches and the kitchen gas stove fire are open flames. If there are paint stains, oil or other flammable materials at the construction site or in the ship's cabin, then sparks with high temperature falling on these objects will easily cause fire.

(2) Fires caused by hot surfaces

The main engine and other machines on the ship are always running, and the surfaces of the exhaust pipes, steam pipes and boiler shells connected to them are very high. If there are oil

spill drops on these hot surfaces, or some flammable objects, such as cotton items, paper, etc., accidentally approach these surfaces, they will reach the ignition point and cause combustion. paper, etc. accidentally approaching the surface of these objects will reach the ignition point and cause combustion.

(3) Fire caused by self-ignition

In the ship's cabin or during the ship's maintenance stage, workers will use cotton yarn or rags to wipe the oil stains, if not cleaned off in time or piled up these things randomly, and these oil-stained objects are flammable, plus the cabin If you don't clean them up in time or pile them up randomly, and these oiled items are flammable, plus the poor ventilation, high humidity and high salinity of air in the cabin, then these exposed items will The increase of oxidation reaction and spontaneous combustion phenomenon.

(4) Electrical fires

Electrical fire is one of the main causes of ship fires, according to statistics, fires caused by electricity account for all ship 45.33% of the total number of fires [2]. During the voyage of a ship, the electrical equipment works almost all the time, and the long time operation will accumulate a lot of heat. A large amount of heat will be accumulated during long time operation. The ship is always sailing in the sea, and it is often tilted sideways or longitudinally, which leads to collision and impact inside the electrical equipment. This means that the loss of electrical transmission lines or other devices is very high. This means that the loss of electrical transmission lines or other devices is very high. If a short circuit occurs, the circuit insulation layer is subject to high temperature, humidity, corrosion, aging and then If a short circuit occurs, the insulation layer of the circuit is exposed to high temperature, humidity, corrosion, aging and loss of insulation, overloading of electrical appliances and tugging of lines, etc., it may lead to overcurrent in the line and cause a Fire.

2. Fire Detection Research Status

2.1. Traditional fire detection technology

Conventional fire detectors are those that use specific sensors to detect the main characteristic parameters of the combustion reaction as follows The main characteristics of the above combustion response parameters are detected, and when the detected parameter value reaches the alarm threshold, it will trigger the alarm When the detected value reaches the alarm threshold, the alarm system is triggered. Based on the characteristics of the detector to detect the combustion reaction, the traditional fire detectors can be divided into smoke detectors, temperature detectors, light detectors, combustible gas detectors and composite fire The fire detectors are classified as smoke detectors, temperature detectors, light detectors, combustible gas detectors and composite fire detectors.

2.2. Video-based fire detection technology research status

With the development of image processing technology, deep learning technology and the increasing configuration of computer hardware, people are beginning to try to monitor fires with the help of computers combined with surveillance equipment. With the development of image processing technology, deep learning technology and the increasing configuration of computer hardware, people have started to try to monitor fires with the help of computers combined with monitoring equipment. Video-based fire detection technology uses image processing techniques to The video-based fire detection technology uses image processing techniques to analyze the fire images and find the common features of flame or smoke images in terms of color, texture and shape. These features are then used to analyze and identify frames in the video, and if some pixels in the image satisfy these features, they are If some pixels in the

image satisfy these characteristics, they are considered as flames or smoke, and then trigger the alarm system for fire alarm.

3. Image pre-processing

Image pre-processing is a key step before performing image analysis. Image preprocessing of the input video can eliminate some noise due to physical vibrations, light and shadow changes, or the camera itself, and restore the real image information. The image preprocessing techniques used in the smoke detection system proposed in this paper mainly include image grayscale, image denoising, etc.

3.1. Image Grayscale

In the RGB color model, each pixel is represented in 24-bit binary, called a 24-bit map, which can represent 224 or 16777216 colors. This can represent 224 or 16777216 colors. To simplify calculations, color images are sometimes grayed out if the R component of a pixel in the RGB color space is equal to the G component. If the R component of a pixel in the RGB color space is equal to the G component and the B component, then the color value of that point is called grayscale. After the Gray value is obtained by the above method, all the pixel points in the image are uniformly replaced with Gray, and the resulting image is a grayscale image.

3.2. Image denoising

In the process of capturing images or recording videos or in the process of image interconnection or compression and decompression, images or videos sometimes contain noise due to the influence of the imaging equipment or the environment where they are located, called noisy images. Linear filtering, nonlinear filtering, and morphological filtering. Among them, there is an arithmetic operation relationship between the initial data of linear filtering and the result after filtering, i.e., it is realized by arithmetic operations such as addition, subtraction, multiplication and division, mainly including mean filtering and Gaussian filtering. There is a logical relationship between the initial data of nonlinear filtering and the result after filtering, i.e., it is realized by logical operations, such as finding the maximum value and median value, etc. The most common one is median filtering. Morphological filtering is also a logical operation in nature, and the most basic operations include expansion and erosion.

4. Moving object detection

4.1. Background difference method

The background difference method is based on the difference between the background frame and other frames to get the target of motion, the motion detection initially sets the first frame or the average of the first few frames as the background frame, and for each subsequent frame the difference between it and the background frame is calculated. In the process of background difference method, the background frames need to be updated continuously, and the update of background frames is the key of background difference method. In practice, the background frames and each subsequent frame need to be converted to gray scale and denoised, and then the background frames and video frames are differenced to get the difference image.

4.2. Frame difference method

The frame difference method is based on the difference between the current frame and the previous frame or the previous frames to get the motion target, the number of interval frames can be can be set manually. In practice, it is also necessary to convert the current frame and the video frame with which the frame difference is made to gray scale and Then the two frames are differenced to obtain the difference image.

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4.3. Optical flow method

The concept of optical flow was first proposed by Gibso [3] in 1950.The optical flow method is based on the principle that each pixel in each frame of the video is given a motion velocity and motion direction to form a pixel motion vector field, and then the motion target is determined by finding the motion velocity and motion direction of the pixel.In 1981, Horn and Schunck [4] associated the velocity field of motion with a grayscale pixel points associated to introduce the fundamental constraint equation, which can be calculated to obtain the optical flow.

4.4. Motion detection results

As shown in Figure 1, Figure (a) is taken from frame 120 of the video, and Figure (b) is frame 121 of the video. Figure (c) shows the effect of frame difference between frame 120 and frame 121 after using the frame difference method on the video, and figure (d) shows the effect of frame difference after using the background compensation proposed in this paper.

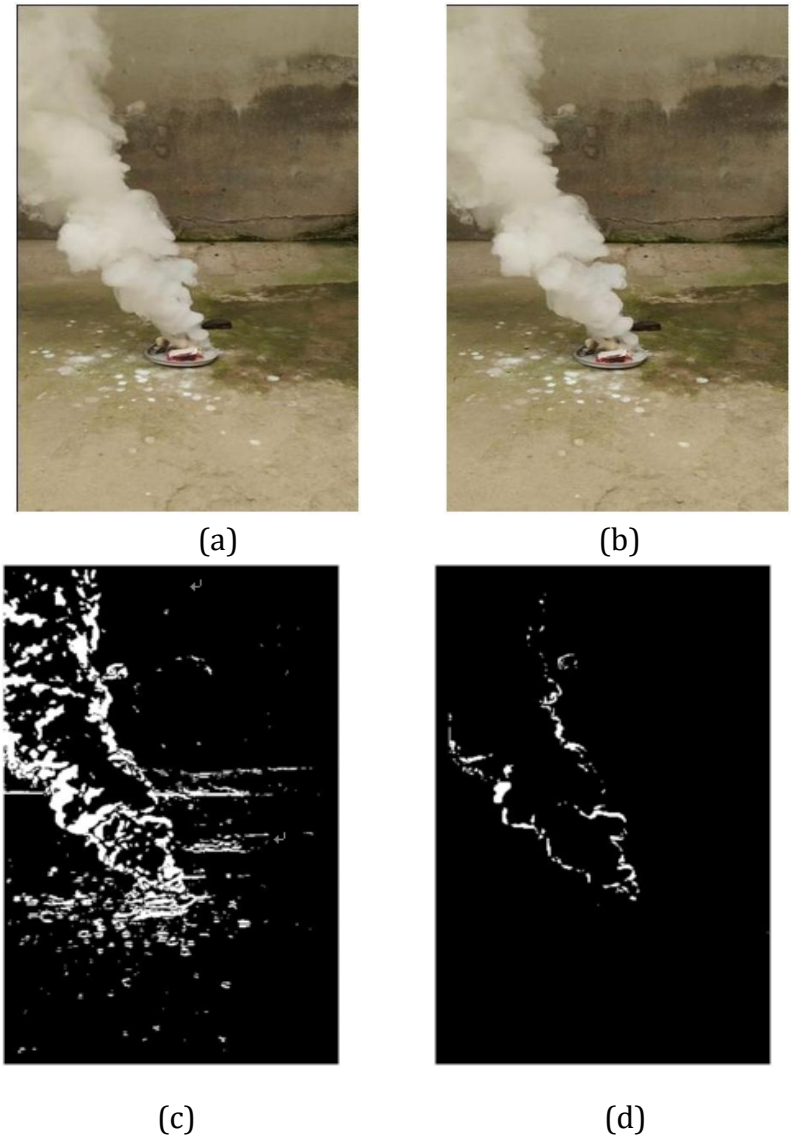

Figure 1 Detection results

5. Smoke characteristics

5.1. Color characteristics

Fire smoke is generally gray or white and can be clearly distinguished from the background image. The pattern of fire smoke varies as the burning material changes, while the grayscale

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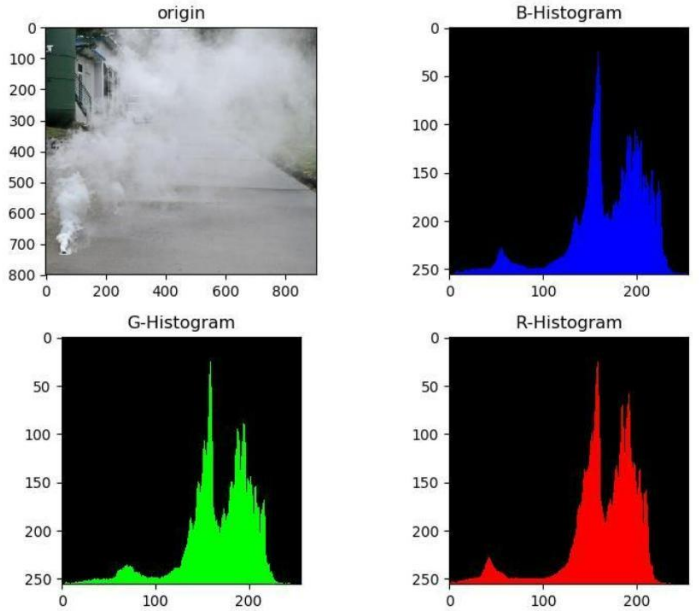
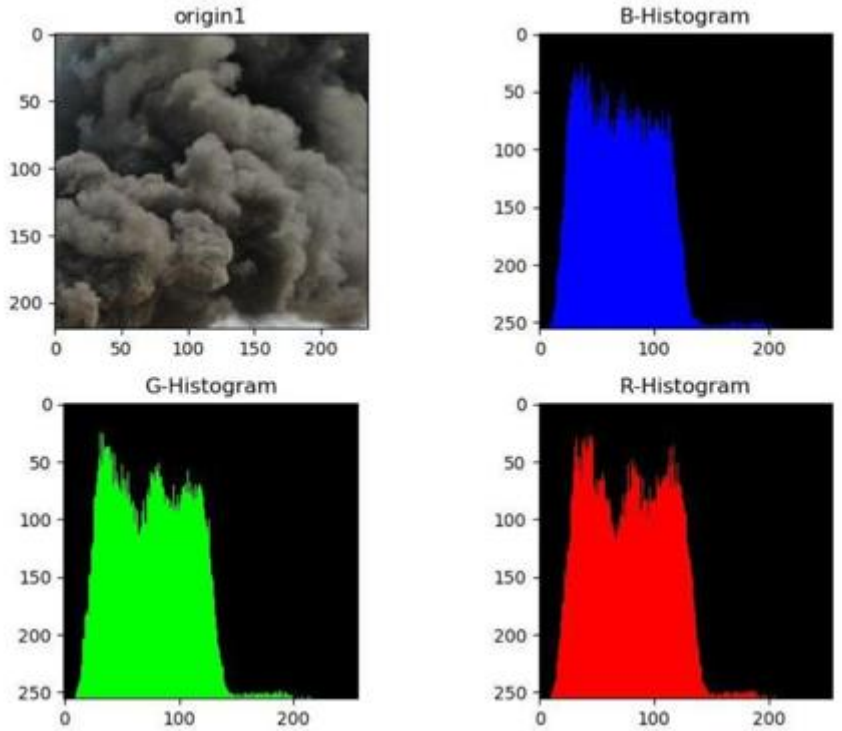
values of the RGB channels where the fire produces smoke do not change much. The color characteristics of fire smoke are statistically based on the gray value of pixel points, which is a global feature. Histogram statistics are usually used to extract the color of smoke.

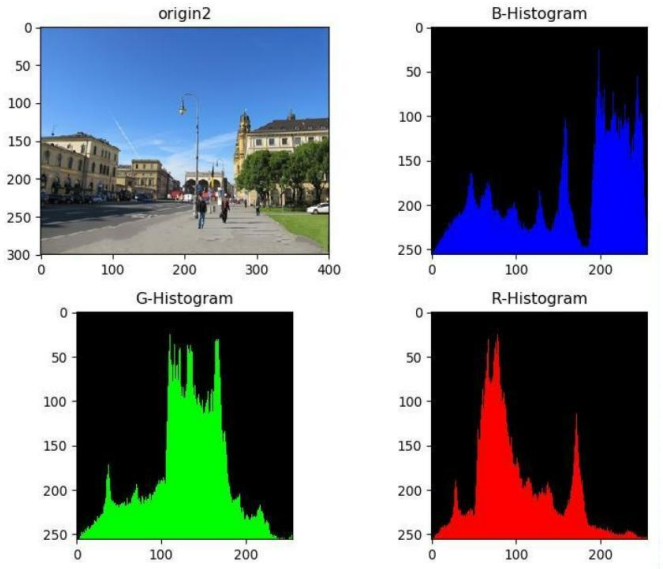
For a typical two smoke images and a non-smoke image, the histograms of their RGB three-color channel values are analyzed as shown in Figure 2, where Figure (a) shows a typical white smoke image, Figure (b) shows a typical gray-black smoke image, and Figure (c) shows a non-smoke image.



(a)



(b)



(c)

Figure 2 Smoke and non-smoke images and histogram

5.2. HOG feature

HOG feature is a feature composed of gradient orientation by calculating and counting the local area of the image. The basic principle is to use edge or gradient orientation density of the image to represent the image features. The process of extracting HOG features can be divided into three parts, i.e., calculating First, the gradient amplitude and direction of all cells in the image are obtained, and then the gradient direction is divided into The number of intervals corresponding to each gradient direction in the cell is then calculated, so as to obtain the The directional histogram of each cell is obtained.

5.3. Texture characteristics

Texture can be expressed as a homogeneous phenomenon in the appearance and layout of objects, and it is a kind of visual feature for human perception of things in nature. It is a visual feature for human perception of natural things. Texture features have good noise immunity and are very stable. In the study of image processing, texture features of an image are usually used as relevant statistical features. features are usually described by the associated statistical features. Some objects have a very slow change in layout, and the texture feature is able to express the intensity and color distribution in this space. Texture Texture is usually expressed as a description of the characteristics of the image itself, so it has a good robustness.

6. Convolutional neural network-based smoke recognition

In recent years, with the development of artificial intelligence, deep learning has gradually entered people's vision, and it has emerged in the field of image recognition and classification, such as the successful applications in cat and dog recognition, Mnist [5] handwritten digit recognition, cifar10 [6] classification and cifar100 classification have proved its advantages.

From 2006 onwards, some classical CNN structures have been introduced. Among them, the most famous one is the AlexNet framework proposed by Krizhevsky A , which has made a major breakthrough in image recognition. the success of AlexNet was followed by VGGNet [7], GoogleNet [8], ResNet [9] and DenseNet [10].

6.1. Smoke recognition CNN structural model

An 8-layer convolutional neural network is built for smoke image training, including 5 convolutional layers, 5 pooling layers, 1 Since there is no parameter calculation for the pooling

layer, the pooling layer is not counted when counting the number of layers in the network. The pooling layers are not counted in the network count because there is no parameter calculation for the pooling layers. The detailed network structure is designed as follows.

Input layer. The smoke images to be trained are captured from smoke videos or downloaded from the Internet. The resolution of the images is inconsistent, so it needs to be processed uniformly before the training of the network model. For convenience, it is appropriate to reduce the The size of the input images is set to 224×224 pixels. The training is performed on smoke image is an RGB color image with a channel value of 3, so the total image format size is expressed as 224×224×3.

Convolution layer Conv1. The input image has three dimensions of width and height and depth (RGB), also known as 3D tensor. The convolution layer computes the convolution of the input 3D tensor and outputs a feature map. Different convolution layers can yield different feature maps. In the convolution layer, the depth parameter, the convolution kernel size and the activation function are defined. The depth parameter for a The depth parameter is 3 for a normal color image, which is the RGB color channel. In the convolution layer, the depth parameter can be set after the convolution calculation, which no longer represents a specific color channel value, but is called It is called a filter. In this convolutional layer, the filter is set to 32, so the input size is 224×224×3 smoke image. After this layer, a feature map of size 222×222×32 is output. For each feature map contains a 222×222 size for each feature map contains a numerical grid of size 222×222. The convolution kernel size is usually set to 3×3 or 5×5, and when the convolution kernel size is small, the corresponding output When the size of the convolution kernel is small, the corresponding output is large and the network parameters are large, which makes the convolutional neural network run slowly and affects the efficiency. In this section, the size of the convolutional kernel is 3×3 and the step size is 1. The step size is chosen as 1 and the activation function is chosen as ReLU function.

Pooling layer pool1. In this section, the maximum pooling operation is used to downsample the feature image of the upper convolutional layer, with the window size set to 2×2 and the step size set to 2. The feature image of the upper convolutional layer is 222×222×32, and after the pooling layer, it is 111×111×32, which means that the feature image is downsampled by a factor of 2. The pooling operation facilitates the convolutional neural network to learn the pattern space hierarchy, each convolutional layer in the convolutional neural network learns the pattern consisting of the features output from the previous layer. If the output 222 × 222 × 32 is passed directly to the next convolutional layer without pooling, the high-level patterns that the next convolutional layer can learn will be small relative to the original input smoke image. Pooling operations after each convolutional layer can effectively compress the number of parameters and reduce the dimensionality of the feature image.

Convolutional layers Conv2, Conv3, Conv4, and Conv5 serve the same purpose as Conv1. The depth parameter of the Conv2 layer is set to 64, and the output is The depth parameter of Conv2 layer is set to 64, and the output is 109×109×64. The depth parameter of Conv3, Conv4, and Conv5 layers is set to 128. The rest are the same as Conv1, and the output is 52×52×128, 24×24×128, and 10×10×128, respectively.

Pooling layers Pool2, Pool3, Pool4 and Pool5 are also set to a window size of 2×2 and a step size of 2. The corresponding outputs are 54×54×64, 26×26×128, 12×12×128, and 5×5×128, respectively.

Fully connected layer. The last three layers are fully connected layers, and the fully connected layers can integrate the abstract features of the smoke image extracted by the convolution layer. The last three layers are fully connected layers, which can integrate the abstract features of the smoke image extracted by the convolution layer. The first fully-connected layer is the Flatten layer, which can compress the multi-dimensional data output from the convolutional layer. The

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first fully-connected layer is the Flatten layer, which can compress the multi-dimensional data output from the convolution layer into a one-dimensional vector, and then transfer the one-dimensional vector to the next fully-connected layer. The last The second fully connected layer contains 512 neurons, and the activation function uses the Reasoning layer. The last fully connected layer has only one neuron and the activation function uses the sigmoid function. The sigmoid function outputs a probability value in the range of 0-1, and the closer the value is to 0, the lower the probability of smoke. The closer the output value is to 0, the lower the probability of smoke, and the closer the output value is to 1, the higher the probability of smoke.

6.2. Experimental data set

The smoke data used for training are from the smoke images captured in the experimental video shoot and the smoke public video set and downloaded from the web. 10,000 smoke images, including 5000 smoke images and 5000 non-smoke images, are created in two folders named train and validation, and smokes and nonsmokes are created in these two folders respectively. Two subfolders are created for comparison. The smokes folder in the train folder contains 4000 smoke images and the nonsmokes folder contains 4000 non-smoke images. The nonsmokes subfolder contains 1000 smoke images and 1000 non-smoke images, respectively. The smoke training data accounted for 80% of the total data. Some of the experimental smoke images are shown in Figure 3 and non-smoke images are shown in Figure 4.

Figure 3 Smoke image sample picture

Figure 4 Non-smoke image sample picture

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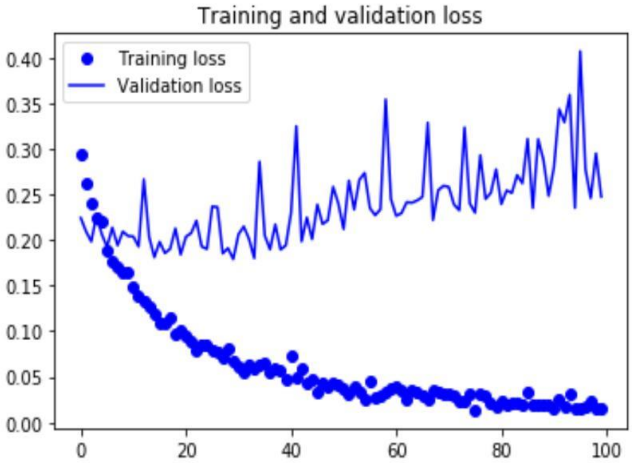
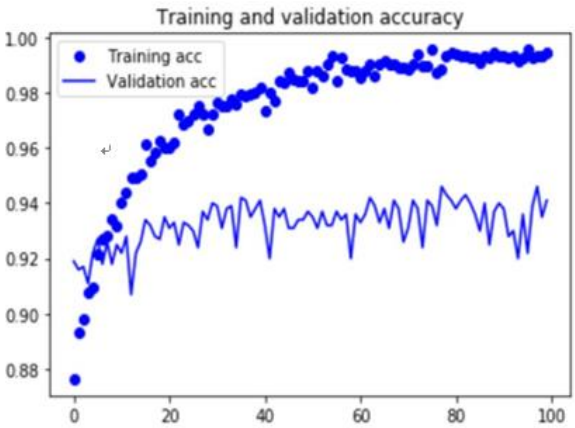
6.3. Training results

The smoke data were trained using the designed 8-layer convolutional neural network with a convolutional kernel size of 3×3 and a maximum pooling method with 100 epochs, as shown in Figure 5.



(a)



(b)

Figure 5 Training results

As can be seen from Figure .4, the training results include the loss variation trend of the CNN model on the smoke training and validation sets and the trend of accuracy variation. From Fig. (a), it can be seen that the loss values on both the training and validation sets show a decreasing trend. The loss value in the training set decreases quickly and gently, and finally tends to zero. The loss value in the validation set decreases more slowly, and the trend fluctuates a lot, up and down, and finally fluctuates around 0.2. From the figure (b), it can be seen that the loss values in the training and validation sets are not as high as those in the validation set. The accuracy on the training set increases parabolically with the number of iterations, and finally increases parabolically with the number of iterations. The accuracy on the training set increases parabolically with the number of iterations and finally approaches 100%, while the accuracy on the validation set reaches its maximum value around 40 rounds and finally The accuracy on the validation set reaches a maximum around 40 rounds and finally fluctuates in the range of 92% to 94%.

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7. Conclusion

Vessel fire monitoring has always been a difficult and hot research point in ship safety design, which requires research on the structural characteristics of ship cabins, ship fire characteristics and fire monitoring technology. The traditional sensor-based fire detection technology is easily restricted by the space environment, and the situation of missed detection and false detection often occurs. In recent years, due to the development of computer image processing technology, video-based fire detection technology has gradually become a hot spot for research.The histogram distribution of the RGB color channels of some typical smoke images on the RGB three color channels was found to be roughly similar for both light white smoke and gray-black smoke, i.e., the magnitude of the RGB three color components is almost the same at a certain color value. Using this color criterion for smoke image detection can detect most of the smoke areas.Deep learning techniques are introduced into the smoke recognition, and the smoke dataset is trained using 8-layer convolutional neural network. The results show that the proposed smoke The results show that the proposed smoke recognition algorithm achieves excellent performance in terms of smoke recognition accuracy and false detection rate. The video-based fire detection method in ship compartment is an important research topic with practical and theoretical significance. It is of great significance to promote the development of ship fire monitoring technology.

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