Belt Deviation Detection System Based on Deep Learning under Complex Working Conditions

Peng Zhang, Shaochuan Xu and Wenzhu Wang

***Abstract*—As one of the important transportation tools for coal transportation, the operating efficiency of belt conveyor is directly related to the production efficiency of coal. However, belt conveyor failures often occur due to belt deviation. Generally speaking, the transportation distance of belt conveyors is relatively long, and the transportation environment is relatively harsh. The use of manual monitoring of the operation status of belt conveyors is inefficient and increases labor costs. The existing belt deviation detection system can play a good role in some conventional environments. However, under complex working conditions such as heavy dust, insufficient light, and camera deviation, existing detection systems will be affected. Therefore, this paper proposes a belt deviation detection system based on deep learning under complex working conditions. The characteristics of the belt and idler are extracted through the convolutional neural network, so as to position the belt and idler. With the characteristic points on the belt and idler as input, a mathematical model of belt deviation is established to calculate the degree of belt deviation, and alarms according to different degrees of deviation. The system has been tested in the actual field, and has a certain accuracy and real-time, which largely solves the problem of belt deviation detection under complex working conditions, reduces the fault frequency of belt conveyor, and thus improves the working efficiency of belt conveyor.**

***Index Terms*—belt conveyor, belt deviation, complex working conditions, deep learning**

I. Introduction

As one of the important equipment for coal mine transportation, belt conveyor has deviation faults from time to time, which reduces the production efficiency of the coal mine. Therefore, many experts and scholars have studied the belt deviation detection and proposed many solutions, hoping to minimize the frequency of belt deviation and reduce the belt conveyor faults. For example: Wang and Dong et al. had determined the three-level deviation correction equipment for mining. From the experimental data it can be seen that the belt deviation detection system based on machine vision can effectively detect the deviation fault, and can well control the deviation correction equipment, which is characterized by high efficiency and fast processing speed [1]. Sun and Wang designed an automatic deviation rectifying device and control system for the belt [2]. Wang, Xu and Teng proposed a method to identify the belt edge by using straight line detection, and detect the degree of belt deviation by calculating the deviation distance of the belt edge [3]. Zeng and Zheng et al. proposed a multi-scale feature fusion method, which fused the low-level features and high-level features to improve the detection performance of the network and designed a new weight loss function to improve the detection effect of belt edges [4]. Based on the high brightness linear light source to improve the image quality, Yang et al. proposed a fast image segmentation algorithm to process the belt image and developed an online belt visual inspection system [5].

The existing belt detection methods can play a good role in some conventional environments, but the actual working environment of the belt conveyor is not the ideal environment, which will be mixed with many interference factors. For example, the vibration caused by wiping the dust on the camera surface or the on-site noise will cause the camera head to shift in a small range, resulting in changes in the ROI area, insufficient on-site light and other complex working conditions. Many belt deviation detection systems based on traditional machine vision are not very stable and are easily affected by the on-site environment. To solve the above problems, this paper studies a belt deviation detection method based on deep learning under complex working conditions [6]. The contribution of this paper is that the method based on the deep learning is proposed to locate the belt and idler, which reduces the impact on the detection system under complex working conditions. With the characteristic points on the belt and idler as input, the degree of belt deviation is judged by establishing the mathematical model of belt deviation, and finally the intelligent alarm of belt deviation is realized. At present, the system has been tested in the actual working environment of the belt conveyor, and has achieved good results in various complex working conditions.

II. Fault Causes and System Composition

A. Analyze the cause of the failure

When using the belt as a transportation tool, the belt deviation is a very common but not negligible fault type. It can cause great harm [7]. In general, this kind of fault is difficult to be found and will not affect the operation of the belt conveyor in the early stage. However, with the belt running for a long time, it is likely to cause some potential safety hazards and other larger failures, which will affect the production of enterprises. After analysis, it is found that the main reasons for the belt deviation are as follows: (1) The

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belt is unevenly stressed. Generally, the distance of the belt transportation is very long and the belt is overloaded, which produces greater pressure on the idler, and the friction force on the belt is not enough to support the normal operation of the belt, so the belt deviation will occur. (2) The quality of the belt joint is poor, the joint of the belt is mainly connected by cold patching. During the cold patching process, it is impossible to ensure that the position of the joint is straight. Therefore, the uneven joint will also cause the belt deviation. (3) The tension of the belt is unreasonable. If the belt is too tight, it will consume more energy. If the belt is too loose, it will reduce the friction between the belt and the idler, resulting in lateral vibration and deviation.

B. System composition

The system mainly obtains the video recordings of the belt during operation through a camera, intercepts the video into images as a dataset, randomly divides the dataset into training and validation sets according to the ratio of 9:1, trains the labeled images on the network, and then uses the trained model to predict the images. The feature points on the belt and idler are selected as inputs to establish a mathematical model of deviation detection. This is used to judge whether the belt deviates and the degree of deviation. Once the degree of deviation reaches the alarm threshold, the alarm device will be started, and the operator can see the running status of the belt in video monitoring, verify the system detection results, and make timely treatment.

The belt deviation detection system designed in this paper mainly includes an image acquisition module, a belt and idler recognition module, a belt deviation judgment module, and an alarm module. The image acquisition module collects images of the belt during operation through the on-site camera device; The belt and idler recognition module extracts the current state of the belt and idler through a trained model; The belt deviation judgment module determines the current operating status of the belt through the established mathematical model; Then, the current operating status of the belt will be displayed in the alarm module to warn of belt deviation. The system function blocks are shown in Fig. 1.

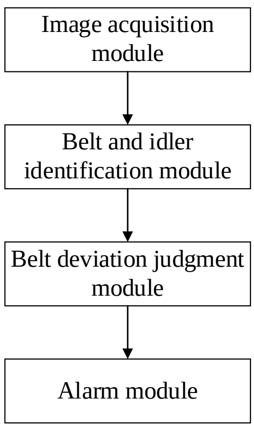


Fig. 1. System function modules

C. The main content of this article

In the actual working environment of belt conveyors, there is a lot of dust and noise, and some belt sections have relatively dark light, making the on-site situation more complex. When there is a lot of dust on the surface of the camera, manual cleaning of the camera surface will inevitably cause a small range of deviation of the camera hair. When applying traditional machine vision, the deviation of the camera will directly change the ROI area, thereby affecting the judgment of belt deviation. And traditional machine vision is easily affected by light. Once the light changes, it will cause interference to the system, making it difficult to identify the belt deviation. Therefore, this article designs a belt deviation detection system based on deep learning under complex working conditions. Deep learning extracts features through convolution network, learns the features of objects in the image, and does not have high requirements for light and ROI areas. Therefore, when the camera hair deviates in a small range or lacks light, it can still maintain good results.

III. MULTI-TASK LEARNING MODEL FOR JOINT OBJECT DETECTION AND SEMANTIC SEGMENTATION

A. Advantage of multi-task learning

Belt conveyors are used for coal mine transportation mostly, and their transportation efficiency is directly related to the production efficiency of coal mine. Coal mine transportation generally requires multiple belts to work together. The main line of belt transportation is very long, so a camera is installed at one end of the belt, and the belt captured by it generally presents a trapezoidal or irregular shape in the picture. In this situation, a single object detection algorithm cannot fully fit the shape of the belt in the field of view, and the area occupied by the idlers in the field of view is small. While recognizing the belt, it is also necessary to consider the recognition of the idlers. Therefore, a multi-task learning model that combines object detection and semantic segmentation can effectively meet the needs of the system [8]. In addition, under complex working conditions such as dust, noise, and insufficient light, traditional machine vision cannot achieve good detection results [9]. When the camera has a small range of deviation under the interference of human or noise, its preset ROI area cannot be adjusted automatically. In addition, traditional machine vision is particularly vulnerable to the interference from light sources, and when the illumination of some interval segments is weak, the belt deviation detection based on traditional machine vision cannot achieve the ideal effect. The misjudgment rate is high.

B. Object detection and semantic segmentation based on YOLOv5

YOLOv5 is the fifth generation detection algorithm in the YOLO series. As a milestone in single-stage target detection algorithm [10]. YOLO series algorithms have been rapidly applied in a wide range of industrial fields with the advantage of fast computing speed. YOLO divides the whole image into S * S grids, extracts feature of each grid through convolution network, and finally performs regression prediction by full connection layer [11]. According to the depth and width of the network, YOLOv5 can be divided into 4 versions, namely

YOLOv5s, YOLOv5m, YOLOv5l, YOLOv5x [12]. The detection accuracy different versions and size of the model are improved in turn. In this paper, we choose YOLOv5s_v6.0 with a smaller model as the basic model. In this way, it can reduce the pressure of the computer on the amount of calculation and maintains a fast reasoning and calculation speed.

Based on the idea of YOLOP(You Only Look Once for Panoptic Driving Perception) [13]. Dividing the model into three parts: Backbone, Neck, and Head. The Backbone part still uses the backbone network of YOLOv5s_v6.0, which mainly includes three structures: CBS, C3 and SPPF. The CBS layer is composed of Conv+BN+Silu activation function; YOLOv5s_v6.0 uses the C3 structure instead of the original BottleneckCSP structure [14]. It makes the model more lightweight, improves the model learning ability and saves computing resources. The SPPF structure specifies only one convolution kernel, and the output after each pooling will become the next pooling input, which is faster than SPP. For the Neck part, the bottom-up PAN is combined with the top-down FAN to obtain better feature fusion effect. The Head part uses the detection head of YOLOv3. At the same time, a segmentation head is introduced to perform semantic segmentation by using the feature extraction network of YOLOv5. The overall framework is shown in Fig. 2.

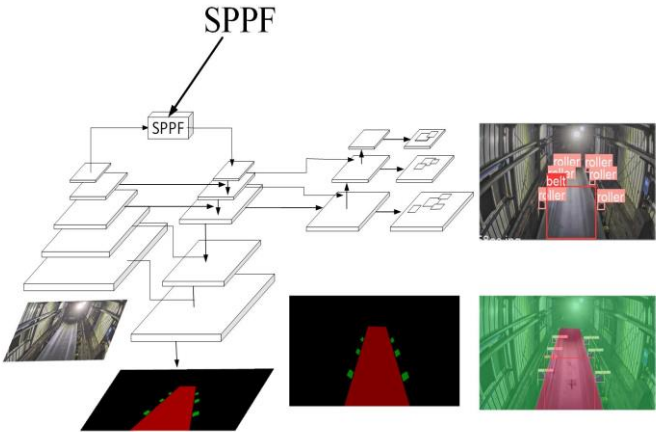


Fig. 2. Model overall framework

IV. Belt Deviation Detection Based on Deep Learning under Complex Working Conditions

A. Model training and prediction

Process the collected image data and manually label using Labelimg and Labelme [15]. Based on the excellent performance of YOLOv5, despite the addition of segmentation head, the trained model can still achieve good accuracy. The detection and segmentation results are shown in Fig. 3.

In the model segmentation inference stage, a mask distribution map corresponding to the image size will be generated according to the identified belt, idler and background. Different numbers represent different categories. As shown in Fig. 4, "0" represent the background, "1" represent the belt, "2" represent the idlers. The mask distribution map is actually a two-dimensional array with elements "0", "1", "2", and each element is equivalent to a pixel on the image.

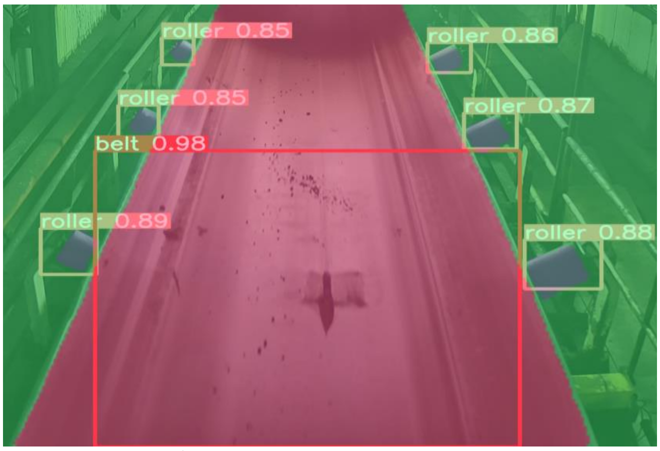
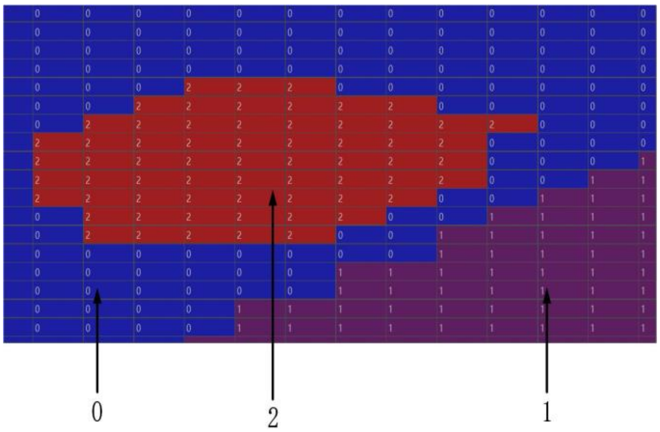
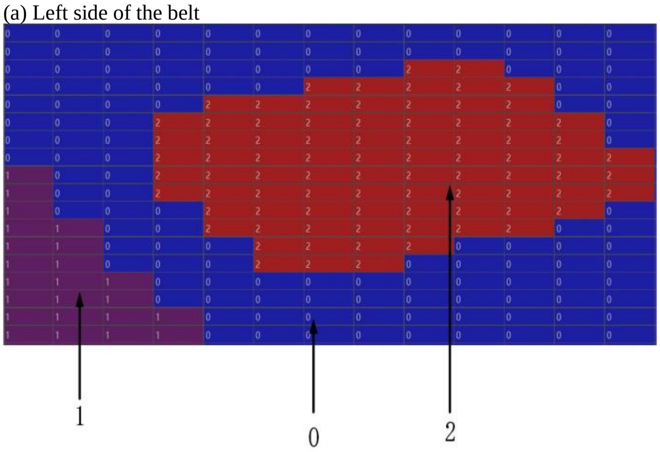


Fig. 3. Renderings of joint detection and segmentation



(a) Left side of the belt



(b) Right side of the belt

Fig. 4. Schematic diagram of the segmentation mask distribution

B. Establish a mathematical model for belt deviation detection

Most belts are in working condition, and as the belt deviates, the shape of the belt will change with the amount of material being transported or other factors. It is difficult to find a reference point on the belt. In complex working conditions such as camera displacement, only the relative position of the idlers on both sides will not change. After research, it was found that the outermost edge of the idler is in the same straight line, each pixel in Fig. 4 has its fixed coordinates. A virtual image coordinate system is established, with the upper left corner point of the image as the origin O, the horizontal down is the y-axis and the horizontal right is the x-axis. The specific schematic diagram is shown in Fig. 5.

As shown in the Fig. 5, a is the connecting line of the left idler, m is the connecting line of the right idler, b is the straight line of the left edge of the belt, n is the straight line of the right edge of the belt, segment AB is a straight line on the belt, segment OP is the connecting line of the left and right idlers, e is the middle line of segment AB, f is the center line of segment OP, N is the intersection point of segment AB and line e, M is the intersection point of segment AB and f, E is the intersection point of segment OP and line e, and F is the intersection of segment OP and line f.

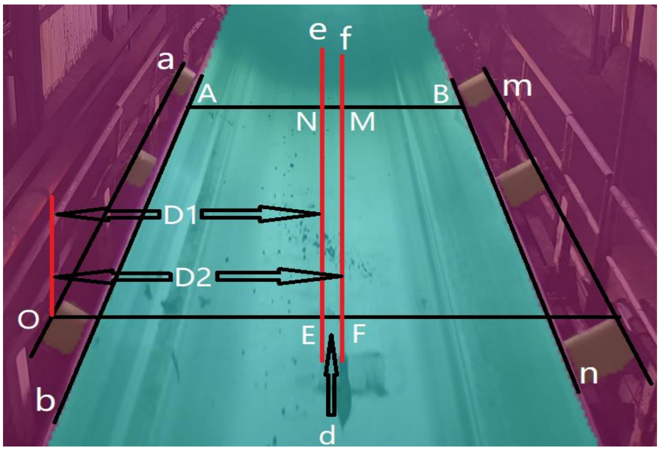


Fig. 5. Schematic diagram of belt misalignment judgment model is established

According to the coordinates of each pixel, the straight line b and the straight line n at the left and right edges of the belt and the outermost straight line a and straight line m on both sides of the idler can be fitted. Select a point O and P on the straight line a and the straight line m, whose y-axis coordinates are equal, then the coordinates of the two points are: $O(x_o,y_o)$, $P(x_p,y_p)$, where $y_o=y_p$, Then the distance between the two points of the line a and the straight line m is:

$$|OP| = |x_P - x_O| \tag{1}$$

According to the midpoint of the idler, the midline f of the distance between the left and right idlers can be obtained. According to the above method, select two points $A(x_A,y_A)$ and $B(x_B,y_B)$ on the line b and the line n, where $y_A=y_B$. Then the distance between the line b and the line n at these two points is:

$$|AB| = |x_B - x_A| \tag{2}$$

From this, the midline e of the actual position of the belt can be obtained, where the intersection point of the line e and the line segment AB is $N(x_N,y_N)$, and the intersection point of the line segment OP is $E(x_E,y_E)$, The intersection point of the line f, and the line segment AB is $M(x_M,y_M)$ and the intersection point of the line segment OP is $F(x_F,y_F)$.

When the belt does not deviation, the straight line e coincides with the straight line f. When the belt deviation, the distance D_2 from point O to the straight line f is the distance from point O to point F, then:

$$D_2 = \sqrt{(x_F - x_O)^2 + (y_F - y_O)^2} \tag{3}$$

The distance D_1 from O to the line e is the distance from point O to point E, then:

$$D_1 = \sqrt{(x_E - x_O)^2 + (y_E - y_O)^2} \tag{4}$$

So the distance between the straight line e and the straight line f is:

$$d = |D_2 - D_1| \tag{5}$$

From this, the actual deviation distance of the belt can be obtained.

When the edge of the belt coincides with the outer connecting line of the idler, it is the maximum value of the belt deviation. When the straight line a coincides with the straight line b, the calculation steps for D_{1min} are the same as above. Then the maximum distance between a straight line e and a straight line f is:

$$d_{\max} = |D_2 - D_{1\min}| \tag{6}$$

From this, the actual deviation percentage of the belt is:

$$\mu = \frac{d}{d_{\max}} \times 100\% \tag{7}$$

When the belt is deviation to the left, then $D_1<D_2$. When the belt is deviation to the right, then $D_1>D_2$. When only one side of the idler is detected, it can be directly judged to be a serious deviation. Using the number of idlers on both sides of the belt to determine if there is serious deviation. If the number of idlers on the left side is 0, the belt is seriously deviation to the left; If the number of idlers on the right side is 0, the belt is seriously deviation to the right. In cause of serious belt deviation, if it is not handled in time, material sprinkling or other faults may occur. Therefore, as long as the system detects that the idler on the one side or the deviation percentage exceeds the threshold value of serious deviation, it must immediately carry out a serious deviation alarm to prevent other accidents.

V. TEST RESULTS AND ANALYSIS

The above proposed model and belt deviation detection method are verified. In this paper, the joint object detection and semantic segmentation model are used as the support for detecting belt deviation. Using the mask generated by semantic segmentation to establish a mathematical model to calculate the proportion of belt deviation, combined with object detection to judge the number of idlers, a comprehensive detection of belt deviation from 0%~100% was achieved. Based on the excellent feature extraction effect of YOLOv5 [16]. In terms of identifying belts and idlers, its accuracy and reasoning speed can still meet the needs. In this paper, the accuracy P and recall R are selected as the evaluation indicators of the YOLOv5 model. The detection results of the model are shown in TABLE I.

TABLE I
MODEL DETECTION EFFECT

Category	P	R
belt	0.995	1
idlers	0.991	0.996
all	0.993	0.995

From TABLE I, the comprehensive identification accuracy of the belt and idler has reached 99.3%. In other words, the model can accurately identify the belt and idler, which provides a good guarantee for the calculation of the subsequent deviation model.

In order to verify whether the detection model and the deviation calculation model can meet the detection requirements in the actual complex working conditions. Building the software system through the LabVIEW platform [17]. The Python language is called to realize the detection of belts and idlers and the judgment of the degree of deviation, so as to verify the performance of the system. The system interface is shown in Fig. 6.

The system operation interface is divided into three parts: Area 1 is the real-time image of the belt work that calls the Python language to detect and segment; Area 2 is the current belt status display area, which can display the degree of deviation of the belt, the direction of deviation and the percentage of deviation. The operator can select the appropriate alarm threshold according to the different requirements of different stations for the degree of belt deviation [18]. The belt parameter information and alarm log at the time of alarm will be uploaded to the database and remind the staff [19]. The on-site staff can carry out quantitative maintenance and repair of the belt conveyor according to the previous alarm log. Area 3 include login interface, image interface, alarm log, system parameters, start operation, stop operation and some other relevant settings.

When dividing the degree of belt deviation. According to the standard given by the field staff, it is specified that when the percentage of belt deviation is less than 20%, it is within the normal acceptable range, and no alarm prompt is required; When the percentage of belt deviation is 20%~50%, the belt is slightly deviated; When the percentage of belt deviation is greater than 50% or only one side of idler is detected, the belt is in a serious deviation state. The specific criteria for determining the degree of deviation are shown in TABLE II.

TABLE II
BELT DEVIATION JUDGMENT STANDARD

Degree of deviation	Basis for judgment
Normal state	$0 \le \mu \le 20\%$
Mild deviation	$20\% \le \mu \le 50\%$
Seriously deviation	$\mu > 50\%$

In order to verify the actual detection effect and detection speed of the system, the model accuracy and belt deviation function of the system are tested in different time periods and working conditions at the working site of the belt conveyor, and the working effect of the system in the actual site is counted [20].

3,000 collected images are randomly selected to verify the system. The first step is to verify the accuracy of the deep learning model. Count the number of images that can accurately identify belts and idlers and have a good segmentation effect. The number of images with good detection results is 2982 after statistics, with an accuracy rate of 99.1%. Then, these images with good detection effect were used to test the established mathematical model of belt deviation judgment. The test results are shown in TABLE III.

As can be seen from TABLE III. The false detection rate of the system is about 0.02%, and the missed detection rate is about 0.0375%. It can be found that there are still some false judgments and missing detection. But from the overall detection effect, the system can achieve good results in the actual belt transportation site, basically meeting the user's demand for belt deviation detection. The possibility of belt conveyor failure caused by belt deviation is minimized, and a large part of unnecessary losses are reduced.

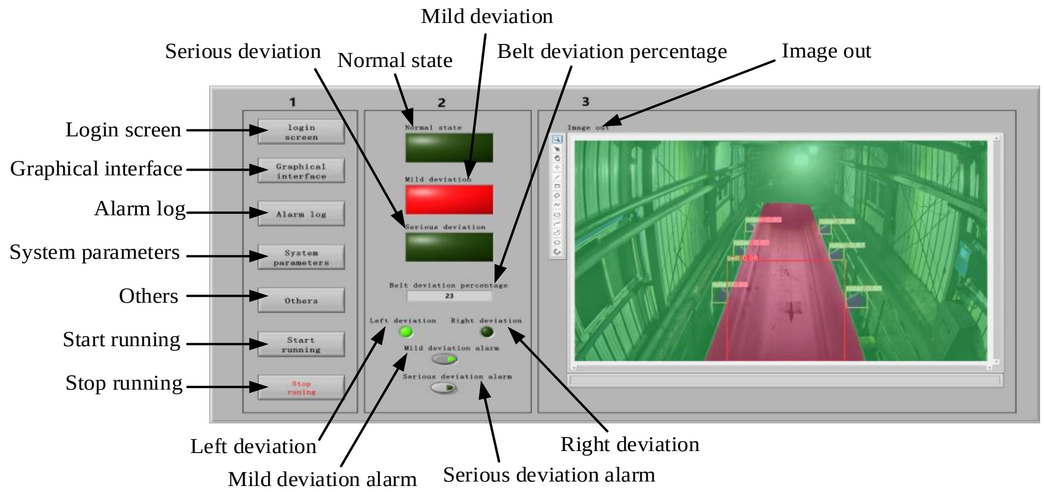


Fig. 6. System operator interface

TABLE III
SYSTEM TEST RESULTS

Belt status	Total number of samples	The number detected	The number of judgment errors	The number of not detected	False detection rate/%	Missed detection rate/%
Normal state	800	770	0	30	0.0000	0.0375
Mild deviation	1477	1507	30	0	0.0200	0.0000
Seriously deviation	705	705	0	0	0.0000	0.0000
all	2982	2982	30	30	0.0200	0.0375

IV. Conclusion

In this paper, a belt deviation detection system based on deep learning is designed. The multi-task learning model of joint object detection and semantic segmentation is used to judge the position of the belt and idler. The degree, direction and percentage of belt deviation are calculated by establishing a mathematical model of belt deviation. The operation interface is written by LabVIEW software. It makes the operation interface simpler and more convenient, and on-site operators can master it more quickly. The deep learning method is used to position the belt and idler, which improves the adaptability of the mathematical model of belt deviation judgment and avoids the influence on the belt deviation detection system under complex working conditions. The experiment shows that the error rate of the deep learning model for the belt and idler is almost zero, and the detection accuracy is high. Through the field test, it meets the actual user’s needs for belt deviation detection. Therefore, the system provides a guarantee for the normal operation of the belt conveyor to a certain extent, reduces the probability of failure, and provides a foundation for the detection of belt deviation under complex working conditions.

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