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Research on Classroom Lighting Automatic Control System Based on Personnel Target Detection

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Abstract. With the popularity of digital campus and the proposal of building a conservation campus, classroom lighting power saving is an important expense of electricity consumption in universities. Since most classrooms are equipped with cameras, this paper proposes an automatic classroom lighting control system based on personnel target detection to achieve intelligent lighting control and power saving. The main research consists of three parts. One is to study and optimize the YOLO personnel target detection algorithm, and use the data set for model training to improve the recognition accuracy of the system. The second is to build the hardware platform of the system, using the Raspberry Pi with GPU as the controller to improve the image processing speed. The third is to carry out the control flow design of the light groups and the design of the image display window to realize the centralized seating and lighting control of classroom. Classroom personnel identification experiments and ambient light brightness detection experiments were carried out respectively, and the experimental results showed that the system had faster response time consumption and higher classification accuracy. The system is simple and cost-saving to implement with the help of existing equipment, and the study has certain practical application value and universality.

Keywords. Target detection, Classroom lighting, Image segmentation, Deep learning, neural network.

1. Introduction

The learning situation of students in school classrooms can be divided into classroom and self-study room. The classroom usually has a capacity of 30 or 60 students, and students attend classes according to the class schedule, in which situation students can fill the entire classroom. Some classrooms provide the needs of large classes, the construction area is relatively large, there will be a large classroom and relatively few students, or the study room itself is rarely full of students. For the above two situations, it is necessary to locate and count personnel targets through personnel target detection in order to centralize seating and control the switch of light groups in classroom lighting areas to save electricity and provide an intelligent and comfortable learning environment.

There are two types of lighting control systems in classrooms, manual mode and automatic control mode [1], in which automatic control use infrared sensors to collect signals and determine the number of people in the area by infrared scanning, with a relatively large misjudgment rate, troublesome sensor arrangement, and susceptibility to natural light and angle. The control system usually uses PLC as the central controller to control the operation of the underlying field devices [2], and the fieldbus protocol is complex. A faster and smarter method for classroom lighting control is to perform personnel target detection with the help of computer vision, applying deep learning to image target detection can learn advanced features of images [3], single-stage target detection algorithms based on deep learning have been applied in several fields, and multi-channel ground target detection algorithms based on convolutional neural networks [4-5] can be solved for less real-world data and difficult to obtain samples of moving targets, and the above literatures provide the theoretical basis for this paper.

Based on the above theory, this paper proposes a classroom lighting automatic control system based on personnel target detection, investigates the personnel target detection and YOLO personnel detection algorithm, and builds the software and hardware environment. The experimental accuracy rate can achieve the requirements, and the system has certain universality, which further improves the intelligence and comfort of automatic control of classroom lighting. The systematic research framework is shown in Figure 1.

2. Related technologies

2.1. Personnel target detection

The purpose of personnel detection is to identify and locate all the people in a classroom by using deep learning algorithms to detect people in an image or video. Personnel detection is a challenging computer vision task which can be seen as a combination of image classification and localization. The personnel detection system has to be able to identify targets in an image and obtain their locations. Personnel detection is more complex than classification tasks because the number of persons in an image is variable and the precise location of the persons has to be obtained. Personnel detection can be used to record data about persons in a scene, determine and track their exact location, and also precisely tag them to control classroom lighting to save electricity.

Personnel detection is often confused with personnel identification. When there are any persons in the image, person identification assigns a "person" label to the image. Personnel detection draws a rectangle around the detected person and labels the "person" label. Personnel detection draws a rectangle around the detected person and labels the rectangle with the "person" label, and the model predicts where each person is and what label should be applied. Personnel detection provides more information about the image than Personnel recognition. A comparison of Personnel detection and Personnel identification information is shown in Figure 2.

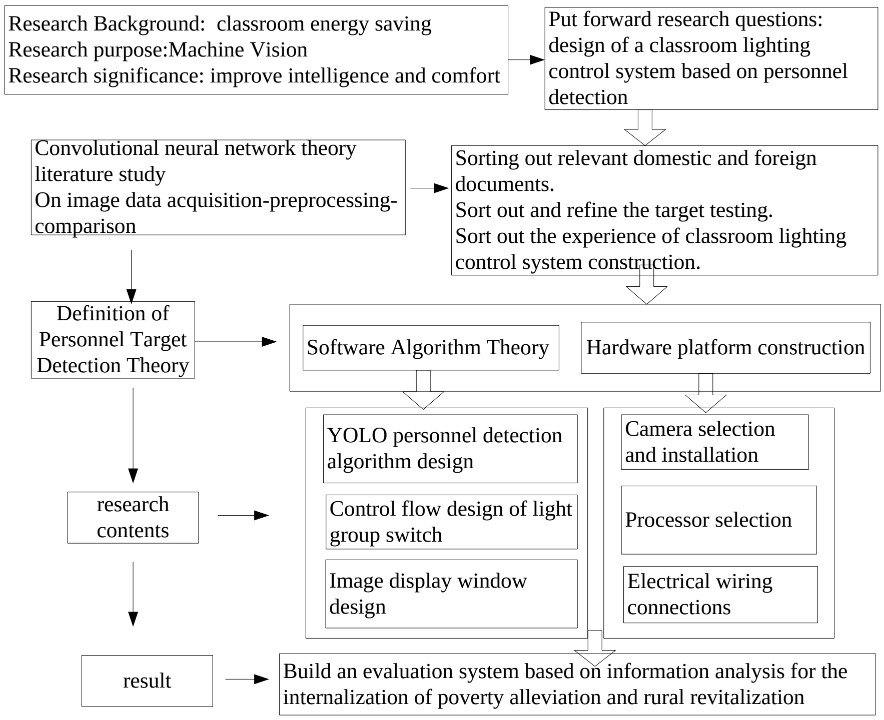

Figure 1. Research block diagram

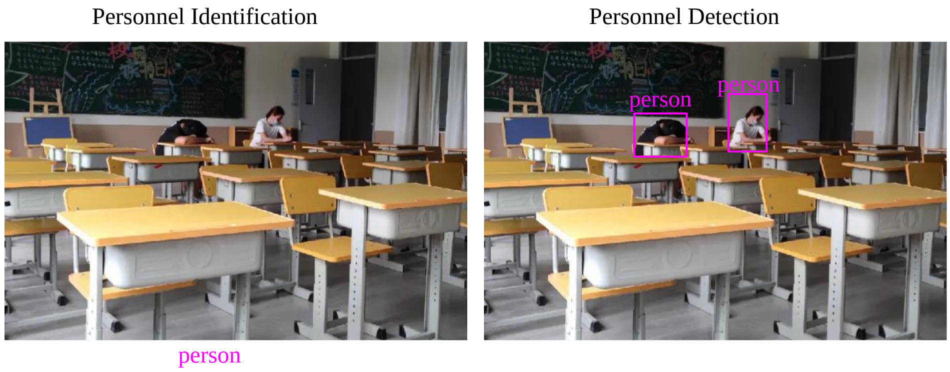

Figure 2. Comparison of Personnel Detection and Identification Information

Personnel detection is inextricably linked to other similar computer vision techniques such as Personnel identification and image segmentation. In automatic classroom lighting control systems, Personnel detection facilitates crowd counting to centralize seating, and presence/absence detection for lighting control.

This paper uses the VOC2012 dataset, which stands for Visual Object Classification Challenge 2012 [9-10]. This dataset contains data from the PASCAL visual object classification challenge, corresponding to the detection competition for classification. The training data consists of a set of images with 20 classes in the images. Each image has an annotation file that provides a bounding box and object class label for each object in the class, where only persons (i.e., person class) are detected. There are 17,125 images available for training, and the size of the data is approximately 2 GB, which can guarantee accuracy and confidence.

2.2. YOLO personnel detection algorithm

In this paper, we use the YOLO (You Only Look Once) target detection algorithm in machine vision technology to detect areas of people in a classroom by capturing classroom images with a camera [11-13]. The algorithm applies a single neural network to the whole image, then divides the image into regions and predicts the bounding boxes and probabilities for each region. These bounding boxes are weighted by the predicted probabilities.

Firstly, the input image is divided into S*S grids, where S is the number of grids. Then for each grid, there are B predicted bounding boxes, where B is the number of targets for each grid, and each bounding box contains 5 predicted values: x,y,w,h and confidence. Here the coordinate of the upper left corner of the grid is (0,0) and the coordinate of the lower right corner of the grid is (1,1). x and y are the horizontal and vertical coordinates of the center of the bounding box, so the values of x and y are numbers between 0 and 1. w and h represent the width and height of the bounding box relative to the percentage of the grid. If the bounding box exceeds the boundaries of the grid, the values of w and h may be more than 1.

Confidence contains two aspects, one is the size of the probability that the bounding box contains the target, and the other is the accuracy of the bounding box. The confidence represents the twofold information that the predicted bounding box contains the confidence of the person and the accuracy of the bounding box prediction, and its value is calculated as shown in Equation (1).

$$\Pr(Class_i|Object) \times \Pr(Object) \times IOU_{pred}^{truth} = \Pr(Class_i) \times IOU_{pred}^{truth} \tag{1}$$

In prediction, the probability of the category predicted by each grid and the confidence level of the bounding box prediction are multiplied to obtain which category-specific confidence kernel the i-th bounding box belongs to. The first term on the left side of equation (1) is the category information predicted by each grid, and the second and third terms are the confidence level of each bounding box prediction. The product is the probability that the predicted box belongs to a certain category, and also indicates the information about the accuracy of the box. If there is no person in the grid, the first term Pr(Object) is 0, and the confidence is 0. If there is a person, the first term Pr(Object) is 1, and the confidence is directly equal to the IOU value of the bounding box and the real box. The presence or absence of persons in the grid defined by YOLO is based on whether the centroid of a person image falls on that grid. If the centroid of a person image falls on grid A, it is only responsible for grid A, while other grids are not responsible for it no matter what percentage of person images they contain. Also, each grid has to predict the probability of C ($Pr(Class_i|Object)$) categories, where C is the number of categories, and it indicates the probability that a grid belongs to the person category under the condition of containing person images.

The structure of the YOLO model is inspired from GoogLeNet. The model adopts a convolutional neural network structure with 24 convolutional layers and two fully connected layers to which residual blocks are added to solve the gradient disappearance problem. The beginning convolutional layer is used to extract features and the fully connected layer is used to predict category probabilities and coordinates. The network structure of the YOLO personnel target detection algorithm is shown in Figure 3, and the final output is 19×19×30.

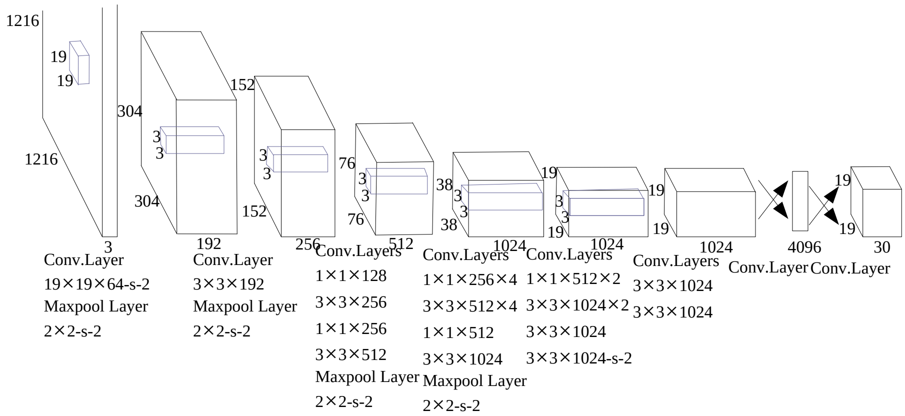

Figure 3. YOLO algorithm network structure diagram

In Figure 3, the YOLO network structure consists of 24 convolutional layers and 2 fully connected layers, with a network entry of 1216 × 1216, the final output dimension of the network is 191930. 1919 means dividing the image into 19 × 19 grids, and 30 indicates the size of the 3rd dimension of each grid, where the first 20 elements are the probability values of the categories, the 2 elements represent the confidence level of the bounding box (B=2), the last 5 elements are the values of the bounding box (x, y, w, h, confidence level). Therefore, the parameters to be predicted for each grid are B ×5+C, with a total of S × S × (B × 5+C) = 19 × 19 × (2 × 5+20) tensors. In this paper, the process of personnel target detection is unified into a single neural network that uses the entire image information to predict the bounding box of the personnel target while identifying the category of the personnel target to achieve an end-to-end real-time target detection task, as shown in Figure 4.

In Figure 4, the confidence information is specific to each bounding box, and the category probabilities are specific to the compartments. Each lattice will correspond to B bounding boxes, and the width and height range of the bounding box is the whole image, denoting the location of the boundary of the object found with that lattice as the center. Each bounding box corresponds to a score that represents the presence or absence of a person at that location and the accuracy of localization $\Pr(Object) \times IOU_{pred}^{truth}$. From equation (1), a kernel matrix of 20 × (19 × 19 × 2) = 20 × 722 will be obtained, where 19 × 19 × 2 is the number of bounding boxes and 20 represents the category. Each grid will correspond to C probability values, the category $\Pr(Class_i|Object)$ corresponding to the maximum probability is found and the grid is considered to contain the person or a part of the person.

The system captures images of the classroom through a camera and uses the YOLO algorithm to detect personnel targets and extract their location information. After predicting the category probabilities, the next step proceeds with non-maximal suppression, which helps the algorithm to eliminate unnecessary anchor points. After completing, the algorithm then finds the enclosing box with the next highest category probability and proceeds with the same process until all enclosing boxes of unequal size remain. The algorithm finally outputs the required vector showing the enclosing frame details of the person category.

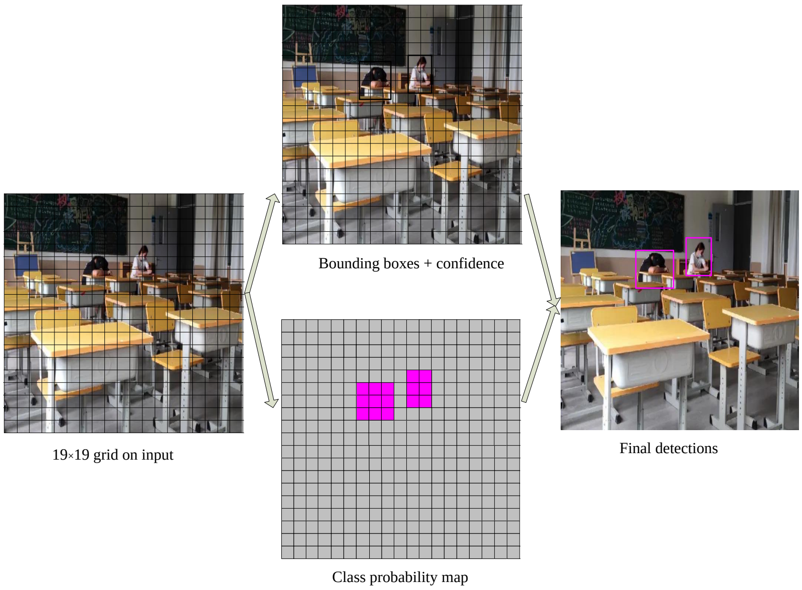

Figure 4. YOLO Algorithm Network Personnel Target Detection

The process of training a YOLO model to detect personnel targets in images is as follows:

Step 1: Data collection. Collect actual scene data, which is captured in real-time through cameras in the classroom.

Step 2: Data labeling. Using LabelImg annotation, add a bounding box and a category label for each human target object in each image. As described in this article, add a bounding box for each human target and label it as "Person".

Step 3: Data preparation. Convert to YOLO model format and convert annotation data into a format that can be read by the YOLO model. The YOLO model requires training data to be organized in a specific format, typically storing all annotation information in a CSV file and pointing the file path of each image to the corresponding line in the file.

Step 4: Model training. Use the selected deep learning framework PyTorch to implement the YOLO model and train it. The training requires defining the model structure, setting hyperparameters and providing training data.

Step 5: Model evaluation. During the training process, the performance of the model on the validation set is usually evaluated periodically, metrics are calculated based on the prediction results, and the model is adjusted based on these metrics.

Step 6: Model application. The model is called by OpenCV and used to detect person target information, including whether it is a person, person location information, and person statistics.

3. System Design

3.1. Establishment of hardware environment

Based on the size of the classroom and the usual layout of classroom lighting, the lighting area is divided into four areas: A, B, C, and D. Each area is controlled separately. Whether the lighting group needs to be turned on depends on the brightness of the classroom. The hardware composition is shown in Figure 5.

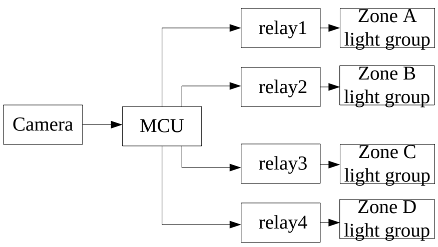

Figure 5. Hardware composition of classroom lighting automatic control

In Figure 5, the images are captured by the camera, analyzed by the MCU to determine if an area is occupied, and the four relays are controlled separately to control the lighting of the four groups of lights [14-15]. If there is no one in the classroom, it is not study time, or there is no need for supplemental lighting, all four sets of lights will be turned off. When there are fewer people in the classroom, if only one area is occupied, the light group in this area lights up. If there are fewer people and people are scattered, but the number of people is lower than the maximum number of seats available in an area, then determine which area is relatively more people, open which area of the light group to warn people to focus on the seat. Similarly, when the number of people is relatively large, the people are counted so as to determine the minimum number of groups of lights to be turned on to concentrate the seats.

3.2. Control process design

After the camera has captured the image, the system will analyze the image. When someone is detected, then check whether the current time is the system preset open time period of the classroom. If in the open time period and the light intensity is less than 100, the system will control the lights on. If in the set time period and light intensity more than 100, the system will control the lights off. If the time is not within the open time period, the lights will be turned off. If no person is detected, the lights will remain off. The control process is as follows:

Step 1: Input the image. Judge whether it is the classroom opening time. If the time is not in the open time period, the system will standby. Otherwise, the system will collect the luminosity information and determine whether the lights need to be turned on; if the lights need to be turned on, the system will start the camera to capture the image.

Step 2: Personnel identification. After format conversion of the captured image and image pre-processing, the area markers will be added. The system extracts the feature information of the person in the image and matches with the person model. That is, the system invokes the target recognition model for the recognition of the person target to determine whether there is information about the person.

Step 3: Personnel detection. If a person is detected, the system will add a person classification label and mark the person information precisely, including the location and confidence.

Step 4: Personnel count. Count the number of persons in the four areas of the classroom to centralize the seats.

Step 5: Control lighting. According to the result of personnel count, the system controls the switch of light groups in four areas of the classroom.

3.3. Design of Image Display Window

To facilitate experimental validation, the project has created an image display window for recognition and display of detection results. Firstly, store all the paths of the image in a file, read the data starting from the annotations of the file, and download the Yolov3 weights from the Internet, then convert the Darknet YOLO model into a Keras model, and finally implement the target detection [16-18]. Train the model and add model checkpoints, decrease the learning rate, stop in advance and tensor plates, then train the model with a freeze layer to get a stable loss and Adam Oprimizer compilation.

Freezing a layer is also a technique to accelerate the training of a neural network by progressively freezing the hidden layers. Freezing a layer in the context of a neural network is a way to control the update of weights. When a layer is frozen, which means the weights cannot be further modified. After completing the above actions, the training of the model is continued and the model is fine-tuned. To apply the change, the model will be recompiled with Adam Optimizer and then wrapped once more, thus saving weight.

To apply the model to the images of classroom scenes captured by the camera, it starts by taking the paths of the input and output images as parameters and loading the model and passing the configured paths and weights, followed by using Cv2 video capture to point to the output video file and determining the number of frames in the video, constructing a blob from the input frames, then performing a forward pass of the YOLO object detector, and finally giving the bounding box.

After performing the above operations, iterate through the output layers, add a border after each output, define its dynamic shape, filter out weak probabilities based on object size, apply non-maxima to suppress overlapping bounding boxes and ensure that at least one detection exists. Finally draw a bounding box rectangle and mark it on the frame, and then write the output frame to disk.

In the design of the classroom lighting control system, the distribution of persons in the classroom needs to be detected by the images taken by the camera. The human body model is trained by YOLO deep learning algorithm, and the YOLO algorithm is integrated with OpenCV. The whole system is completed by calling YOLO trained model and together with Qt UI interface.

To facilitate the invocation, the project encapsulates a yolo_Hand_Image() function in the code, which is used to implement OpenCV to invoke the YOLO model to recognize the input image and get the labeling result of the person target in the image. The specific implementation of the function is as follows:

QImage ImageHandle: yolo_ Hand_ Image (QImage m_image)

Set formal parameters in the function to pass in images of type QImage; First, save the size of the incoming image to m_ Center_ W and m_ Center_ H, and then set the parameters for processing the data, including the width and height of the input image, threshold, etc. Next, convert the QImage type image to the Mat type in OpenCV and convert the image from RGB format to BGR format. Next, calculate the average pixel value of the image and save it as the brightness of the image to m_ In lux.

Next, input the blob into the neural network and run forward propagation to obtain the output of the output layer. Subsequently, the output results are post-processed by calling the postprocess function to obtain the position information of the recognized human body region, and annotated on Mat type images.

During the recognition process, the running time of each layer was also counted and the processing time of the entire network was calculated. Finally, convert the processed Mat type image back to the QImage type and return the processed image.

4. Experimental Results and Analysis

4.1. Personnel Identification Experiment

Use ImageNet 1000 class dataset to pre train convolutional layers. In the pre-training, we used the first 20 convolutional layers in the Figure 2 network, plus the average-pooling layer and the fully connected layer. The model was trained for one week and obtained a top-5 accuracy of 0.88 (ImageNet2012 validation set), which is comparable to the accuracy of the GoogleNet model. Afterwards, the model was converted to a detection model by adding four convolutional layers and two fully connected layers to the pre-trained model, which improved the model input resolution (608×608 -> 1216×1216), the top layer predicted the category probability and the bounding box coordination values, and the width and height of the bounding box were normalized to the 0-1 interval by normalization. The personnel target detection UI is shown in Figure 6, which shows that effective detection is performed.

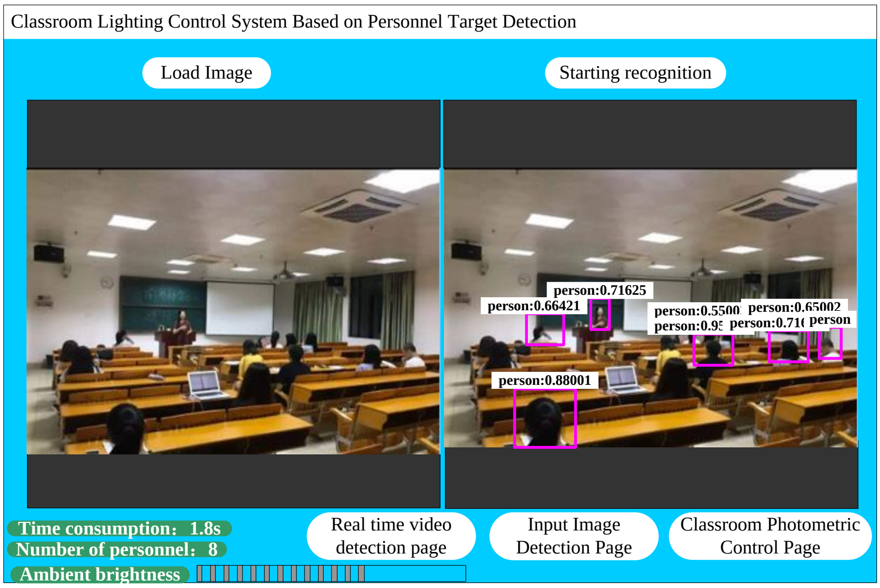

Figure 6. Personnel Target Detection

By clicking the load image and starting recognition button and uploading the image of the interior of the classroom that needs personnel recognition, the system can detect the number of persons and light intensity in the room. There are originally 12 people in the classroom. It takes 1.8 seconds to detect the number of the 8 persons. There are two reasons for the error. One is limited by the light of the classroom, the edge area is not well illuminated and the captured image is not clear. The other is affected by the training model, the comparison error caused by sitting upright or face-to-face camera recognition rate is higher. The other is the influence of the training model, resulting in a comparison error. The recognition rate is higher when sitting upright or facing the camera.

The image processing in the literature [19] uses the calculation of grayscale averages, which requires storing a frame to an internal Flash and calculating the grayscale average of two specific areas, using an embedded processor.

The image processing in the literature [19] uses the calculation of grayscale averages, which requires storing a frame to an internal Flash and calculating the grayscale average of two specific areas, using an embedded processor. The background is not updated when the person's position is not changed. The image is reread from Flash, binarized according to the threshold, then denoised, and finally the person location detection algorithm is executed for person detection. The background template will be updated when the person's position is changed.

The image processing in this paper is pre-trained with the YOLO deep learning algorithm, using the Python development language, and accelerated by GPU to complete 51,000 rounds of training on the model. When the number of iterations is 35000, the total loss of the model tends to level off and the model reaches the optimal state. We extract part of the image and classify the extracted image for area localization. The specific operation is to obtain a rectangular bounding box of persons in the classroom by YOLO deep learning algorithm human detection model, and take the human image coordinates of the center point of the rectangular bounding box. Assuming that the classroom is unoccupied and the illumination level is sufficient. The image coordinates of the person are mapped to the standard image of the classroom (which is unoccupied and the illumination level is sufficient) as the input image acquisition point of the person area localization model, and the input resolution of the model is used as the feature input of the model, and the classification is performed by the classification neural network to obtain the probability tensor of the coordinate point belonging to each area to determine the output of the illumination area where the person is located.

The response time consumption of the present system is compared with that of the literature [19] and the results are shown in Table 1.

Table 1. Comparison of system response time consumption

Serial number	Situation	Time consumption of literature [19]	Time consumption of the present system
1	Image data processing	2-3s	0.7s
2	No change in personnel position	5-6s	1.8s
3	change in personnel position	7-8s	2.3s

As can be seen from Table 1, the response time of the proposed scheme in this paper is significantly shorter than that of the system in the literature [19].

4.2. Environment brightness detection

For the PASCAL VOC dataset, the model needs to observe 19 × 19 × 2 = 722 bounding boxes and corresponding categories for each image. Training and testing are performed on the PASCAL VOC2012 dataset with 135 training rounds, a batch size of 64, a momentum of 0.9, and a learning rate delay of 0.0005. The ambient light brightness detection UI is shown in Figure 7.

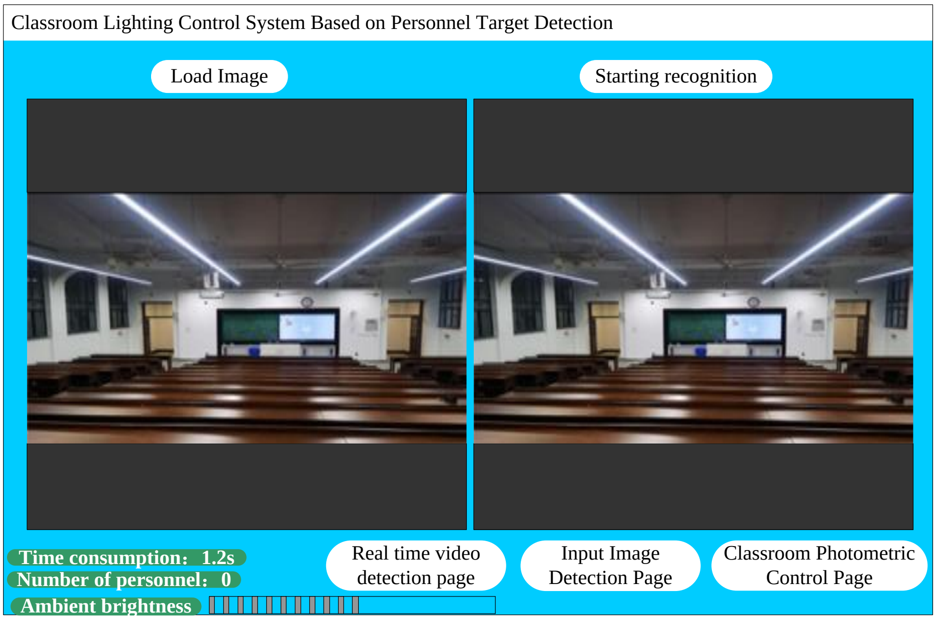

Figure 7. Detection of ambient light brightness

Based on the uploaded image, the system automatically determines the number of classroom personnel to be 0, while giving information on the detected light intensity. The detection time is shorter due to no human target markers.

Since ambient luminosity is the main factor affecting person target detection, insufficient luminosity cannot capture the person information, it is necessary to detect the ambient luminosity. The early target detection [20] uses the sliding window method to select candidate regions of different sizes on the image, and then uses manually designed features to extract features from the candidate regions, and finally uses a trained classifier for classification. There are some disadvantages of early target detection. On the one hand, the region selection of sliding window is traversing the whole image, which will generate more redundant windows, so the time complexity of this part is high and cannot meet the real-time application requirements. On the other hand, manually designed features tend to focus only on the target objects of the specific scene, and the model generalization ability is poor. In this paper, we adopt YOLOv3 for multispectral target detection, in order to achieve multimodal input. On the premise of ensuring the ambient luminance, by detecting the light radiation of the substance and the imbalance of foreground to background, different normative gradients are formulated according to the range of loss function during detection to calculate different ambient luminance values in order to obtain the target quickly and accurately from one image, and the most optimal strategy is used, which can improve the classification accuracy.

5. Conclusion

This paper designs and implements an intelligent classroom lighting control system based on machine vision technology. The system captures images through external surveillance cameras, with YOLO algorithm to identify the personnel area in the classroom, while calling OpenCV to judge the brightness of the ambient light and then according to the classroom open time range concentrating seats. Based on the above conditions, the system automatically turns on or off the lights in the classroom area based on comprehensive judgment to achieve intelligent lighting control. After practical experiments, the design can effectively achieve intelligent lighting control based on the number of persons and location information in the classroom, light intensity conditions. YOLO prediction process is convenient and quick and it can basically achieve real-time detection with a low prediction error rate. With full-image information for prediction, YOLO can learn the generalized information of the target, which has certain universality and high accuracy of target detection. The design does not take into account the issue of accuracy, and some persons may not be accurately identified due to their posture or the size of the target, which is a deficiency that needs to be improved. In the future, we will continue to perfect the system, further improve its intelligence and adaptability, and prepare for a wider range of application scenarios. As far as the current development is concerned, the system has good scalability and reliability, can be applied in different occasions and environments, and has certain promotion and application value.

Conflicts of Interest

The author declares no conflict of interest.

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