American Journal of Engineering Research (AJER) 2024
American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-13, Issue-2, pp-64-73
www.ajer.org
Research Paper Open Access

A Study of Teaching Quality Evaluation Based on YOLOv5 Classroom Field Detection

Xin-Ying Li, Rong Zhou
(School of Control and Computer Engineering, North China Electric Power University, Beijing, China)
Corresponding Author: Xin-Ying Li

ABSTRACT :*Teaching quality evaluation serves as a valuable tool for assessing both teachers' instructional methods and students' learning outcomes, making it instrumental in enhancing teaching quality and fostering the growth of students. In this paper, the YOLOv5 detection technology is utilized to detect the classroom field, which introduces a fresh perspective to teaching quality evaluation. Firstly, to address the issue of incomplete capturing of the entire classroom image by the rear camera, panoramic image stitching was used to restore the overall appearance of the classroom. Then, we utilized the YOLOv5 algorithm to accurately detect the classroom field from behind. Furthermore, we made modifications to the YOLOv5 network structure to enhance the accuracy of detection. Finally, we utilized the HSV color space and perspective transformation techniques to address the size variation problem in classroom images. This allowed us to effectively divide the classroom field into distinct areas. Subsequently, we developed an appropriate teaching quality evaluation algorithm based on these divisions. According to the experimental results, the average AP accuracy of the improved model is 3.2% higher than that of the YOLOv5s model. The proposed evaluation algorithm aligns with the classroom field theory and the resulting error falls within an acceptable range.*

KEYWORDS : *teaching quality evaluation; classroom field; YOLO target detection; panoramic image stitching; perspective transformation*

Date of Submission: 27-01-2024 Date of acceptance: 08-02-2024

I. INTRODUCTION

National development is inherently tied to the nurturing of talent, with colleges serving as pivotal cradles for cultivating such talent. In recent years, college education has garnered widespread attention across various sectors of society. The enhancement of teaching quality plays a crucial role in propelling the development of colleges and elevating the standard of talent cultivation. Teaching quality assessment forms the bedrock for continuous improvement in educational standards. Traditional methods of evaluating teaching quality primarily encompass the coursework achievement evaluation system and student final evaluation system, among others. While assessing teachers' performance based on students' coursework grades constitutes a significant aspect of teaching quality control in basic education, this approach may inadvertently foster a test-oriented atmosphere. To address the challenges associated with evaluating teachers' teaching quality through students' coursework grades, some colleges and universities have introduced a teachers' final evaluation system. However, it's important to note that this method tends to be more subjective and time-consuming[1].

With the development of various information technologies, numerous new forms of teaching quality evaluation have emerged. Principal component analysis stands out as a commonly employed statistical method in teaching evaluation. Ming-Ya Zhang [2] innovatively combined principal component analysis with machine learning algorithms. The researcher initially used principal component analysis to select appropriate evaluation indices and then utilized SVM to obtain the teaching quality evaluation results. This approach presents an effective framework for teaching quality evaluation. However, it's worth noting that different parameters exert a certain influence on the results, and the determination of optimal parameters remains an area requiring further exploration. Feng-Qing Li [3], on the other hand, devised a hybrid teaching quality evaluation model that integrates process evaluation and summative evaluation. The evaluation results were obtained through an analysis of students' comprehensive learning experiences before class, during class, after class, and at the end of the term. The classroom serves as the primary setting for teaching, with the classroom situation being a focal point of the teaching evaluation system[4]. Scholars often gauge the quality of teaching directly through the classroom environment. Classroom videos, capable of capturing a plethora of details, offer diverse data for teaching analysis[5]. The observation of classroom videos facilitates the analysis of teaching situations, providing abundant and objective evidence for research on classroom teaching[6]. In addressing the challenges associated with manual classroom observation, which is time-consuming and prone to oversight, Cong-Hua Xie [7] conducted an analysis and processing of classroom videos based on visual and textual features. This approach effectively overcomes the limitations of manual observation, meeting the demands of teaching evaluation more efficiently. There is a significant correlation between students' facial expressions and their mastery of knowledge points during classroom learning[8]. Han Li[9] utilized facial expression recognition technology to document students' states in the classroom, enabling a more accurate analysis of teaching and learning effectiveness. However, this approach carries a certain risk of compromising students' privacy. Research by Rainer[10] demonstrated that head posture serves as an excellent indicator of attentional focus. Meanwhile, Zaletelj and Kosir[11] employed a Kinect camera to determine students' head posture, gaze direction, facial expression, and body posture. Features were extracted through computer vision techniques, and five observers assessed students' attention levels for each second in the image. The data were incorporated into a training set for model training, resulting in a 75.3% accuracy in automatically detecting student concentration. While this method aids in determining student attention levels during teaching, there is a potential for misjudgment of body posture in real classroom settings.

To address the challenges associated with privacy concerns in evaluating teaching quality through facial expressions and other methods, as well as the time-consuming and labor-intensive nature of traditional evaluation methods, this paper introduces a teaching quality evaluation approach grounded in the classroom environment. This method involves the utilization of a rear camera to capture classroom images, enabling real-time detection of the evaluation effect while safeguarding students' privacy.

Bourdieu highlighted that "a field can be defined as a network of objective relations between various positions"[12]. Similarly, the classroom constitutes a field, representing a relatively independent space characterized by distinct positional relationships. The selection of seating positions by students in the classroom is intricately linked to their motivation to learn[13], prompting extensive analysis and study by scholars. Vander Schee[14] categorized seating into four groups: front, middle-front, middle-back, and back rows, discovering a gradual decrease in students' scores in the course with increasing distance from the podium. Naz Kaya's study[15] revealed that students positioned in the front and center rows exhibited the best classroom performance.Ya-Li Yao et al.'s research[16] demonstrated a high positive correlation between teacher evaluation scores and the number of students choosing front-row seats, as well as a high negative correlation with the number of students opting for back-row seats. Koneya[17] found that students displayed greater creativity, motivation, and attentiveness within the triangular area formed by the middle seats from the front to the middle rows. In summary, students' positioning within the classroom field serves as an indicative factor for teaching quality evaluation.

The main contributions presented in this paper are as follows:

- This paper presents an extensive study of teaching quality evaluation.
- This paper constructs a classroom dataset based on classroom rear camera shots and uses image stitching techniques to restore the overall appearance of the classroom, solving the problem that a single camera angle cannot capture the complete image of the classroom.
- In this paper, the network structure is improved based on YOLO to enhance the classroom field detection accuracy.
- This paper proposes a teaching quality evaluation algorithm based on classroom field, which provides a new perspective for teaching quality evaluation.

The next sections of this paper are organized as follows: Chapter 2 describes the dataset acquisition sources and the classroom image panorama stitching process. Chapter 3 details the YOLO algorithm which is used to detect classroom fields, and improves the network structure. Chapter 4 proposes a specific algorithm for teaching quality evaluation and analyzes the evaluation results. A conclusion of our work is shown in Chapter 5.

II. CLASSROOM IMAGE PANORAMA STITCHING

2.1 Image Stitching Process

The installation of front and rear surveillance cameras is becoming increasingly common in university classrooms for the purposes of maintaining school security and facilitating examination supervision. Considering the potential privacy concerns that may arise with the use of front-facing cameras, this paper chooses rear cameras to capture classroom photos for experiments. Due to camera scaling limitations in some schools, it may be difficult to capture the entire classroom with just one camera angle. To address this issue, classroom photos are taken from multiple angles before conducting field detection. These photos are then stitched together using panoramic image stitching techniques to restore the overall appearance of the classroom, which serves as the foundation for subsequent field detection and teaching quality evaluation.

Image stitching technology is a technique that stitches together several images with overlapping parts in the same scene to form a panoramic view image[18]. Generally speaking, the image stitching process is shown in Fig.1.

Fig.1. Image stitching process

Among them, image registration mainly refers to the process of determining the overlapping areas of images, which includes feature point detection, feature matching and image transformation. Image fusion mainly refers to the process of stitching the aligned images together to form a panoramic image. Since there may be differences in resolution and lighting between the aligned images, a certain fusion process is needed to make the stitched panoramic image appear more natural and visually appealing. This enhances the overall visual effect of the image.

2.2 Image Registration

Due to the difference in shooting angles, the angles of the images to be matched are often different. Therefore, these images need to be standardized under one standard before stitching. Image registration is a crucial aspect of panoramic image stitching, and the key is to find out the common features of the images to be matched, calculate the appropriate transformation model through the correspondence between images, and unify multiple images to be matched into a common image plane. The image registration steps in this paper are as follows:

1. The Scale Invariant Feature Transform (SIFT) algorithm is utilized for feature matching of images. SIFT was proposed by David G. Lowe[19] and is based on the local appearance of objects, which remain invariant to scaling, rotation, and luminance transformation. This algorithm has strong stability and is widely used in image feature extraction.
2. The Random Sample Consensus (RANSAC) algorithm is used to eliminate mismatched points and find the optimal homography matrix, which is then applied to transform all the images to be matched onto the common image plane. After obtaining the correspondence between the feature points through feature matching, the homography matrix can be computed. The homography matrix reflects the coordinate transformation relationship of points in space between different projection planes, which can align the images to be matched into a common reference frame. However, incorrect matches may occur during feature matching, and the homography matrix obtained from these mismatches can cause large errors in image registration. To address this issue, this paper employs the RANSAC algorithm to iteratively find the optimal homography matrix and eliminate the mismatched points, thus completing the image registration process.

2.3 Image Registration

This paper has chosen to use the left, middle, and right images for image stitching. The captured images are shown in Fig.2, where there are overlapping areas between the left and middle images, as well as between the middle and right images. By stitching these three images together, the complete classroom seating area can be captured, which meets the requirements for image stitching and subsequent experiments.

Fig.2. Pending stitching image

The collected classroom images are stitched together to create a composite image, which is presented in Fig.3. The stitching effect is satisfactory, as the stitched image effectively restores the overall appearance of the classroom and the stitching traces are not noticeable.

Fig.3. Panoramic image of the classroom after stitching

III. YOLO CLASSROOM FIELD DETECTION

3.1 Overall Algorithm Structure

To evaluate the classroom, the first step is to detect the location of students within the classroom field. This paper uses YOLOv5 object detection to identify the backs of students' heads and determine their locations, laying the foundation for subsequent teaching quality evaluation. The YOLOv5 target detection algorithm was proposed by Ultralytics in 2021 which belongs to the single-stage detection algorithm category[20]. Compared to two-stage algorithms, it is faster and performs well in real-time data processing. Compared to other versions of YOLO, YOLOv5 exhibits the highest stability on this dataset, making it the chosen model for experimentation. The YOLOv5 algorithm consists of four main components. The first is the Input, which handles data enhancement and some preprocessing operations. The second component is the Backbone, which extracts features from the input data. The third component is the Neck, which is responsible for fusing the features extracted by the Backbone. The last component is the Head, which performs category and location regression detection. Together, these components allow YOLOv5 to efficiently detect and classify objects in real-time data processing.

In this paper, we propose an algorithm based on an improved YOLOv5 classroom field detection method to address the characteristics of having more small target objects in the experimental dataset. We achieved this by adding the Convolutional Block Attention Module (CBAM) to enhance the key features and improve the model's attention to small target objects. The overall structure of the improved algorithm is shown in Fig.4.

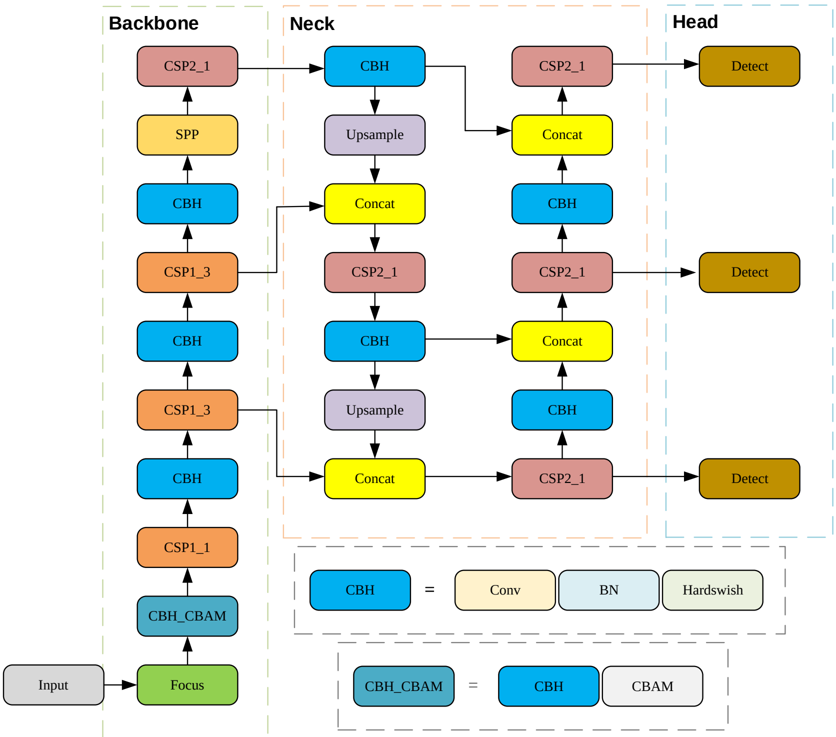

Fig.4. The structure of the improved YOLOv5 network

3.2 Adding CBAM

As the depth of the network increases, it is possible that some of the details of small targets may be lost, leading to a decrease in detection accuracy. To overcome this issue, one approach is to introduce an attention mechanism in the shallow layers of the network. This can help improve the model's focus on important details and prevent the loss of relevant features required for detecting small target objects in the deeper layers of the network. In this paper, there are many small target objects in the dataset, so we consider adding the CBAM to the convolution operation after the Focus layer in Backbone to improve the attention of the shallow network to small targets.

The attention mechanism simulates how the human brain processes information, making further feature extraction for specific feature maps, boosting the weights of focused regions and suppressing the weights of useless regions. CBAM is a type of attention mechanism that consists of two parts: Channel Attention and Spatial Attention. The Channel Attention module calculates the importance of each channel, and rescales the feature map accordingly, while the Spatial Attention module selectively focuses on important regions and suppresses unimportant regions. By combining both types of attention, CBAM performs better on the classroom dataset compared to focusing on only Spatial Attention or Channel Attention.

The schematic diagram of the CBAM module, as shown in Fig.5, first passes through the Channel Attention Module (CAM), obtaining two $1 * 1 * C$ feature maps by global max pooling (GMP) and global average pooling (GAP). These features are then fed into a Multi-Layer Perceptron (MLP) to reduce the number of parameters, and the resulting features are summed and passed through a sigmoid function to generate the channel attention *Mc*. *Mc* is then multiplied with the initial input feature map *F* to generate the input feature map *F'* for the Spatial Attention Module (SAM). In the SAM, channel-based GMP and GAP are performed on *F'*, and the resulting feature maps are spliced in the channel direction. These feature maps undergo convolution operations and sigmoid functions to generate the Spatial Attention *Ms*. Finally, *Ms* is multiplied with *F'* to obtain the output feature map *F''*. The combination of CAM and SAM helps improve the model's attention to small target objects, enhancing the detection performance.

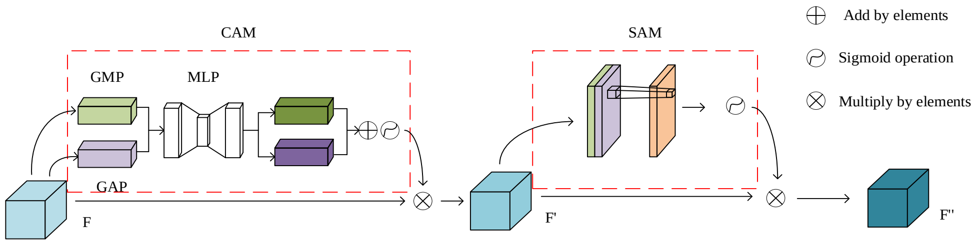

Fig.5. CBAM structure

3.3 Ablation Experiments

To assess the efficacy of the proposed enhanced strategy, an ablation experiment was conducted. YOLOv5 was partitioned into four versions, namely YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x, based on distinct network depth and width configurations. YOLOv5s, characterized by its streamlined design in terms of network depth and feature graph width, stands out for its computational efficiency and swift detection speed. It particularly excels when deployed on devices with limited computing resources. Given the experiment's emphasis on real-time performance and the aspiration for streamlined deployment in future applications, the YOLOv5s version was selected as the benchmark algorithm. This version demonstrates commendable real-time reasoning capabilities, and its lightweight design streamlines subsequent deployment, facilitating seamless integration into real-world applications and adaptability to diverse environments.

In the realm of target detection, the primary metric for assessing model performance is *AP* (Average Precision). *AP* takes into account Precision and Recall across various confidence thresholds, computing the area under the precision-recall curve. This comprehensive evaluation considers both the accuracy and recall aspects of the model in the detection task, providing a nuanced understanding of its effectiveness. Their calculation methods are shown in Eq. 1, Eq. 2 and Eq. 3.

$$\mathrm{Recall} = \frac{TP}{TP + FN} \tag{1}$$

$$\mathrm{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\mathrm{AP} = \int_0^1 P(R)\mathrm{d}R \tag{3}$$

Where *TP* is which the predicted result of the classifier is positive samples, and the actual samples are positive samples, that is, the number of positive samples correctly identified; *FP* is which the predicted result of the classifier is positive samples, but the actual sample is negative samples, that is, the number of negative samples that are falsely positive; *FN* is which the predicted result of the classifier is negative samples, but the actual sample is positive samples, that is, the number of positive samples missed; *TP+FN* is the number of all positive samples; *TP+FP* is the number of all positive samples divided into positive samples; *P* and *R* represent Recall and Precision, respectively, which are calculated in the first two formulas.

In this experiment, the model performance was evaluated using *AP@.5* and *AP@.5:.95* metrics. *AP@.5* was computed with an *IoU* threshold of 0.5, while *AP@.5:.95* extended the assessment across multiple *IoU* thresholds. The *AP* values under different thresholds were calculated and averaged, providing a more comprehensive evaluation of the model's performance by considering variations in *IoU* thresholds.

The results of the ablation experiments are presented in Table 1, indicating that the inclusion of CBAM resulted in an increase of 3.2% in *AP@.5*, and a 2.2% increase in *AP@.5:.95*. In addition, the *P* and *R* scores also increased by 2.7% and 0.4%, respectively. These results indicate that adding CBAM to the shallow network enhances the model's attention to small targets, which leads to improvements in all model metrics, and thus confirms the effectiveness of the proposed improvement strategy.

Table 1. Ablation experiments

Model	P(%)	R(%)	AP@.5(%)	AP@.5:.95(%)
YOLOv5s	0.649	0.831	0.757	0.459
YOLOv5s+CBAM	0.662	0.835	0.789	0.481

IV. TEACHING QUALITY EVALUATION

4.1 Classroom View Transformation

As illustrated in the stitched classroom images in Fig.3, the photos captured by the rear camera suffer from the issue of small pixels in the front row and large pixels in the back row. Consequently, they cannot be directly used to evaluate and partition the classroom area. To overcome this challenge, the classroom must first be transformed into a top-view image with uniform pixel density in each row. This process involves the following steps:

1. The HSV color space is employed to identify the seating area in the classroom. Typically, school desks are uniformly colored and have a significant color difference from other objects present in the classroom. Hence, this characteristic can be leveraged to isolate the classroom area in the image. The HSV color space comprises three components: Hue, Saturation, and Value. In comparison to the RGB color space, it is more in line with human visual perception and allows for easier adjustments to color saturation and brightness. Therefore, this paper employs the HSV color space to filter the seating areas in the classroom successfully. Table 2 displays the parameter intervals in the HSV color space that were identified for the seating section of the classroom photos used in the experiment. It has been confirmed that these intervals are suitable for filtering out the classroom seating area. Fig.6 depicts the outcome of applying the color filtering using the parameters outlined in Table 2, where the white area represents the filtered seating area. However, due to occlusion caused by students, certain seat areas could not be filtered out. Nevertheless, the edges of the seat areas remain distinct, allowing the subsequent operation of identifying the boundary points to be executed accurately.

Table 2. Seating area parameters

Parameter	Value
Hue Minimum	0
Hue Maximum	32
Saturation Minimum	135
Saturation Maximum	48
Value Minimum	239
Value Maximum	255

Fig.6. HSV seating area

2. Find the four boundary points of the seating area. Determine the minimum external matrix of the region after performing HSV color space detection. As shown in Fig.7, the blue part represents the minimum external matrix of the seating area, while the green part denotes the rotatable minimum external matrix of the seating area. Due to significant deviations between the four corner points of the blue part and the actual boundary points, the paper adopts a loop approach to gradually approximate the seating area by iteratively adjusting the step size for each corner point. The upper step size is set to 10 pixels and the lower step size is set to 20 pixels. The red part in Fig.7 depicts the seat area obtained after the loop, with the four corner points representing the desired boundary points.

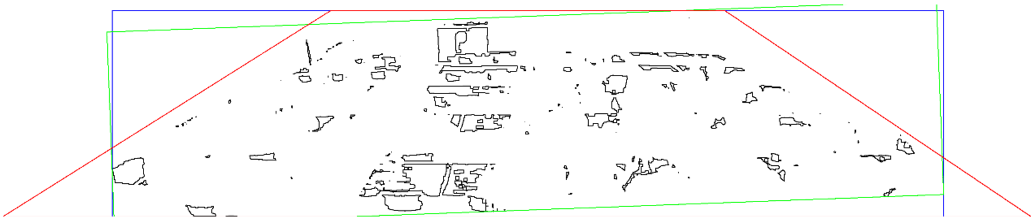

Fig.7. Seating boundary area

3. Use perspective transformation to adjust the image to the top view. Using the obtained four boundary points and their corresponding points on the target image, calculate the perspective transformation matrix by Eq. 4 and Eq. 5, and then apply this matrix to the whole seating area to realize the effect of adjusting the image to the top view.

$$\begin{pmatrix} x' \\ y' \\ w \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \tag{4}$$

$$\begin{cases} X = \dfrac{x'}{w} \\ Y = \dfrac{y'}{w} \end{cases} \tag{5}$$

Where, $\begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}$ is the perspective transformation matrix, (x, y) is the coordinate of the boundary point, (x', y') is the coordinate of the transformed point, w is an auxiliary variable used for normalization, and (X, Y) is the corresponding point on the target image.

4.2 Teaching quality Evaluation Criteria

In the classroom field, the area shaped like a "T" that forms between the front and center rows is where teacher-student interaction and student performance are the highest, followed by the other areas in the middle row, with the back row having the worst performance. Under the same classroom size, a higher number of students in the "T"-shaped area leads to a better overall evaluation of classroom teaching, while a higher number of students in the back row area results in a worse overall evaluation of classroom teaching. In this paper, the classroom field is divided into nine parts: left front, middle front, right front, left middle, middle, right middle, left back, middle back, and right back. The left front, middle front, right front and middle form the "T" advantaged area *A*, the left middle and right middle form the general area *B*, while the left back, middle and right back form the disadvantaged area *C*.

The study counted the number of students in each of the divided zones and calculated the proportion of students in each zone. Classroom scores were then calculated for students in the advantaged, average, and disadvantaged areas using a ratio of 10:5:1, as illustrated in the following Eq. 6:

$$E = \frac{n * (10 * a + 5 * b + c)}{t} \tag{6}$$

In this formula, *E* represents the overall teaching quality evaluation, *a* represents the percentage of students in the advantaged area, *b* represents the percentage of students in the average area, and *c* represents the percentage of students in the disadvantaged area. The variables *n* and *t* represent the count of students attending classes and the total number of students selecting courses, respectively.

According to this formula, the spectrum of classroom evaluation spans from 0 to 10, encompassing the desired range. In this context, the lowest possible evaluation occurs when all students who have chosen the course fail to attend, resulting in an evaluation score of 0. Conversely, the highest possible evaluation is achieved in the scenario where all students attend the class and opt to sit in the front row, yielding a class evaluation score of 10.

4.3 Evaluation Results

The above evaluation algorithm was applied to assess the classroom teaching of each of the three classrooms depicted in Fig.8, Fig.9, and Fig.10, which were captured using the classroom rear camera. These classrooms vary in seating layout, classroom size, and student distribution, among other factors.

Fig.8. Classroom 1

Fig.9. Classroom 2

Fig.10. Classroom 3

The evaluation results of the three classrooms are shown in Table 3 , where A, B and C represent the number of students in area A, B and C respectively.

Table 3. Evaluation results

	A	B	C	Algorithm evaluation results
Classroom 1	8	5	3	6.75
Classroom 2	9	3	3	7.2
Classroom 3	0	0	9	1

The results in Table 3 reveal that Classroom 3 had a low evaluation score, likely due to the fact that students were mainly seated in the back row. On the other hand, Classrooms 1 and 2, where students were concentrated in the middle and front rows, received evaluation scores in the upper-middle range, which is consistent with the classroom field theory.

4.4 Comparative Experiments

To assess the validity of the algorithm, a comprehensive comparison was conducted with the National Survey of Student Engagement (NSSE) questionnaire. Serving as an industry benchmark for evaluating learning engagement, NSSE questionnaires have significantly contributed to enhancing the learning quality of American undergraduate students[21]. This study specifically delves into various dimensions of the NSSE questionnaire, including Academic Challenge, Quality of Interaction, among others. Surveys were conducted among students in 50 classes, and the questionnaire options, along with their corresponding results, were quantified into a scale of 10 points. The experimental results, depicted in Fig.11, showcase the correlation between the 50 classes and their respective classroom evaluation scores. This comparative analysis seeks to provide a thorough insight into the algorithm's accuracy in assessing student classroom engagement, ultimately validating it against established industry standards.

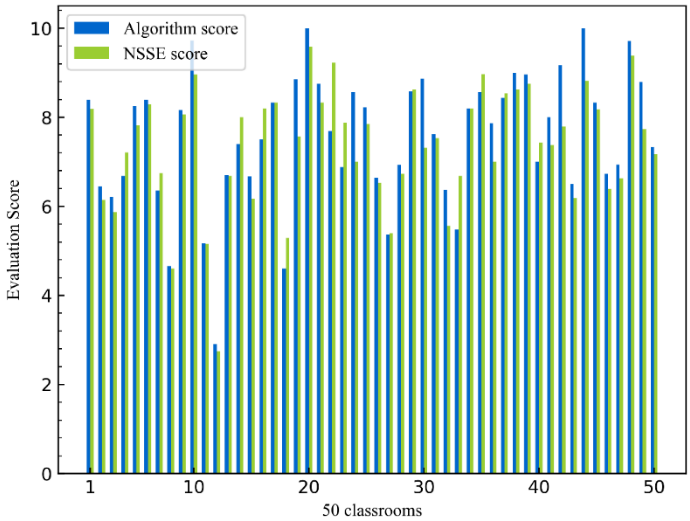

Fig.11. Comparison results

The bar chart shows that the algorithm evaluation results are approximately consistent with the expected results, with an average deviation of 0.5. The study found that the algorithm performed better in small classrooms, where the classroom areas were more accurately delineated, and the results were basically consistent with the expected results. Additionally, there were few instances of missed target detections. Some classrooms had larger errors in their teaching evaluation results, which were found to be larger in size and with more occlusions compared to other classrooms. Larger classrooms tend to be more sensitive to pixel changes when dividing regions, resulting in more chances for students at the intersection of regions to be incorrectly divided into other regions. Additionally, due to the high number of students in the classroom, many seat positions may be obscured during HSV filtering of the seat regions, leading to inaccuracies in the region screening process. Despite this, most of the evaluation deviations were within acceptable limits, indicating the feasibility of the teaching quality evaluation approach proposed in this paper.

V. CONCLUSION

In this paper, we propose a teaching quality evaluation algorithm based on the classroom field, leveraging the correlation between the location of students in the classroom field and the teaching quality evaluation elements. We also introduce the concept of classroom panoramic stitching during the algorithm design process to address the issue of a single photo from the rear camera being insufficient to display the overall appearance of the classroom. Additionally, we improve the YOLOv5 algorithm to enhance the detection accuracy of the classroom dataset. After testing, the teaching quality evaluation algorithm proposed in this paper has met the expected results and can serve as a powerful tool and reference for future teaching quality evaluation. Additionally, the proposed evaluation algorithm can be combined with other algorithms to evaluate and analyze classroom teaching from multiple perspectives, further improving the quality and effectiveness of classroom teaching. However, subsequent research will focus on optimizing the algorithm to address the aforementioned issues, enabling it to be applied to classrooms of varying sizes and improving its overall applicability.

ACKNOWLEDGEMENT

This paper is supported by the project "Research on Key Technologies of Real-time Visual Monitoring of High Voltage Line Operating Status Based on LOF" (No.2023-769) of North China Electric Power University.

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